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Original Article

Geospatial Analysis of COVID-19 Death Rate and Influencing Factors in the Middle East and North Africa Region

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ABSTRACT

Introduction: This study uses advanced geospatial modeling to analyze key determinants of COVID-19 death cases across the Middle East and North Africa (MENA) region, aiming to reveal spatial patterns and inform targeted interventions for enhanced public health response.

Methods: This study employs GIS and geostatistical models, including OLS, SLM, SEM, GWR, and MGWR, to analyze spatial and demographic determinants of COVID-19 mortality across MENA. By examining socioeconomic, medical, and demographic factors, it identifies key drivers and explores spatially non-stationary relationships impacting death rates.

Results: The study found that hospital bed allocation, unemployment rate, and vaccination doses positively correlate with COVID-19 death cases in MENA, likely due to better reporting and healthcare access. The OLS model ($R^2 = 0.7346$) highlighted spatial autocorrelation, prompting the use of SLM and SEM, which confirmed predictor significance. GWR ($R^2 = 0.8140$) and MGWR ($R^2 = 0.8187$) revealed spatially non-stationary relationships, with hospital beds impacting the northwest (GWR) and southwest (MGWR). Unemployment was significant in the northeast (Iran, Turkey) and northwest (Morocco), while vaccination doses were notably influential in Iran and Somalia.

Conclusion: This study emphasizes the significant roles of healthcare capacity, socioeconomic factors, and vaccination coverage in influencing COVID-19 mortality across MENA. It highlights the vulnerability of healthcare systems in developing countries and underscores the need for targeted resource allocation. Using spatial models like GWR and MGWR, the research reveals regional variations, especially in the northwest, advocating for tailored, region-specific interventions. By integrating GIS and geostatistical models, this analysis lays a foundation for future research on COVID-19 dynamics, providing crucial insights to inform policy measures for better public health crisis management.

Introduction

The Middle East and North Africa (MENA) region has been severely affected by the COVID-19 pandemic. According to Our World in Data, as of August 2023, the region has reported over 28 million COVID-19 cases and more than 800,000 deaths.[1] Spatial

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analysis can be used to identify the factors that are associated with the high death toll from COVID-19 in the MENA region. This information can be used to develop targeted interventions to reduce the spread of the virus and improve the health outcomes of people in the region.

There are several studies on COVID-19 around the globe, but not much about the death incidence. However, they all focused on the factors that led to an epidemic in a particular area or nation and used various statistical techniques. Using spatial autoregressive models (SAR) and geographically weighted regression (GWR) models, Ganasegeran and co-workers in Malaysia discovered that the spread of COVID-19 has been shown to be influenced by density of population, followed by average household income per capita and the GINI.[2] Bayode and colleagues combined the spatial statistical methods (SEM, SLM and OLS), and they discovered that the population density is statistically meaningful.[3]

From the methodological perspective, to identify the death incidence, Urban and Nakada used the (GWR) model to analyze the relationship between COVID-19 death incidence and several socioeconomic and environmental factors.[4] The research has demonstrated the spread of COVID-19 in regions with very vulnerable populations, and these results reflect current studies, highlighting the need for particular attention in outlying regions and rural villages.[4] Kotov and co-workers used the excess mortality as a measure of fatalities direct and indirect caused by COVID-19; their results showed that, the number of older people is one of the most important things that contribute to the high death rate, and the structure of jobs shown by the number of people working in manufacturing by using global OLS and SEM models.[5]

To effectively stop the spread of COVID-19, it is important to know how often people die from this epidemic. Therefore, this research aimed to do a geographical modeling analysis of COVID-19 in the MENA region utilizing GIS.

Materials and Methods

Background and Study Database

The COVID-19 disaster is not the first to hit the area. Even before the coronavirus (COVID-19) pandemic reached MENA countries in March 2020, the region faced several serious social and economic challenges exacerbated by the outbreak, the fall in oil prices from 2014 to 2016, and the resumption of demonstrations in 2019 in nations that had avoided the first wave in 2010–2011.[5] According to studies, the death rate was lower the earlier the government acted.[6] Even though school closures significantly influenced them, they were not as successful as earlier government initiatives. The government must decisively and quickly combat the infection.[7] It is easier to fight COVID-19 in nations with strong democratic institutions, the rule of law, property rights protection, and political stability. Government actions are, therefore crucial in helping the country combat the COVID-19 outbreak.[8]

Several classifications exist for the Middle East and North Africa, and we would use the categories of the World Bank and United Nations Statistics Division (UNSD).[9] The World Bank and UNSD provide a list of the countries in the MENA region including Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq,

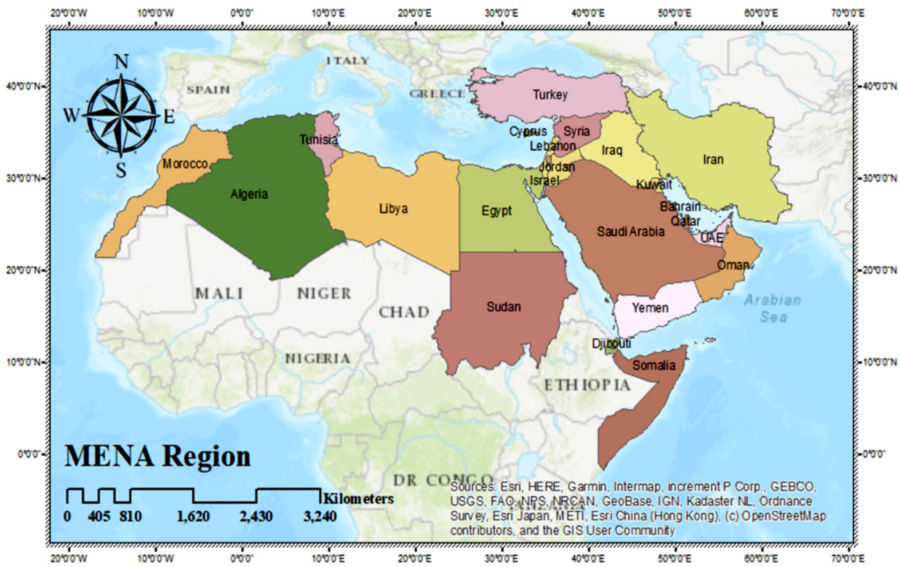

Figure 1. The MENA region map

Sudan, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Tunisia, Palestine, Qatar, Saudi Arabia, Syria, Somalia, Turkey, Cyprus, the United Arab Emirates, and Yemen (Figure 1).[10, 11]

The data used in this analysis was gathered from the organizations Our World in Data https://ourworldindata.org/covid-cases, the International Labor Organization https://ilostat.ilo.org/data/, and PEMANDU Associates https://covid19.pemandu.org/, who oversee tracking COVID-19 and other explanatory factors throughout the MENA region. Data on disease prevalence was gathered from the first case in each nation until December 2022. The crude death number was calculated at the whole region level (Figure 2). The geodatabase was created through the GIS environment software (GeoDa 1.20.0.20, QGIS 3.30.2, and ArcMap 10.8.2) and RStudio 2023.06.0 was used to connect the demographic, health care, and socioeconomic dependent and independent variables to the boundary shapefile of administrative geographical in the MENA region (Table 1). To figure out whether sociodemographic characteristics are connected to the occurrence of COVID-19 in the MENA region, three global OLS, SEM, and SLM and two local GWR and Multiscale-GWR models were used. By enabling the computation of non-stationary (local) parameter values instead of stationary parameter estimates, the local modelling procedure significantly improves upon conventional global regression. The R^2 and the Akaike Information Criterion (AIC) were used to analyze the performance of the models to explain death incidence in the MENA region.

The non-spatial global regression model

The Ordinary Least-Squares model is a linear connection between a continuous response variable and a group of predictor variables; it presupposes steady and stable geographical correlations.[6] The OLS model presumes independence among all observations. Here

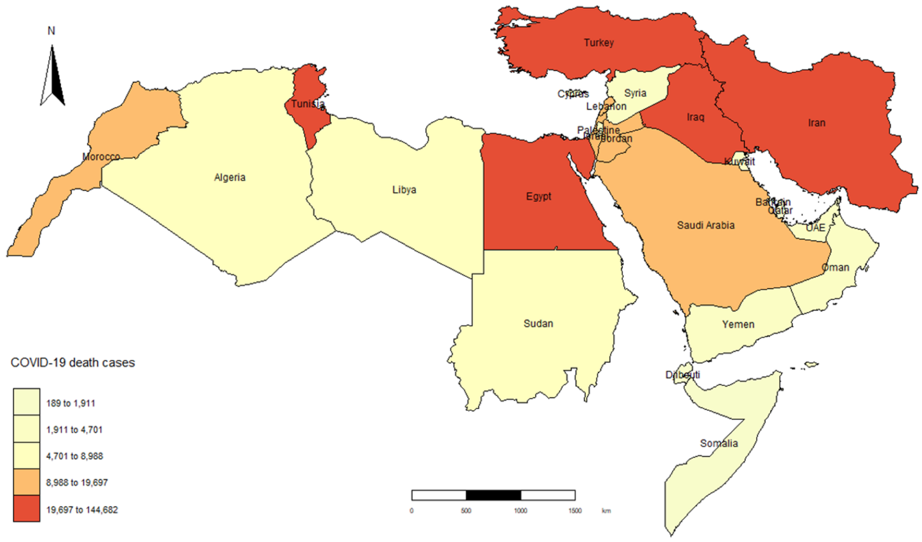

Figure 2. Distribution of COVID-19 death number across the area boundaries

Table 1. Description of response and explanatory variables and data sources.

Parameters	Description	Measurement unit	Source
Death cases (response variable)	Cumulative Death cases of COVID-19 cases in period (Jan 4, 2020, To Dec 31, 2022)	No. of cases	‹https://ourworldindata.org/coronavirus›
Population density (explanatory variable)	The number of people per MENA country calculated by dividing the total number of people by total land area	people per sq. km of land area	https://data.worldbank.org/indicator/
GDP per capita (explanatory variable)	GDP per capita is gross domestic product divided by midyear population. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources	Most Recent Value in US$	https://data.worldbank.org/indicator/
Total vaccine doses (explanatory variable)	All COVID-19 vaccine doses, including boosters, are counted individually till Dec 31, 2022	No. of cases	‹https://ourworldindata.org/coronavirus›
Unemployment (explanatory variable)	Unemployment refers to the share of the labor force that is without work but available for and seeking employment of MENA countries in 2022	Index	https://ilostat.ilo.org/data/
People fully vaccinated (explanatory variable)	Total number of people who received all doses prescribed by the initial COVID-19 vaccination protocol till Dec 31, 2022	No. of cases	‹https://ourworldindata.org/coronavirus›

Continue table 1.

Parameters	Description	Measurement unit	Source
GDP Gross Domestic Product (current US$) (explanatory variable)	Total monetary or market value of all the finished goods and services produced within a country's borders in 2021	Most Recent Value (Millions)	https://data.worldbank.org/indicator/
Population (explanatory variable)	The last population count of MENA countries in 2022	Total number	https://data.worldbank.org/indicator/
Population aged 65+ (explanatory variable)	Total population 65 years of age or older in each MENA countries in 2022	Total number	https://data.worldbank.org/indicator/
Inflation (explanatory variable)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals	Index	https://data.worldbank.org/indicator/
Severity index (explanatory variable)	The Severity Index factors information on proportionate death rates due to COVID-19 and confirmed cases as a factor of the country›s population	Index	https://covid19.pemandu.org/
Recovery index (explanatory variable)	The Recovery Index considers recovery rates, active cases per population, testing levels, and countries› ability to detect, respond, and treat epidemics based on the Global Health Security Index.	Index	https://covid19.pemandu.org/
Hospital beds (per 1,000 people) (explanatory variable)	The total number of beds available in public, private, general, and specialized hospitals, and rehabilitation centers in each MENA countries in 2022	Index	https://data.worldbank.org/indicator/
Nurses and midwives (per 1,000 people) (explanatory variable)	Nurses and midwives include professional nurses, professional midwives, auxiliary nurses, auxiliary midwives, enrolled nurses, enrolled midwives, and other associated personnel in each MENA countries in 2022	Index	https://data.worldbank.org/indicator/

are the characteristics of this study's OLS form:

$$y_i = \beta_0 + x_i\beta + \varepsilon_i \quad ; \; i = 1, \ldots, n. \quad (1)$$

Assuming that y_i is the response variable (COVID-19 death cases); intercept is defined as β_0; x_i is the matrix of explanatory variables related to the demographic, health care, and socioeconomic;[7] ε_i is the random error; and β is the regression coefficients matrix.[6, 8]

The spatial global regression models

When a geographically lagged dependent variable is included into the SLM, spatial autocorrelation between the response and explanatory variables may be accounted for. The SLM is defined as follows[9, 10]:

$$y_i = \beta_0 + x_i\beta + \rho W_i y_i + \varepsilon_i \quad ; \; i = 1, \ldots, n. \quad (2)$$

Where, y_i= COVID-19 death incidence in area i ; β_0= intercept; x_i= the matrix of explanatory variables that are related in the area i; ρ= the parameter of spatial autoregressive; Wi= spatial weight matrix. In addition, Rho measures spatial interdependency, and W_i explains how observations are interrelated.[11, 12]

The SEM model assumes a spatial correlation between OLS error components or residuals.[8] The terms of error are thus separated into two categories: random error terms and error terms.[13] The given formula illustrates the SEM model:

$$y_i = \beta_0 + x_i\beta + \lambda W_i \xi_i + \varepsilon_i \; ; \; i = 1, \dots, n. \tag{3}$$

Where, at an area i, $\xi\, i$ = the spatial element of the error; Lambda (λ) represents the strength of correlation between the elements; the uncorrelated standard error is represented by ε_i ; W_i = spatial of weights matrix; $W_i\, \xi_i$ reveals the strength of the connection between the spatial ingredient of the errors and each other for close data.[14] The SEM model compensates for spatial error autocorrelation through the spatially weights matrix.[9, 15]

The spatial local regression models

When spatial datasets are used, global regression models have a significant flaw.[16, 17] This model fails to account for aspects of spatial heterogeneity. This attribute demonstrates that the connections between the response and predictor variables change throughout geographic space.[18] By contrast to global regression models, which share the same estimated parameters for the entire study area.[19, 20] GWR is utilized to create a local regression model for each area to highlight the changing spatial correlations between response and explanatory variables.[21] Typically, the GWR model is stated as the equation below:

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_{ij} X_{ij} + \varepsilon_i \; ; i = 1, 2, \dots, n \; ; \; j = 1, 2, \dots, m. \tag{4}$$

Where, at an area i, X_{ij} = the value of the jth independent variable; β_{ij} = the local regression coefficient for the jth predictor variable; β_{i0}= the intercept parameter; and ε_i= the random errors.

On the basis of a consistent geographical scale which the global bandwidth across the research region, GWR models may capture spatial changes in the interactions between response and independent variables.[18, 22] In some cases, however, this technique may not be suitable when the relationship between response and explanatory variables varies at different scales.[23]

Multiscale-GWR modelling solves this issue by raising data-driven local models at different spatial scales for exploring local associations between independent and dependent variables. On the basis of this model's broad outline,[20] different bandwidths (local bandwidths) can be incorporated within the study area,[21] and it can be used to model the following areas:

$$y_i = \sum_{j=1}^{m} \beta_{bwj} X_{ij} + \varepsilon_i \; ; i = 1, 2, \dots, n \; ; \; j = 1, 2, \dots, m. \tag{5}$$

In this equation, all the parameters are the same as in equation 4, except for β_{bwj} which is the bandwidth parameter that is used for the estimation of the jth relationship.[24]

The local models account for locational details by providing location-specific parameter estimations.[25] The GWR takes into account data's geographical heterogeneity, and the Multiscale-GWR takes into account shifts in the investigated connections across spatial scales.[26, 27]

Framework and calibration of spatial regression models

Figure 3 shows our suggested spatial modelling framework for examining the impacts of demographic, health care, and socioeconomic factors on COVID-19 death incidence, which incorporates spatial autocorrelation and spatial heterogeneity. In the development of this framework, previous literature has been consulted.[15, 17, 18, 28]

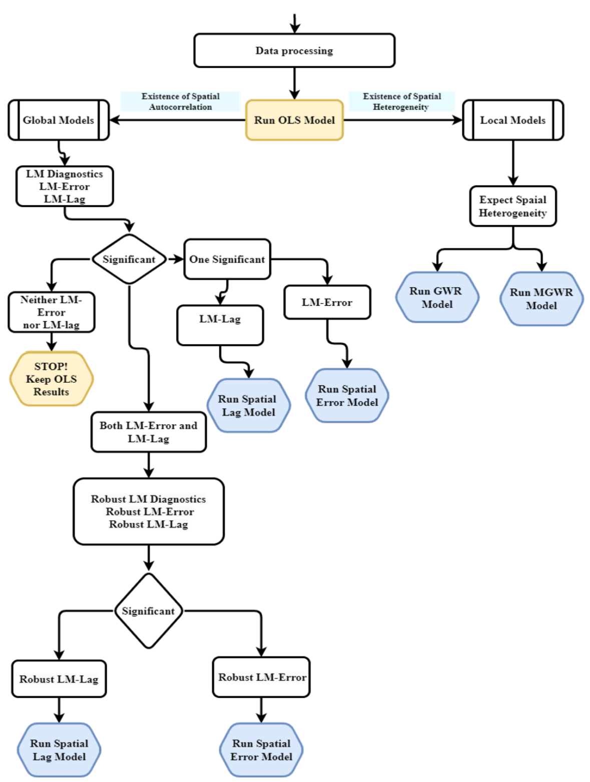

Figure 3. Spatial regression modeling framework.

The Ordinary Least Squares (OLS) model is the best place to begin any spatial regression analysis.[9, 29] The first part of this research entails calibrating an OLS model utilized a stepwise regression technique and evaluating whether the model exhibited multicollinearity through the variance inflation factor (VIF).[30]

The OLS model is unsuitable when residuals are spatially correlated and/or spatially heterogeneous.[31, 32] Following the creation of the OLS model, global Moran's I test was used to evaluate spatial autocorrelation. Significant Moran's I value imply spatial autocorrelation, which implies the necessity to build the spatial global regression models including SLM and SEM.[33, 34] Incorporating the first-order Queens' contiguity weight matrix, these two models were created using the software mentioned in the database section. These two models were calibrated using the same significant explanatory variables as the OLS model so that they could be compared.

To determine whether of SLM or SEM models are superior, the results of Lagrange Multiplier (LM)-lag and Lagrange Multiplier (LM)-error tests must be examined.[28] If the LM-lag is significant and the LM-error is not, it should be appropriate to implement the SLM model. The SEM model should be developed when LM-error is significant while LM-lag is not. There should be a check of the Robust LM-lag and Robust LM-error results if LM-lag and LM-error are both significant.[35] The SEM model should be implemented if the Robust LM-error is significant, and the Robust LM-lag is not. The SLM model should be developed if the Robust LM-lag is significant while the Robust LM-error is not.[28, 36] suggests that in the presence of both Robust LM-lag and Robust LM-error, it is important to examine the test that has the lowest p-value.

To assess whether the residuals of OLS exhibit spatial non-stationarity, we used a scale-location plot.[37, 38] It is used to check for the assumption of homoscedasticity, which is the assumption that the variance of the residuals is constant across all fitted values if the red line is approximately horizontal across the plot, then the assumption of homoscedasticity is satisfied.[37-40] Another approach to checking for spatial non-stationarity is using local spatial association indicators (LISA). LISA statistics measure the spatial autocorrelation of a variable at a specific location relative to its neighbors. It allows you to identify areas where the spatial relationships differ from the overall trend.[41-44] That highlights the need to design the spatial local regression models including GWRs and Multiscale-GWR.[45] This study used the software described in the database section to calibrate these two models, which incorporate the similar significant explanatory variables as the non-spatial model. We utilized the adaptive kernel since, in comparison with fixed-bandwidth kernels have the limitation that calibration may be problematic in sparsely populated regions, the adaptive bandwidth kernel avoids this issue.[13, 46, 47] That is why MGWR implements an adaptive bandwidth kernel as default.[13, 48, 49] In furthermore, these two local models were optimized using AICc.[50] After building all five models, we compared their results using the, R^2, the Akaike information criterion (AIC), and the residual sum of squares (RSS) to draw conclusions about which one was most effective. The present work considers demographic, health care, and socioeconomic factors. Some diagnostics tests, such as the VIF test and the stepwise forward technique, were utilized to identify the most relevant predictor variables for regression models. We find Hospital beds, unemployment, and the total number of vaccination doses are three critical characteristics that are important in determining the death incidence of the virus.

Results

Table 2 displays the results of the estimated OLS model. Three variables are highly relevant: hospital beds, unemployment rate, and total vaccine doses. Multicollinearity was nonexistent among the model's explanatory variables since all the VIF statistics were less than 2.[51] The model results indicate that the model was statistically significant (p-value <0.0001). The model exhibited an R^2 value of 0.7346, showing the three significant predictor variables could justify 73.46 % of the variance in COVID-19 death cases across MENA and that all important variables had a positive connection with the response variable (Table 2). Since the residuals of OLS exhibited spatial autocorrelation, it was required to build the SLM and SEM models. The overall findings of the SLM and SEM models are presented in (Table 3). In all models, the three predictor variables of the OLS were found to be statistically significant, and their coefficients indicate a positive relationship with the dependent variable. Both Rho and Lambda were statistically significant at 5% level, and the R^2 and AIC values of SLM and SEM models were close similar to the results of the OLS model (Table 3). This research shows that, contrary to popular belief, these two models only marginally outperform the OLS model.

Figure 4, the scale-location plot shows a slight upward fanning pattern. That suggests that the variance of the residuals is increasing with the fitted values, the red line is not horizontal, and then the assumption of homoscedasticity is violated. In addition, Local indicators of

Table 2. Summary statistics of global OLS model.

Variable	Coefficient	St. Error	t- Statistic	p-value	VIF
Intercept	-7.2214***	2.17494	-3.320	0.0034	–
Hospital beds	0.5235**	0.2320	2.256	0.0354	1.0499
Unemployment	0.0638**	0.0254	2.511	0.0207	1.1668
LnTotal vaccine doses	0.8825***	0.1224	7.210	0.0001	1.1155

* p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01
1. Standard Error (St. Error) 2. t-Statistic (t-Stat) 3.Variance Inflation Factor (VIF)

Table 3. Summary statistics of SLM and SEM models.

Variable	Coefficient		St. Error		Z-score		P-value	
	SLM	SEM	SLM	SEM	SLM	SEM	SLM	SEM
Intercept	- 8.531***	-5.334***	1.8981	1.9230	-4.4944	-2.773	0.0000	0.0055
Hospital beds	0.3726*	0.3303*	0.1923	0.1967	1.9372	1.6792	0.0527	0.0931
Unemployment	0.0606***	0.0540**	0.0206	0.0245	2.9396	2.2039	0.0032	0.0275
LnTotal vaccine doses	0.8110***	0.7949***	0.1030	0.1061	7.8724	7.4891	0.0000	0.0000
Rho	0.3134**	-	0.1347	-	2.3265	-	0.0199	-
Lambda	-	0.4077**	-	0.1930	-	2.1117	-	0.0347

*p-value < 0.1, **p-value < 0.05, ***p-value < 0.01
Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.

spatial association (LISA) maps allow us to identify areas where the spatial relationships (spatial non-stationarity) are different from the overall trend (Figure 5).

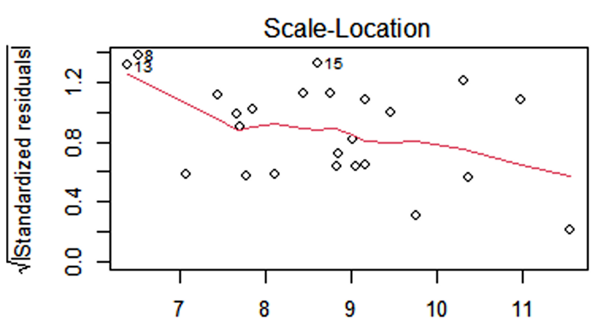

Figure 4. Scale-location plot to test for Heterogeneity.

To deal with the issue of the OLS model's spatial non-stationarity, we utilized two local spatial regression models: GWR and multiscale-GWR. Table 4 provides the goodness-of-fit Measures of all models, and we found a much higher R^2 and a much lower AIC for the GWR and multiscale-GWR models than all global models. The R^2 (0.8140), and AIC (54.343) of the GWR model. Besides, we found R^2 (0.8187) and AIC (53.785) for the Multiscale-GWR model. All these results suggest that while the GWR model performed comparably to the Multiscale-GWR model, the Multiscale-GWR model showed a slightly better performance. Figures. 6 and 7 exhibit the spatial pattern of the predictor variables coefficients of the GWR and Multiscale-GWR models. A comparison between the coefficients would assist in acquiring a clear view to understand the spatial variance of the interactions and the relevance of taking into consideration spatial scale variation. In Figure 6, the coefficients' spatial

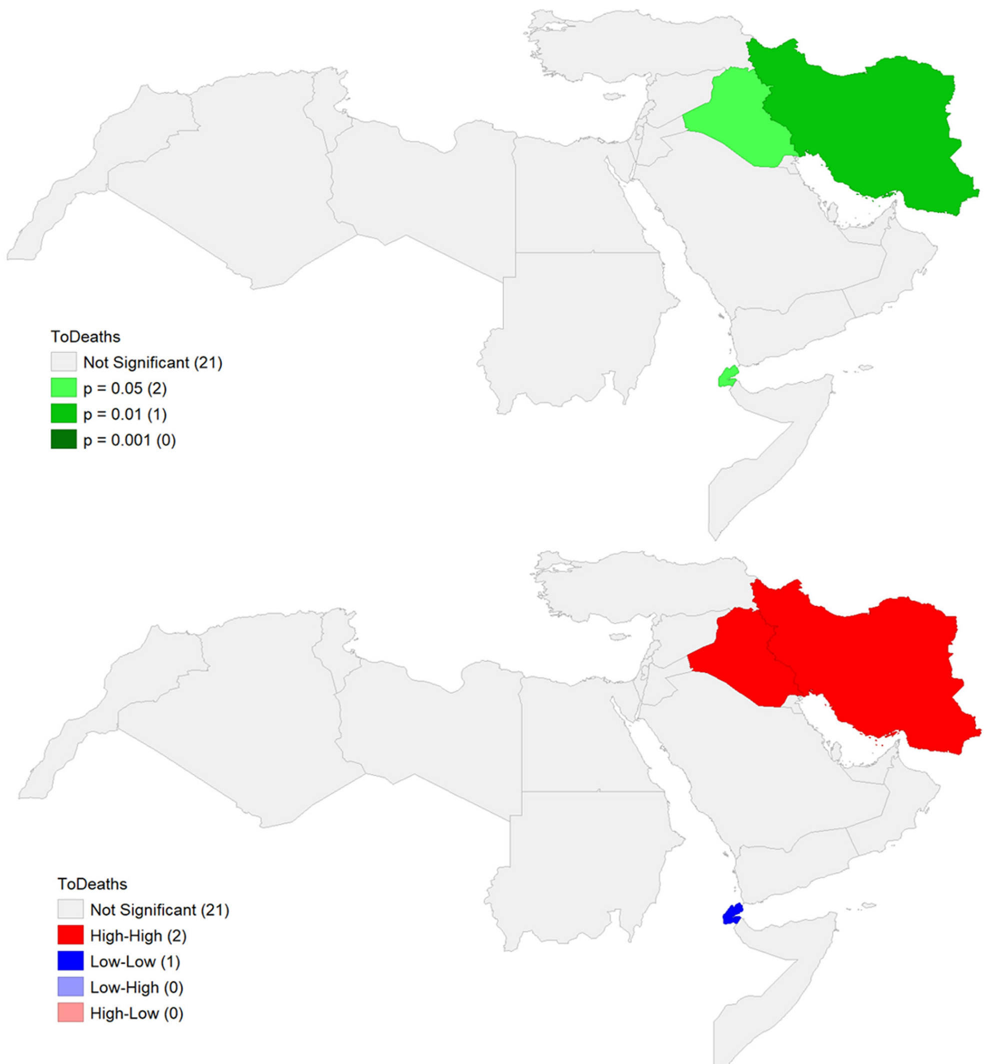

Figure 5. LISA maps for identifying and exploring spatial non-stationarity.

Table 4. Measures of goodness-of-fit for OLS, SEM, SLM, GWR, and MGWR in modeling COVID-19 Death cases.

Criterion	OLS	SEM	SLM	GWR	MGWR
R2	0.7346	0.7686	0.7898	0.8140	0.8187
AIC	65.652	65.165	62.857	54.343	53.785
RSS	14.28	12.45	11.31	10.01	9.75

OLS= Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.
SEM= Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.
SLM= Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.
GWR= Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.
MGWR= Y= Death cases, X1= Hospital beds, X2= Unemployment , X3= LnTotal vaccine doses.

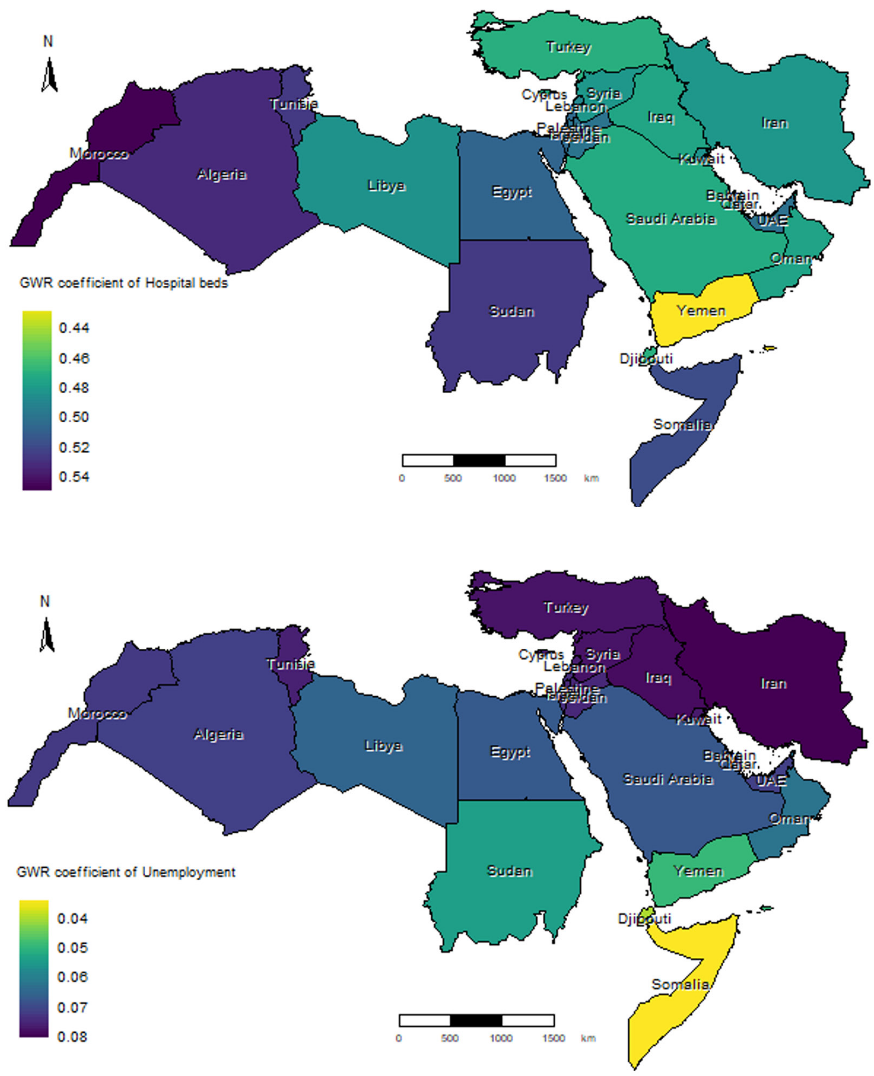

Figure 6. The effects of Hospital beds, %Unemployment, and Total vaccine doses in describing COVID-19 death cases using the GWR model across the MENA region.

distribution of hospital bed numbers displayed a distinctive pattern in the GWR model; the coefficients became larger in the northwestern area and dropped across the eastern and northeastern of the region. On the other hand, Figure 7 exposes the impact of the coefficients of hospital bed numbers as per the MGWR; there is a higher impact in the southwestern part (Somalia) and a moderate impact in the northwestern part of the region. In addition, we can see that in both models, GWR and MGWR, the unemployment index had a strong relationship with COVID-19 death cases in the northeastern parts (Iran, Turkey, Iraq, and Syria) and had a relatively strong connection in the northwestern (Morrocco, Algeria, and Tunisia). Moreover, the total vaccine doses coefficient was extraordinarily strong in explaining the geographical distribution to the response variable in Iran for the GWR model and the region (Iran and Somalia) for the Multiscale-GWR model.

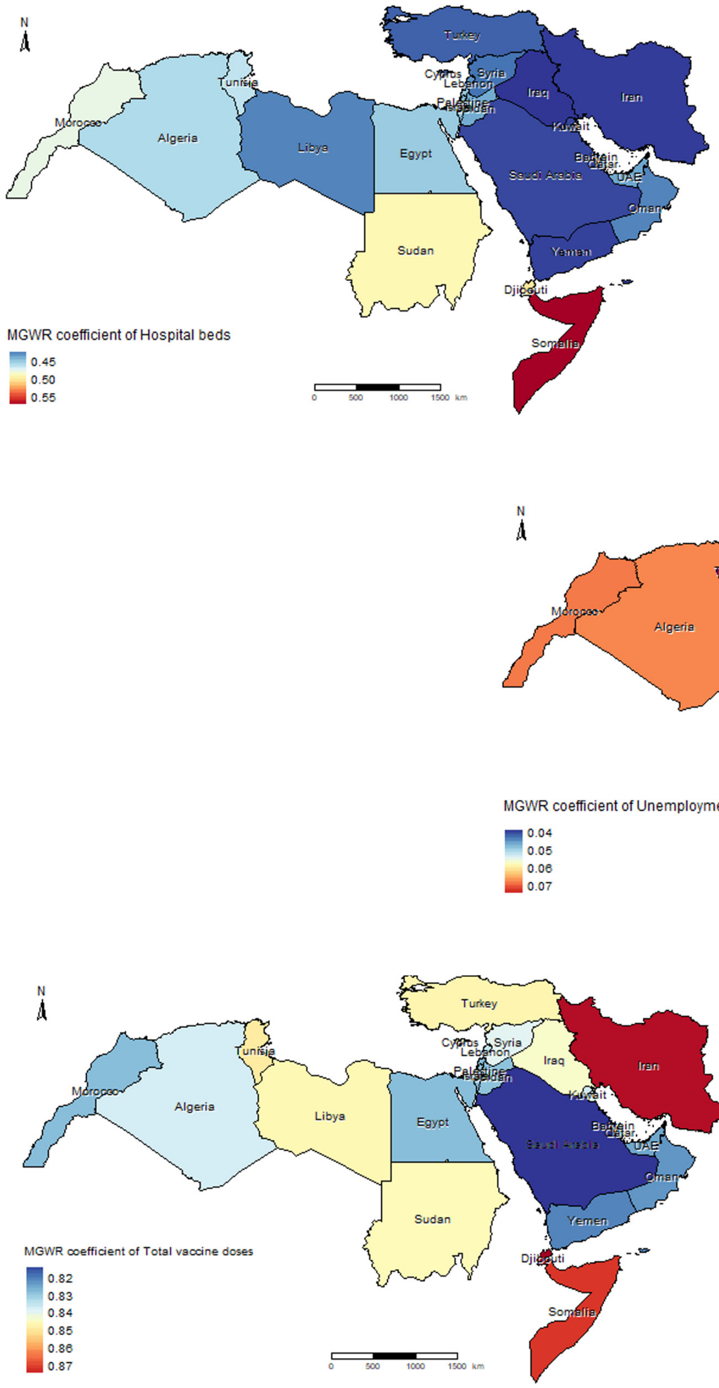

Figure 7. The effects of Hospital beds, %Unemployment, and Total vaccine doses in describing COVID-19 death cases using the MGWR model across the MENA region.

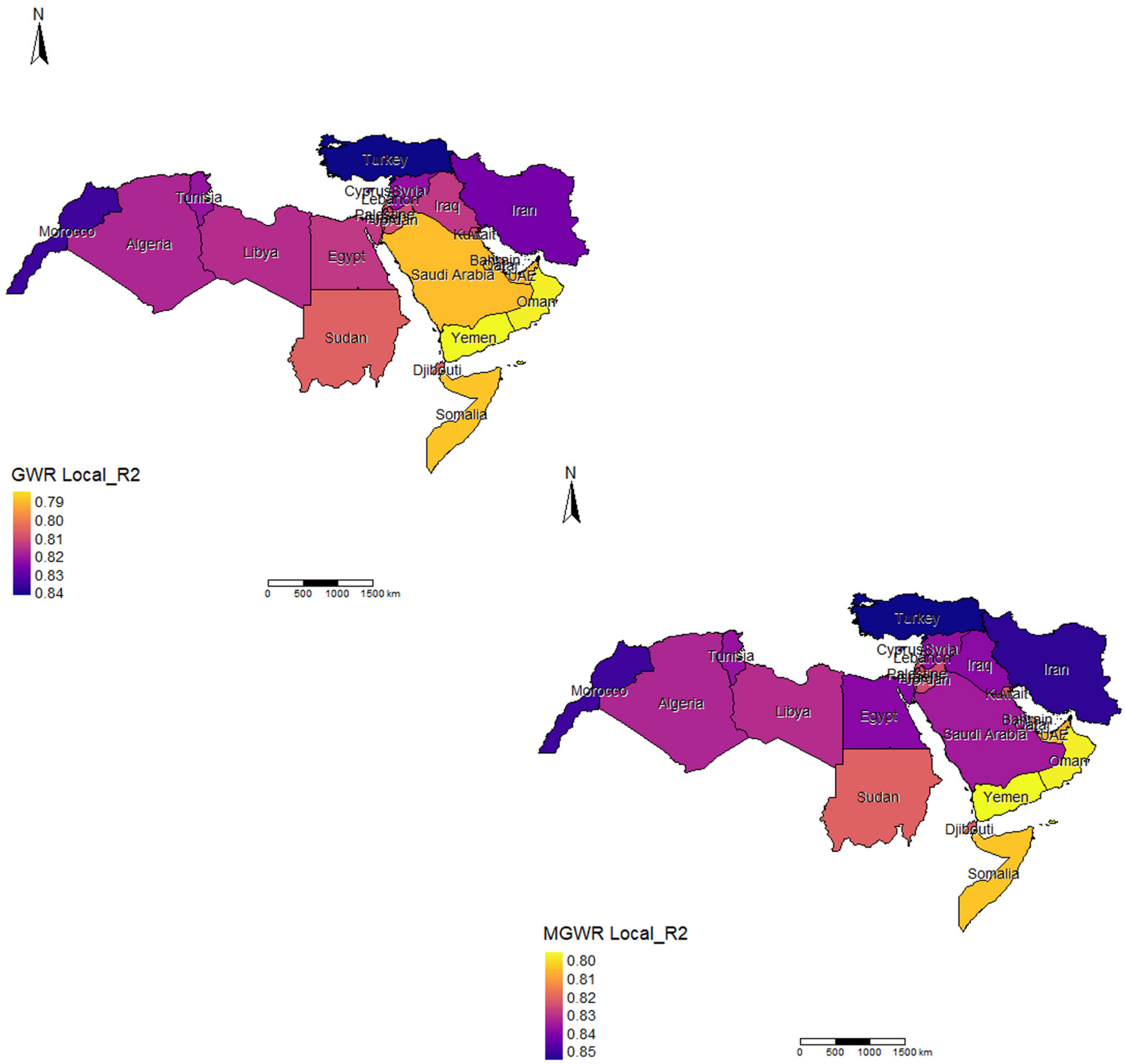

Figure 8. Spatial distribution of local R^2 of GWR model for COVID-19 death cases associated with the significant covariates across the MENA region.

Fig. 8 displays the spatial distributions of local R^2 values for the GWR and Multiscale-GWR models. The lighter tints indicate lower values, whereas the deeper hues indicate greater ones. Although reasonable local R^2 values were reported for all nations (Turkey and Morocco) and were found to be particularly well predicted by the models. Moreover, the explanatory variables expound at least 80% in (Iran and Iraq) according to both models, with Turkey and Morocco having the highest value at 85%.

Discussion

This GIS-based analysis, leveraging

geostatistical models, examined the spatial distribution of COVID-19 death rates across the MENA region using thirteen variables categorized into demographic, medical, and socioeconomic groups. Through a series of spatial regression and autoregressive models, we identified a combination of three key factors (hospital bed availability, unemployment rates, and total vaccine doses) as significant predictors of the variance in COVID-19 death rates across the region.

Since the residuals of the OLS model exhibited spatial autocorrelation, it was necessary to develop the Spatial Lag Model (SLM) and Spatial Error Model (SEM). The findings from these models, presented in Table 3, reinforce the importance of healthcare infrastructure and socioeconomic factors in explaining COVID-19 outcomes. Hospital beds showed positive coefficients of 0.3726 in the SLM and 0.3303 in the SEM, suggesting that areas with more hospital beds tend to have higher reported COVID-19 death cases. This relationship may be due to better reporting and higher accessibility to healthcare facilities, where more severe cases are documented and managed. Studies have similarly found that strain on hospital resources, such as ICU bed occupancy, correlates with higher excess death rates during periods of high COVID-19 incidence.[52, 53]

Unemployment also showed positive coefficients in both models (0.0606 in the SLM and 0.0540 in the SEM), indicating that higher unemployment rates are associated with an increase in COVID-19 death cases. This could be attributed to economic and social stressors that increase vulnerability and reduce access to healthcare. The socioeconomic impact of unemployment has been shown to exacerbate health outcomes, including mortality rates during the pandemic.[54, 55] Furthermore, the Total vaccine doses show a positive association with the death COVID-19 cases, with coefficients of 0.8110 in the SLM and 0.7949 in the SEM. This association might be misleading due to factors such as increased testing and reporting in areas with higher vaccination rates, or the initial surge in cases leading to increased vaccine distribution, as discussed in the results of Model 1.[56, 57] Thus, while there appears to be a positive association between the number of vaccine doses administered and the number of COVID-19 death cases, this should not be interpreted as causation. The observed relationship may be influenced by various factors, including heightened reporting efforts or a time lag between vaccination campaigns and their impact on death rates.[58, 59]

The significant spatial autocorrelation coefficients, Rho (0.3134) in the SLM and Lambda (0.4077) in the SEM, emphasize the necessity of considering spatial dependence in the analysis. Rho indicates that confirmed cases in one area are influenced by those in neighboring areas, while Lambda suggests the presence of spatially correlated unobserved variables impacting the error terms. These findings underscore the need to account for spatial dependence in the models, with the SLM capturing it through the dependent variable and the SEM through the error term.

The GWR and MGWR models maps, revealed a high positive correlation between the death rate and the three key variables (hospital beds, unemployment, and total vaccine doses) highlighting the complex interplay between healthcare capacity, socioeconomic factors, and public health interventions in influencing COVID-19 outcomes. As the disease has spread globally, serious weaknesses in healthcare systems, economic downturns, and rising unemployment rates have been evident. The findings are consistent with the significant role that medical interventions, particularly vaccination efforts, have played during the pandemic.

Despite providing valuable insights into the determinants of COVID-19 death cases in MENA countries, this study is not without limitations. Acknowledging these constraints is essential for a nuanced interpretation of the findings and to guide future research.

First, the reliance on spatial models, specifically Multiscale-GWR, may introduce inherent assumptions and limitations. While these models offer a comprehensive perspective on regional disparities, their effectiveness depends on the quality and accuracy of input data. Any inaccuracies or biases in the data could potentially impact model outcomes and subsequent interpretations.

Second, the study's focus on the MENA region limits the generalizability of its findings to other global contexts. The unique socio-economic, cultural, and healthcare landscapes of MENA countries may introduce specific dynamics that are not applicable elsewhere. Therefore, caution is warranted when extrapolating results to different geographical regions.

Third, while the study focuses on three specific independent variables at the district level, which explain a substantial portion of reported deaths, it may overlook other pertinent variables that could contribute to a more comprehensive understanding of COVID-19 death cases. Future research could explore a broader array of variables to refine and expand upon the current findings.

Fourth, the retrospective design of the study limits the ability to establish causality. While the study identifies associations between variables, it cannot definitively prove cause-and-effect relationships. This limitation underscores the need for complementary research designs, such as prospective studies or randomized controlled trials, to validate and strengthen observed associations.

Finally, the study's acknowledgment that no prior research has undertaken spatial modeling of COVID-19 death cases in the MENA region highlights both the novelty and potential limitations of the research. The absence of a precedent may constrain the ability to directly compare findings with existing literature, emphasizing the importance of cautious interpretation and consideration of future research directions.

In conclusion, while this study significantly contributes to understanding COVID-19 death cases in the MENA region, it is essential to recognize its limitations. Addressing these constraints will facilitate a more comprehensive and nuanced interpretation of the findings, guiding researchers and policymakers in future endeavors aimed at addressing the ongoing challenges posed by the pandemic.

Conclusion

Addressing the factors that influence disease transmission and dissemination is crucial, particularly in the case of COVID-19, a coronavirus epidemic that has caused unparalleled worldwide shock. This research sought to uncover possible characteristics related to COVID-19 death numbers in MENA nations. The local models helped observe the connection between COVID-19 and the variables provided. Our findings confirmed and extended the prior research since Multiscale-GWR had the greatest goodness of fit among the models. The different responses of COVID-19 death numbers to the selected predictor variables, may account for the geographical variation in Multiscale-GWR in other counties. At least 85% of reported fatalities at the district level are represented by the three independent variables included in all examined spatial regression models. This work may be valuable in the future, according to the best of our knowledge, no research has been undertaken in the MENA area utilizing COVID-19 spatial modelling.

References

1. Coronavirus Pandemic (COVID-19) [Internet]. https://ourworldindata.org/coronavirus. (2020).

2. Ganasegeran K, Jamil MFA, Appannan MR, Ch'ng ASH, Looi I, Peariasamy KM. Spatial Dynamics and Multiscale Regression Modelling of Population Level Indicators for COVID-19 Spread in Malaysia. International Journal of Environmental Research and Public Health. 2022;19(4):2082.

3. Bayode T, Popoola A, Akogun O, Siegmund A, Magidimisha-Chipungu H, Ipingbemi O. Spatial variability of COVID-19 and its risk factors in Nigeria: A spatial regression method. Applied Geography. 2022;138:102621.

4. Urban R, C, Nakada L, Y, K. GIS-based spatial modelling of COVID-19 death incidence in São Paulo, Brazil. Environment and Urbanization. 2021;33(1):229–38.

5. Kotov EA, Goncharov RV, Kulchitsky YV, Molodtsova VA, Nikitin BV. Spatial modelling of key regional-level factors of Covid-19 mortality in Russia. Geography, Environment, Sustainability. 2022;15(2):71-83.

6. Ward, Gleditsch. Spatial regression models. china: Sage Publications; 2018.

7. Abolfazl Mollalo, Kiara M. Rivera, Nasim Vahabi. Spatial statistical analysis of pre-existing mortalities of 20 diseases with COVID-19 mortalities in the continental United States. Sustainable Cities and Society. 2021;67:102738.

8. Anselin L, Arribas-Bel D. Spatial fixed effects and spatial dependence in a single cross-section. Papers in Regional Science. 2013;92(1):3-17.

9. Sannigrahi S, Pilla F, Basu B, Basu AS, Molter A. Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach. Sustainable cities and society. 2020;62:102418.

10. Mollalo A, Vahedi B, Rivera K. GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Science of the total environment. 2020;728:138884.

11. Rahman M, Zaman N, Asyhari A, T, Al-Turjman F, Bhuiyan M, Z, A, Zolkipli M. Data-driven dynamic clustering framework for mitigating the adverse economic impact of Covid-19 lockdown practices. Sustainable

Cities and Society. 2020;62:102372.

12. Monica, Mishra R. An epidemiological study of cervical and breast screening in India: district-level analysis. BMC women's health. 2020;20:1-15.

13. Oshan TM, Li Z, Kang W, Wolf LJ, Fotheringham AS. mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. ISPRS International Journal of Geo-Information. 2019;8(6):269.

14. Dutta I, Basu T, Das A. Spatial analysis of COVID-19 incidence and its determinants using spatial modeling: A study on India. Environmental Challenges. 2021;4:100096.

15. Kissling WD, Carl G. Spatial autocorrelation and the selection of simultaneous autoregressive models. Global Ecology and Biogeography. 2008;17(1):59-71.

16. Deilami K, Kamruzzaman M, Hayes JF. Correlation or causality between land cover patterns and the urban heat island effect? Evidence from Brisbane, Australia. Remote Sensing. 2016;8(9):716.

17. Comber A, Brunsdon C, Charlton M, Dong G, Harris R, Lu B, et al. A route map for successful applications of geographically weighted regression. Geographical Analysis. 2022:2022.

18. Chien Y-MC, Carver S, Comber A. Using geographically weighted models to explore how crowdsourced landscape perceptions relate to landscape physical characteristics. Landscape and Urban Planning. 2020;203:103904.

19. Deilami K, Kamruzzaman M. Modelling the urban heat island effect of smart growth policy scenarios in Brisbane. Land use policy. The International Journal Covering All Aspects of Land Use. 2017;64:38-55.

20. Hamad F, Younus N, Muftah MM, Jaber M. Viability of Transplanted Organs Based on Donor’s Age. Sch J Phys Math Stat. 2023;4:97-104.

21. Mansour S, Al Kindi A, Al-Said A, Al-Said A, Atkinson P. Sociodemographic determinants of COVID-19 incidence rates in Oman: Geospatial modelling using multiscale geographically weighted regression (MGWR). Sustainable Cities and Society. 2021;65:102627.

22. Zafri NM, Khan A. A spatial regression modeling framework for examining relationships between the built environment and pedestrian crash occurrences at macroscopic level: A study in a developing country context. Geography and sustainability. 2022;3(4):312-24.

23. Fotheringham A, S, Yang W, Kang W. Multiscale geographically weighted regression (MGWR). Annals of the American Association of Geographers. 2017;107(6):1247-65.

24. Mollalo A, Vahedi B, Rivera KM. GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Science of the total environment. 2020;728:138884.

25. Brunsdon C, Fotheringham S, Charlton M. Geographically weighted regression. Journal of the Royal Statistical Society: Series D (The Statistician). 1998;47(3):431-43.

26. Oshan T, M, Li Z, Kang W, Wolf L, J, Fotheringham A. mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. ISPRS International Journal of Geo-Information. 2019;8(6):269.

27. Shabrina Z, Buyuklieva B, Ng MKM. Short-term rental platform in the urban tourism context: A geographically weighted regression (GWR) and a multiscale GWR (MGWR) approaches. Geographical Analysis. 2021;53(4):686-707.

28. Anselin L. Exploring spatial data wit*h* GeoDaTM: a workbook. Center for spatially integrated social science https://www geos ed ac uk/~ gisteac/fspat/geodaworkbook pdf. 2005.

29. Stimson JA. Regression in space and time: A statistical essay. American Journal of Political Science. 1985:914-47.

30. Thompson CG, Kim RS, Aloe AM, Becker BJ. Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. Basic and Applied Social Psychology. 2017;39(2):81-90.

31. Tu J, Xia Z-G. Examining spatially varying relationships between land use and water quality using geographically weighted regression I: Model design and evaluation. Science of the total environment. 2008;407(1):358-78.

32. Huang Y, Wang X, Patton D. Examining spatial relationships between crashes and the built environment: A geographically weighted regression approach. Journal of transport geography. 2018;69:221-33.

33. Pljakić M, Jovanović D, Matović B, Mićić S. Macro-level accident modeling in Novi Sad: A spatial regression approach. Accident Analysis & Prevention. 2019;132:105259.

34. Cordes J, Castro MC. Spatial analysis of COVID-19 clusters and contextual factors in New York City. Spatial and spatio-temporal epidemiology. 2020;34:100355.

35. Anselin L, Varga A, Acs Z. Geographical spillovers and university research: A spatial econometricperspective. Growth and change. 2000;31(4):501-15.

36. Chica-Olmo J, Sari-Hassoun S, Moya-Fernández P. Spatial relationship between economic growth and renewable energy consumption in 26 European countries. Energy Economics. 2020;92:104962.

37. Tay L, Parrigon S, Huang Q, LeBreton JM. Graphical descriptives: A way to improve data transparency and methodological rigor in psychology. Perspectives on Psychological Science. 2016;11(5):692-701.

38. Pisică D, Dammers R, Boersma E, Volovici V. Tenets of good practice in regression analysis. a brief tutorial. World

neurosurgery. 2022;161:230-9. e6.

39. Zhang Z, Poucke SV. Citations for randomized controlled trials in sepsis literature: the halo effect caused by journal impact factor. PLoS One. 2017;12(1):e0169398.

40. Agnihotri D. Assessing mHealth Motivational Pathways Among Hispanic Individuals Through Technological Affordances. 2022.

41. Anselin L. Local indicators of spatial association—LISA. Geographical analysis. 1995;27(2):93-115.

42. Osborne PE, Foody GM, Suárez-Seoane S. Non-stationarity and local approaches to modelling the distributions of wildlife. Diversity and Distributions. 2007;13(3):313-23.

43. Nelson JK, Brewer CA. Evaluating data stability in aggregation structures across spatial scales: revisiting the modifiable areal unit problem. Cartography and Geographic Information Science. 2017;44(1):35-50.

44. Anselin L. Chapter Eight-The Moran scatterplot as an ESDA tool to Assess Local Instability in Spatial Association. Spatial Analytical. 1996;4:121.

45. Cellmer R, Cichulska A, Bełej M. Spatial analysis of housing prices and market activity with the geographically weighted regression. ISPRS International Journal of Geo-Information. 2020;9(6):380.

46. Bithell JF. An application of density estimation to geographical epidemiology. Statistics in medicine. 1990;9(6):691-701.

47. Kie JG. A rule-based ad hoc method for selecting a bandwidth in kernel home-range analyses. Animal Biotelemetry. 2013;1(1):1-12.

48. Bidanset PE, Lombard JR. 7 Optimal kernel and bandwidth specifications for geographically weighted regression. Applied Spatial Modelling and Planning. 2016.

49. Charlton M, Fotheringham S, Brunsdon C. Geographically weighted regression. White paper National Centre for Geocomputation National University of Ireland Maynooth. 2009;2.

50. Title PO, Bemmels JB. ENVIREM: an expanded set of bioclimatic and topographic variables increases flexibility and improves performance of ecological niche modeling. Ecography. 2018;41(2):291-307.

51. Zin WW, Kawasaki A, Hörmann G, Acierto RA, San ZMLT, Thu AM. Multivariate flood loss estimation of the 2018 Bago flood in Myanmar. Journal of Disaster Research. 2020;15(3):300-11.

52. French G. Impact of hospital strain on excess deaths during the COVID-19 pandemic—United States, July 2020–July 2021. MMWR Morbidity and mortality weekly report. 2021;70.

53. Pecoraro F, Luzi D, Clemente F. The efficiency in the ordinary hospital bed management: A comparative analysis in four

European countries before the COVID-19 outbreak. Plos one. 2021;16(3):e0248867.

54. Geranios K, Kagabo R, Kim J. Impact of COVID-19 and socioeconomic status on delayed care and unemployment. Health Equity. 2022;6(1):91-7.

55. Hawkins RB, Charles EJ, Mehaffey JH. Socio-economic status and COVID-19–related cases and fatalities. Public health. 2020;189:129-34.

56. Mouliou DS, Gourgoulianis KI. False-positive and false-negative COVID-19 cases: respiratory prevention and management strategies, vaccination, and further perspectives. Expert review of respiratory medicine. 2021;15(8):993-1002.

57. Cuadros DF, Moreno CM, Musuka G, Miller FD, Coule P, MacKinnon NJ. Association between vaccination coverage disparity and the dynamics of the COVID-19 Delta and Omicron waves in the US. Frontiers in Medicine. 2022;9.

58. Watson OJ, Barnsley G, Toor J, Hogan AB, Winskill P, Ghani AC. Global impact of the first year of COVID-19 vaccination: a mathematical modelling study. The Lancet infectious diseases. 2022;22(9):1293-302.

59. Bollyky TJ, Hulland EN, Barber RM, Collins JK, Kiernan S, Moses M, et al. Pandemic preparedness and COVID-19: an exploratory analysis of infection and fatality rates, and contextual factors associated with preparedness in 177 countries, from Jan 1, 2020, to Sept 30, 2021. The Lancet. 2022;399(10334):1489-512.