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A Spatial Epidemiological Investigation of COVID-19 in the MENA Region: Modeling Incidence and Impact Factors

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Abstract: The COVID-19 pandemic has negatively impacted the global economy and society. World Health Organization (WHO) reported that as of early July 2023, the virus has infected more than 690 million individuals and has resulted in more than 6.9 million deaths worldwide. This study aims to investigate spatial epidemiological factors of COVID-19 in the Middle East and North Africa (MENA) region. By employing various spatial modeling techniques, this study establishes that multiscale geographically weighted regression (MGWR) is the best-fitted model, with the lowest residual sum of squares (11.22) and the lowest Akaike's Information Criteria (AIC) value (58.41), explaining 84.3% of the variance (R^2=0.843). Our study finds that population density, total vaccination doses, unemployment, and GDP per capita are critical factors associated with COVID-19 in the MENA region. These valuable insights provide policymakers and public healthcare experts with the information needed to develop targeted interventions that can mitigate risk factors related to the COVID-19 pandemic.

Keywords: *COVID-19, GIS modelling, global models, MENA Region, MGWR, spatial modeling.*

1. Introduction

SARS-CoV-2, also known as COVID-19, is a virus that causes severe acute respiratory syndrome. This highly contagious and novel pathogen first emerged in Wuhan, China, in late 2019. It quickly became a global pandemic, posing major challenges to public health systems and negative impacts on the global economy and society. While many COVID-19 studies examined the impacts of epidemic outbreaks, they tend to focus on specific countries. One gap in existing research is the limited use of geospatial data for a comprehensive understanding of the disease's incidence and impact. For example, (Daniel & Adejumo, 2021) found no clear relationship between COVID-19 and population density in Nigeria using a binomial regression model. However, when (Bayode et al., 2022) expanded their analysis in spatial regression, they uncovered the significance of population density. Similarly, (Iyyanki et al., 2020) applied spatial modeling to identify a sudden surge in COVID-19 cases during social isolation or quarantine periods.

In a broader context, the likelihood of COVID-19 cases significantly increased due to urbanization and population density (Dutta et al., 2021). Their study utilized spatial models, along with geographically weighted models, to reach this conclusion. Spatial regression has also contributed during vaccination response (Ahasan et al., 2020; Franch-Pardo et al., 2020), providing valuable insights into the course of COVID-19 and helping identify factors contributing to the disease's spread. Consequently, it has become essential to implement effective strategies for social isolation and mobility restrictions (Jaber, 2022). Thus, geospatial data analysis remains critical for an epidemiological investigation across various spatial and spatiotemporal scales (Mollalo et al., 2020).

Several authors have employed spatial analysis to examine the geographical determinants of COVID-19 (Aboalyem et al., 2024; Abolfazl Mollalo et al., 2021; Dutta et al., 2021; Mansour et al., 2021). They have used methods like GWR, MGWR, spatial lag model (SLM), and spatial error model (SEM). As mentioned earlier, geospatial data analysis provides valuable insights into the course of COVID-19 and helps identify regional factors contributing to the disease's spread. However, prior studies primarily focused on the national level, with no regional analysis conducted in the Middle East and North Africa (MENA) region. This present study represents the first of its kind in utilizing spatial analysis of five distinct models to examine the primary causes of the COVID-19 outbreak and assess the presence of geographical dependence in the MENA region.

Globalization has intensified travel, communication, and socioeconomic participation, of which indirectly amplified the speed, frequency, and geographic reach of diseases (Mansour et al., 2021). There is, for example, a geographical link between the Middle East and North Africa, indicating that the disease's possible effects cannot be overlooked. The aim of this research is to investigate the spatial relationship between 13 independent variables and the incidence of COVID-19 in MENA countries (Table 1). The study utilized five statistical models, namely ordinary least square (OLS), SLM, SEM GWR, and MGWR.

This present study found that GDP per capita, unemployment, total vaccination, and population density are the main factors that

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determine the speed of COVID-19 transmission. The findings of this study can help develop effective strategies to reduce the impact of COVID-19 on people and the global economy. These findings may also contribute to evidence-based decision-making in public health programs to design interventions to reduce transmission and risk causes related to the COVID-19 epidemic in the MENA region. The remainder of the paper is organized as follows: Section 2 presents the study region and database, Section 3 describes OLS and spatial analysis, Section 4 presents results, and Section 4 discusses OLS and spatial regression results. Conclusions are drawn in Section 6.

2. Study Region and Database

Study Region

The MENA region consists of many countries, from rich oil-exporting Gulf countries to low- and middle-income countries. However, different organizations classify the region differently, and the terms (Arab World) and (Greater Middle East) are used interchangeably (Seyfi & Hall, 2020). According to the World Bank, the region covers 19 countries and accounts for 6.03% of the world's population (Wang & Wang, 2021). This includes countries like Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Somalia, Syria, the United Arab Emirates, and Yemen. However, Turkey, Sudan, and Cyprus are occasionally included in the MENA region (Gollin et al., 2016; Karim et al., 2022). This study is based on the World Bank and the United Nations Statistics Division, which listed Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Sudan, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Tunisia, Palestine. Qatar, Saudi Arabia, Syria, Somalia, Turkey, Cyprus, United Arab Emirates and Yemen as part of the MENA region (Fig. 1) (Aminova et al., 2020; Davoodi & Abed, 2003).

Database

In this analysis, we collected data from Our World in Data, International Labor Organization (ILO), and PEMANDU Associates, the responsible body for monitoring COVID-19 across the MENA region. Our data collection began with the initial reported cases in each nation and continued until December 2022. We computed the incidence rate at the regional level (Fig. 2). To achieve this, we established a geodatabase using GIS software, which includes GeoDa 1.20.0.20, QGIS 3.30.2, and ArcMap 10.8.2. Additionally, RStudio 2023.06.0 was deployed to link demographic, healthcare, and socioeconomic variables into geopolitical boundary shapefile (Table 1).

3. Methodology and Methods

Ordinary Least Squares (OLS)

Multicollinearity diagnostics and forward stepwise regression with multiple OLS are used to determine the linear relationship between COVID-19 incidence (dependent variable) and demography, behavioral, medical, and socioeconomic variable groups as follows (Ward & Gleditsch, 2018):

$$y_i = \beta_0 + x_i\beta + \varepsilon_i \tag{1}$$

xi is the explanatory variables, yi is the dependent variable, εi is the error term, $\beta 0$ is the intercept, and β is the coefficients (Anselin & Arribas-Bel, 2013; Ward & Gleditsch, 2018). In OLS, observations must be independent from each other and constant with independent error components (Aboalyem & Ismail, 2023). OLS implies that the observation at the county level is independent and that spatial dependence does not occur (M Rahman et al., 2020).

Spatial Lag Model (SLM)

SLM regression incorporates spatial lagged dependent variables into the OLS equation. According to (Sannigrahi et al., 2020), spatial lag accounts for the influence or impact of neighbor countries or regions (M Rahman et al., 2020). The weight matrix of the SLM takes autocorrelation into account. SLM can be illustrated as below:

$$y_i = \beta_0 + x_i\beta + \rho W_i y_i + \varepsilon_i \tag{2}$$

Wi is the spatial weights vector; ρ is the parameter of spatial autoregressive; and xi ,$\beta 0$, β , εi are same as in Equation 1. The weight matrix (Wi) relates one independent variable to the other independent variable and describes how the both independent variables interact (Anselin & Arribas-Bel, 2013; Ward & Gleditsch, 2018).

Spatial Error Model (SEM)

This model implies that error terms are spatially dependent. Consequently, residuals are dissected into error terms and the model's overall structure (Abolfazl Mollalo et al., 2021):

$$y_i = \beta_0 + x_i\beta + \lambda W_i \xi_i + \varepsilon_i \tag{3}$$

The spatial component of the error term is denoted by ξ_i, while lambda (λ) represents the strength of correlation between the elements. The uncorrelated standard error is represented by εi. Wi is the spatial of weight matrices, $Wi\xi i$ is the strength of the correlation between the spatial component of the error term. The rest, xi, $\beta 0$, and β are as same as in Equation 1 (Ward & Gleditsch, 2018). The SEM model compensates spatial error autocorrelation through the spatially weight matrices (Dutta et al., 2021).

Geographically Weighted Regression (GWR)

The GWR builds spatial modelling between an y and xi variables (Comber et al., 2022). As explained below, GWR is a technique that establishes the spatial association among variables (Abolfazl Mollalo et al., 2021):

$$y_i = \beta_{i0} + \sum_{j-1}^{m} \beta_{ij} X_{ij} + \varepsilon_i \quad ,i = 1,2,3,\dots,n \tag{4}$$

where at country i, yi is the the dependent variable, and $\beta i0$ is the intercept, βij is the jth regression parameter, Xij is the value

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of the jth explanatory parameter, and εi is an error term (Abolfazl Mollalo et al., 2021). Traditional global models cannot consider a non-stationary spatial problem (Sannigrahi et al., 2020). Consequently, these models estimate average throughout the entire area of interest (Deilami & Kamruzzaman, 2017; Hamad et al., 2023). The GWR model, in contrast, overrides this restriction because of its cumulative local efficiency, which incorporates a geographic context from which parameters are estimated individually (Oshan et al., 2019).

Multiscale Geographically Weighted Regression (MGWR)

The Multiscale-GWR is an extension of GWR model that allows analysis at multiple scales and bandwidths (Dai et al., 2022). Therefore, it relaxes the GWR assumption. The ideal bandwidth vector must be derived, with every component representing the spatial scale upon which a certain function occurs (Hamad et al., 2023). Theoretically, MGWR is close to Bayesian framework and may offer a more adaptable and scalable framework for analyzing multiscale phenomena (Abolfazl Mollalo et al., 2021):

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

At area i, βbwj is the bandwidth utilized, Xij is the value of the jth iv parameter (Abolfazl Mollalo et al., 2021; Fotheringham et al., 2017). Its advantages over MGWR include its ability to accurately capture regional heterogeneity, reduce collinearity, and biasedness in the estimates (Oshan et al., 2019). The MGWR is often regarded as the generalized additive model (GAM), for allowing a back-fitting technique in calibrating MGWR models (Buja et al., 1989; Hastie & Tibshirani, 1990).

4. Results

Table 1 presents the description of the response and explanatory variables. At the same time, the statistical summary of the global OLS model is shown in Table 2. The best-fitted model will be chosen after using the forward stepwise regression technique. We found that GDP per capita, unemployment, and the total vaccination are essential explanatory variables and significant at a 5% level, but the population density is significant at a 10% level. Moreover, the significant variables show variance inflation factors (VIF) below 10, indicating the absence of serious multicollinearity issue (Thompson et al., 2017).

However, a moderate level of collinearity is evident between the total vaccination and GDP per capita variables, as indicated by the higher standard errors in the model. Consequently, the OLS regression model produced the lowest R-squared value (R^2=0.743) in comparison to the spatial dependence models. Nevertheless, this finding underscores that approximately 26% of the incidence rate across MENA countries can be attributed to country-level differences, presenting a challenge for OLS in estimating the model. To address this challenge, the SEM and SLM models were added to the OLS. As improvements, all variables became statistically significant at the 5% level, thereby enhancing the OLS model. However, due to the previous underestimation of the spatial process, the SEM and SLM models may exhibit lower standard errors than the OLS estimation (Table 3), indicating limited ability to estimate accurately in modeling.

However, we use GWR and MGWR to solve this issue by exploring any local spatial differences. The results demonstrate that the value of R^2 grew from 80.4% in the SLM model, the model with the greatest R^2 globally to 84.3% in the MGWR model, while the AIC reduced from 70.06 in the SLM model to 58.41 in the MGWR model. Therefore, given that MGWR's coefficient of determination was the highest, the model may account for 84.3% of all variations in COVID- 19 incidence rates. With a higher AIC of 58.82 compared to MGWR's with an AIC of 58.41, regular GWR had a slightly poorer goodness-of-fit score of 0.840 (Table 4). With a higher RSS of 11.38 than MGWR's RSS of 11.22, the residual sum of squares behaves similarly to AIC, slightly different across the local models.

Figure 1 shows how the y_i incidence rate of COVID-19 variable is distributed across subnational borders. Five models (global and local) were to be implemented to understand the linear and spatial relationship of independent variables to the incidence of COVID-19 in MENA countries. By enabling the computation of local levels rather than stationary parameter values, the local-level modelling procedure was a powerful method that improves conventional global regression. Population density and GDP per capita significantly impact the explanation of disease incidence rates in different MENA countries (Fig. 1).

Figures 2 and 3 present the results of GWR and MGWR models. As shown in Figure 3, while the effect of population density is seen at the country level, the COVID-19 infection situation follows a similar trend at the regional level for local models. Population density is crucial in determining COVID-19 infection rates across North African nations, particularly in Morocco, Sudan, Somalia, and Djibouti. However, the impact of GDP per capita on COVID-19 incidences was found to be inconsistent between the models.

Figure 4 shows that the unemployment indices in the GWR and MGWR models are the same and significantly impact the disease incidence rates in parts of Asia (Iran, Jordan, and Palestine) and northern Africa like Algeria, Egypt, Libya, Morocco, and Tunisia. Conversely, both models performed poorly in the countries of the southern MENA, namely Djibouti and Somalia. Furthermore, both models concluded that the geographical distribution of COVID-19 incidence rates in Iran, Djibouti, and Somalia could be significantly explained by the total vaccine doses coefficient.

Finally, the spatial distributions of local R^2 values in the GWR and MGWR models are shown in Figure 5. The darker shade shows higher values, while the lighter shades show lower values. All countries are found to have acceptable local R^2 values, and the model was most suitable for Somalia and Djibouti. Furthermore, the independent variables in both models account for at least 80% of the variation in Egypt and Palestine; the highest explanation percentage comes from Yemen, Somalia, and Djibouti, at 88%.

5. Discussion

In this study, we analyzed 19 variables, divided into four

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categories (demographic, behavioral, medical, and socioeconomic) that describe the geographic distribution of the COVID-19 situation in the MENA countries. We estimated the regional distribution of COVID-19 cases using a spatial regression and autoregressive model. Our analysis suggests that a combination of population density, GDP per capita, unemployment rate, and total vaccination response may be responsible for differences in the disease incidence rates across MENA countries.

Findings from the GWR and MGWR models show a strong relationship between the incidence of diseases in this region and population density, GDP per capita, unemployment, and vaccination. As the virus continued to spread, healthcare systems faced vulnerabilities, the economy declined, and unemployment rates rose. Our findings are also consistent with the importance of vaccination during the epidemic.

According to the positive GDP per capita coefficient, increasing population density in areas with high GDP per capita will increase the probability of contracting COVID-19. The emergence of new or different strains can positively impact overall immunity. This suggests that outbreaks are more severe in areas with higher immunity.

6. Conclusions

Understanding factors that affect incidence of diseases is important, especially for diseases such as COVID-19, which has a global impact. The aim of this study is to identify variables that may affect the incidence of COVID-19 in MENA countries. We investigated the incidence patterns and impact factors of COVID-19 in the MENA region, using spatial models. Among these models, MGWR showed the highest level of fit, strengthening and extending previous findings. Regional differences observed in MGWR may indicate variations in COVID-19 incidence based on the identified independent variables. This study is important for future understanding as, to our knowledge, there have been no previous studies using spatial trends of COVID-19 incidence in the MENA region

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

Parameters	Description	Measurement unit	Source
Incidence rate (response variable)	Cumulative Daily confirmed COVID-19 cases in the 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 is calculated by dividing the total number of people by the 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 in 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'
GDP Gross Domestic Product (current US$) (explanatory variable)	The 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 country 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	Index	https://covid19.pemandu.org/

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	factor of the country's population		
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 country 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 country in 2022	Index	https://data.worldbank.org/indicator/

Table 2. Summary statistics of the global OLS model.

Variable	Coefficient	St. Error	t- Statistic	Probability	VIF
Intercept	-11.6942	3.7859	-3.09	0.0060	–
Population density	0.0011	0.0005	2.04	0.0551	1.195
GDP per capita	0.8735	0.2166	4.03	0.0007	2.141
Unemployment	0.1160	0.0424	2.73	0.0131	2.419
Total vaccine doses	0.9623	0.1536	6.26	0.0000	1.306

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	-13.9003	8.9763	3.1607	3.0262	4.3979	2.9662	0.0000	0.0030
Pop-density	0.0009	0.0012	0.0004	0.0004	2.2372	2.8864	0.0252	0.0038
GDP per capita	0.8201	0.8114	0.1693	0.1509	4.8436	5.3756	0.0000	0.0000
Unemployment	0.1261	0.1173	0.0333	0.0320	3.7811	3.6603	0.0001	0.0002
Total vaccine doses	0.8446	0.8338	0.1244	0.1267	6.7854	6.5770	0.0000	0.0000
Rho	0.3442	-	0.1379	-	2.496	-	0.0125	-
Lambda	-	0.4692	-	0.1815	-	2.585		0.0097

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

Criterion	OLS	SEM	SLM	GWR	MGWR
R2	0.743	0.794	0.804	0.840	0.843
AIC	73.54	72.14	70.06	58.82	`58.41
RSS	18.26	14.63	13.95	11.38	11.22

RSS= Residual sum of squares

Fig. 1. Location of the study area.

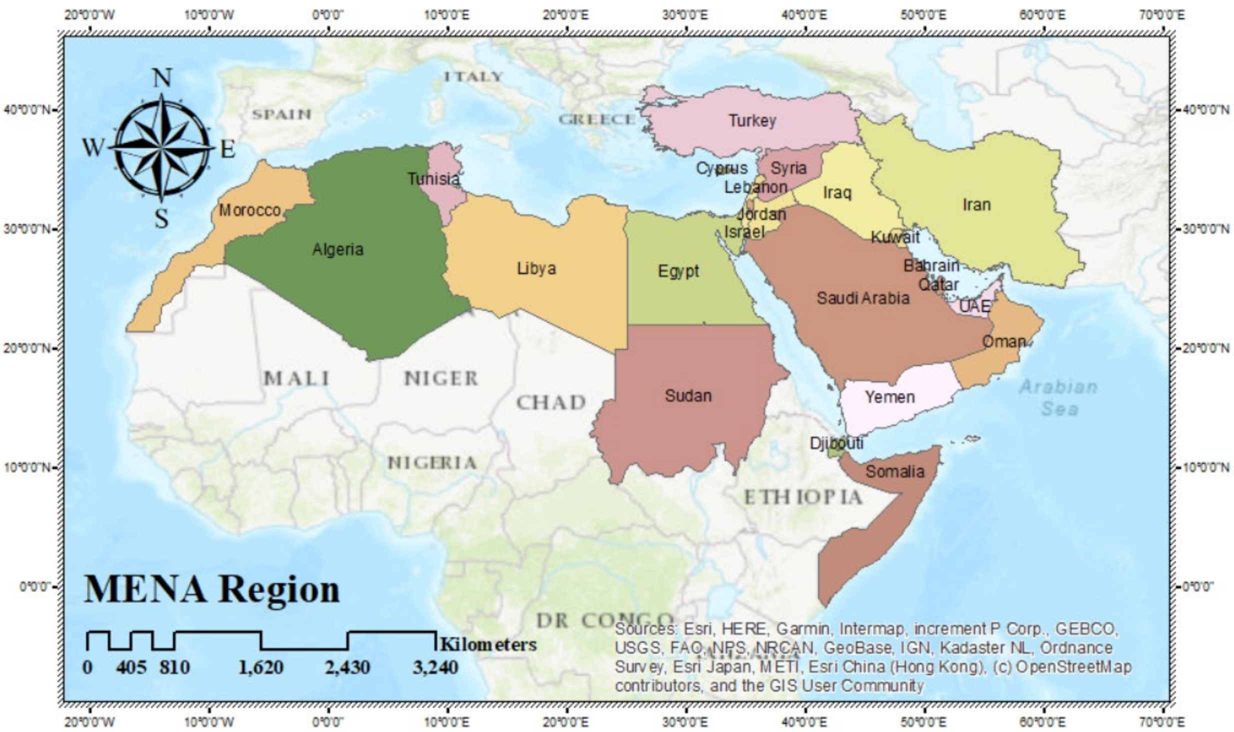

Fig. 2. Distribution of the dependent variable (COVID-19 incidence rate) across subnational boundaries

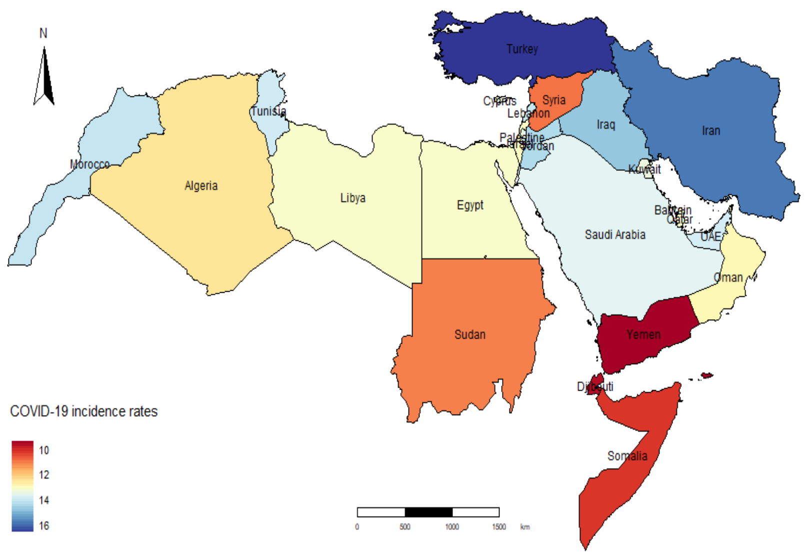

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Fig. 3. The effects of %Population density (above) and GDP per capita (below) in describing COVID-19 incidence rates using GWR (right) and MGWR (left) models across the MENA region.

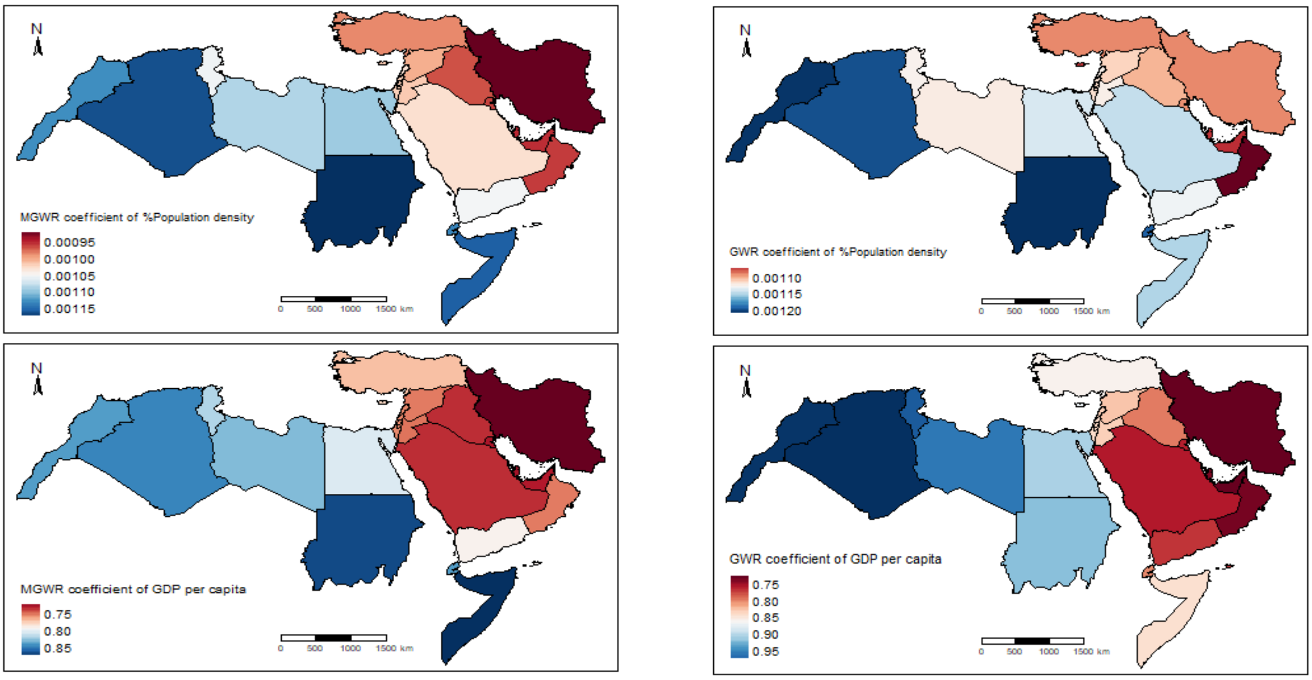

Fig. 4. The effects of % Unemployment (above) and Total vaccine doses (below) in describing COVID-19 incidence rates using GWR (right) and MGWR (left) models across the MENA region.

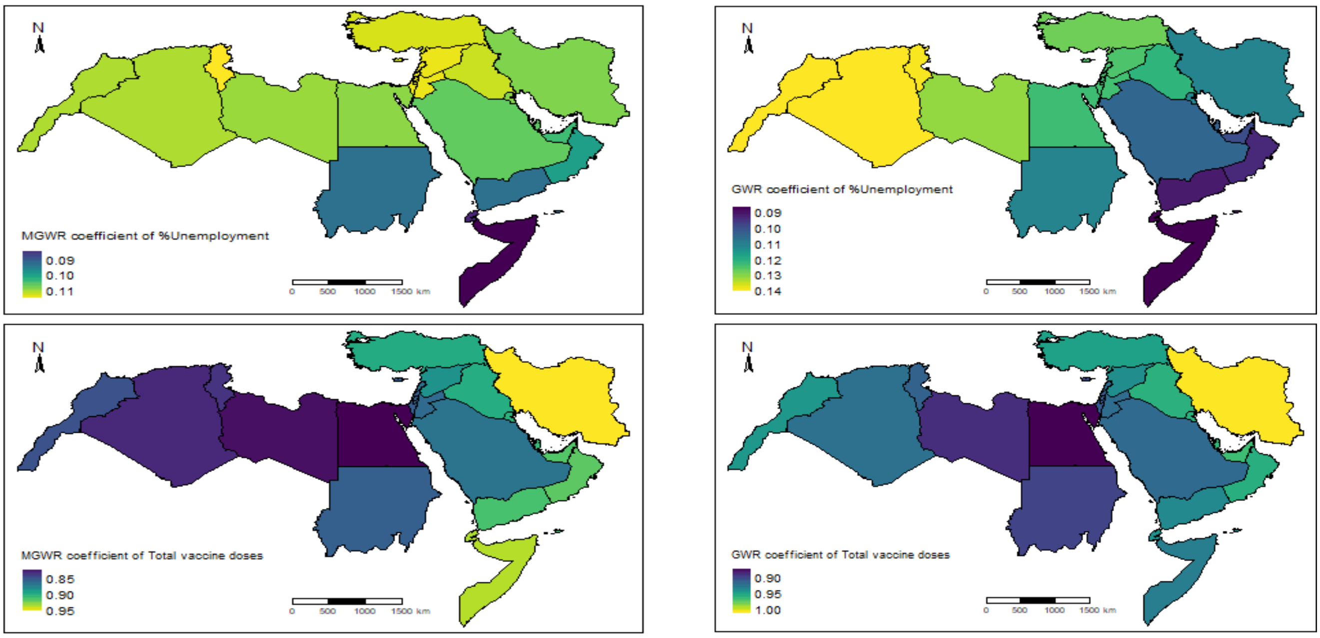

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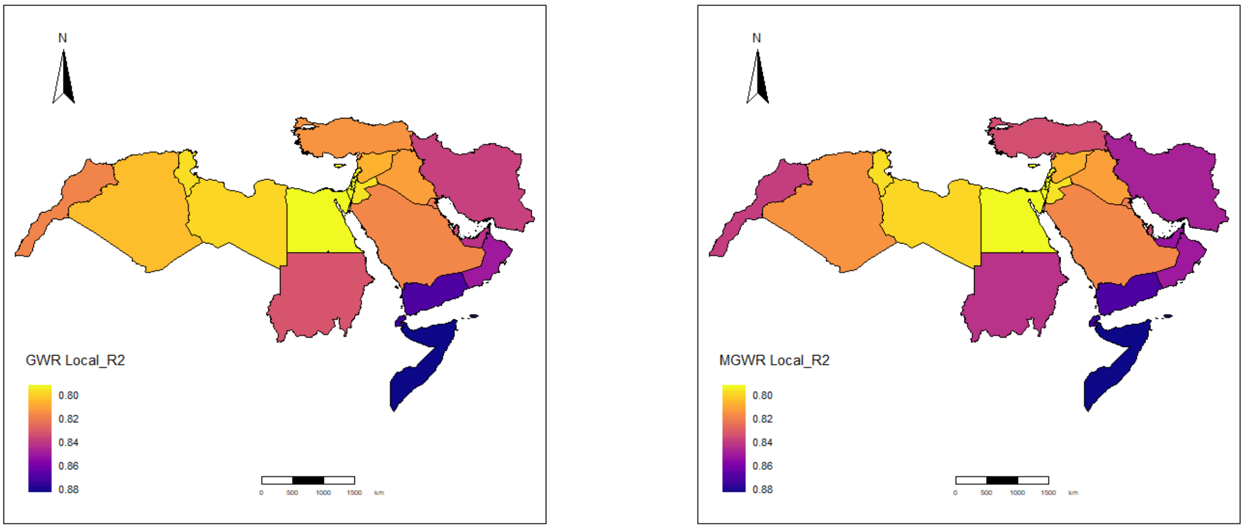
Fig. 5. Spatial distribution of local R2 of GWR and MGWR models for COVID-19 incidence rate associated with the significant covariates across the MENA region.



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