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Geospatial modelling of COVID19 mortality in Oman using geographically weighted Poisson regression GWPR

Shawky Mansour[1]✉, Mohammed Alahmadi[2], Ayman Mahmoud[3], Khalid Al-Shamli[4], Malaak Alhabsi[4] & Waad Ali[4]

The year 2020 witnessed the arrival of the global COVID-19 pandemic, which became the most devastating public health disaster in the last decade. Understanding the underlying spatial variations of the consequences of the pandemic, particularly mortality, is crucial for plans and policies. Nevertheless, few studies have been conducted on the key determinants of COVID-19 mortality and how these might vary geographically across developing nations. Therefore, this research aims to address these gaps by adopting the Geographically Weighted Poisson Regression (GWPR) model to investigate spatial heterogeneity of COVID-19 mortality in Oman. The findings indicated that local GWPR performed better than global Ordinary Least Square (OLS) model, and the relationship between risk factors and mortality cases varied geographically at a subnational scale. The local parameter estimates of the model revealed that elderly populations, respiratory diseases, and population density were significant in predicting mortality cases. The elderly population variable was the most influential regressor, followed by respiratory diseases. The formulated policy recommendations will provide decision-makers and practitioners with key factors related to pandemic mortality so that future interventions and preventive measures can mitigate high fatality risks.

Keywords Geospatial modelling, COVID-19 mortality, Spatial heterogeneity, GWPR, Oman

Research has established that COVID-19 morbidity and mortality severity manifest unequally across space[1,2]. Analysis at the aggregated level of country groupings using the World Bank income classification illustrates this through a stark divide in COVID-19 mortality between high-income countries (HICs) and low-income countries (LICs). HICs constituted 79% of the global share of COVID-19 deaths, while upper-middle-income countries (UMICs), low-middle-income countries (LMICs) and LICs accounted for 17.8%, 3.1%, and 0.2%, respectively[2]. Sorensen et al.[3] and Ghisolfi et al.[4]assert that even after accounting for age, health system capacity, and comorbidities, less-developed countries had lower infection fatality rates (IFRs) than developed countries. However, deaths related to COVID-19 have been projected to increase in developing countries if no public health interventions are taken to limit the contagion of the virus[2,5].

Since the start of the COVID-19 pandemic, Oman has reported approximately 400,000 cases and 5,000 deaths[6], with differing impacts across various regions. Notably, the Governorate of Muscat experienced the highest incidence compared to the less-affected Buraimi[7]. Moreover, during the pandemic from 16 March to 16 August 2020, Oman recorded a 15% increase in all-cause mortality, including a 2% increase in infectious diseases and a 9% increase in unclassified deaths, as reported by Al Wahaibi et al.[8] The authors attributed this excess mortality to the interruption of routine and elective healthcare services, particularly for patients with non-communicable diseases.

Previous studies in Oman revealed several socioeconomic factors strongly associated with COVID-19 infection and mortality rates[7,9,10]. Despite this, few studies employ innovative geospatial modelling techniques (namely, generalised weighted Poisson regression models) to advance our understanding of the spatial dimensions and correlates (sociodemographic and health) of COVID-19 mortality in Oman. Numerous studies beyond the

[1]Geography Department, College of Social Sciences, Kuwait University, P.O. Box 5969, 13060 Kuwait City, Safat, Kuwait. [2]Earth and Space Science Institute, Future Economies Sector, King Abdulaziz City for Science and Technology (KACST), P.O. Box 6086, Riyadh 11442, Saudi Arabia. [3]Geography Department, Faculty of Arts, Zagazig University, Zagazig 44519, Egypt. [4]Geography Department, College of Arts and Social Sciences, Sultan Qaboos University, Al-Khoud 123, P.O. Box 17, Muscat, Oman. ✉email: shawky.mansour@ku.edu.kw

context of Oman have delved into the spatial dynamics of pandemics, including COVID-19, employing various geospatial modelling techniques (see[11–13]in China; Arauzo-Carod[14] in Spain; Zhu et al.[15] and Desjardins et al.[16]in the USA). Specific studies, such as Arauzo-Carod (2021), underscore the importance of spatially informed approaches in understanding COVID-19 mortality for effective healthcare planning, particularly in allocating limited resources to underserved areas to mitigate the spread of the pandemic. Additionally, Arauzo-Carod[14] suggested that empirical evidence derived from spatial analysis can enhance the efficacy of public health policy interventions.

Because COVID-19 mortality in the Gulf Cooperation Council (GCC) region is largely under-researched, this study aims to advance our understanding of COVID-19 mortality in Oman by analysing the spatial dimensions and correlates at subnational boundaries. We capture the spatially varying relationships between COVID-19 mortality and numerous demographic and health variables. To achieve this, we relied on a non-parametric method, Geographically Weighted Poisson Regression (GWPR). Indeed, the adoption of GWPR for disease association mapping reveals geographic variations in relationships between health outcomes and various explanatory variables. Moreover, GWPR has the added benefit of revealing meaningful geographical drifts and spatial clusters in the association between outcome and explanatory variables. To achieve the above aim, the following set of research questions will be answered:

(i) To what extent do the relationships between these sociodemographic characteristics and COVID-19 mortality patterns vary spatially in Oman?
(ii) What significant sociodemographic and health variables impact disease mortality across subnational boundaries?
(iii) What are the potential policy implications of the research findings?

Within the expansive COVID-19 literature, many studies have identified global and country-level risk factors explaining the variability in COVID-19 mortality (e.g[17–21]). For instance, Dudel et al.[19]used decomposition methods to establish that the age structures of COVID-19 cases within specific countries across the globe largely shaped disparities in COVID-19 case fatality rates (CFRs). The findings explicitly indicated that the age structure of COVID-19 cases could explain more than two-thirds of the differences in CFRs across populations in South Korea, China, Spain, Italy, Germany, the USA, and New York. Other studies used geospatial and statistical methods to investigate the prevalence of COVID-19 fatality rates across age groups. Kulu and Dorey[22] computed age-specific fatality rates across spatial units in the UK and used Moran I indices to measure the spatial clustering of IFRs. Their study revealed significant variations in projected death rates from COVID-19 across and within regions in the UK. Differences in population age structures may influence this. For instance, Scotland, Wales, and England, which have older age structures, had higher projected COVID-19 fatality rates than Northern Ireland, which has a younger age structure. The study also identified projected clusters of high IFRs in small towns and rural areas with older populations across the UK. However, a limitation of this analysis is that it assumes uniform infection rates when estimating the total deaths.

The literature has widely documented variations in COVID-19 mortality by social location of gender[23–30]) and race[31–34]). Regarding gender differences in COVID-19 mortality, numerous studies have reported higher risks for males and racialised populations than for females and non-racialised populations across European countries[23], East Asian countries[26], China[28], the USA[33], and the UK[29]. While most of these studies adopt an intersectional framework in their statistical methodology to understand how gender and/or race interact with COVID-19 mortality, they tend to overlook intra-national variation across and within small geographic areas or do not comprehensively explore the extent to which gender or race differences shape COVID-19 mortality across space. This limitation is partly due to the lack of COVID-19 mortality data at the various levels of spatial aggregation.

Other social determinants of COVID-19 mortality noted in the literature include population density and connectivity[17,35,36]). Regarding population density, Chang et al.[17]used Fama and MacBeth regressions to assess the correlates of COVID-19 morbidity and mortality rates in 91 countries worldwide. Their cross-country analyses revealed that population density significantly positively affected COVID-19 mortality across selected countries in Asia, Africa, Europe, North America, South America, and Oceania. These findings were corroborated by studies conducted across various geographies, including Martins-Filho[38] in Brazil and Kodera et al.[37] in Japan, with varying disparities in the strength of association. Contrasting findings were reported by Hamidi et al.[36], who used structural equation modelling to evaluate the direct impact of density on COVID-19 mortality across 913 counties in the USA. After controlling for the effects of healthcare infrastructure, metropolitan area populations, and socio-economics, Hamidi et al.[36] found a negative relationship between COVID-19 mortality rates and population density. The authors attributed these findings to denser metropolitan counties with better access to healthcare systems. Additionally, Hamidi et al.[36]established those larger metropolitan counties with higher connectivity linking economic, social, and commuting relationships had higher mortality and infection rates. Most of these studies presented early findings on the impact of density on COVID-19 mortality and relied on cross-sectional differences within or across countries. As such, longitudinal time-series analyses are required to ascertain the reliability of these results by exploring panel approaches that examine lead-lag relations among countries regarding COVID-19 mortality[17].

Health risk factors comprising underlying population healthcare resources and population health conditions (i.e., comorbidities) have been linked in one way or another to COVID-19 mortality[20,34,39,40]). Karmakar et al.'s[40]country-level analyses using zero-inflated negative binomial regression models demonstrated that an additional year of life expectancy was associated with a lesser risk of COVID-19 mortality. In contrast, Perone's[20]cross-sectional study adopted ordinary least squares multivariate regression models to uncover that healthcare efficiency and physician density across Italian regions reduced CFRs. Cluster analyses (specifically

Ward's hierarchical agglomerative clustering) in their study further illustrated that northern provinces in Italy had the highest risk of COVID-19, whereas the southern provinces had the lowest. Perone's[20]findings were echoed by Chang et al.'s[17]worldwide study establishing a negative association between healthcare infrastructure and COVID-19 mortality, further indicating the importance of healthcare infrastructure in containing the contagion and mortality of pandemics. Perone's[20]and Chang et al.'s[17] studies are limited to cross-sectional regression methodology. However, Chang et al.[17] used a cross-sectional approach because the health and demographic system variables did not change significantly in the short term.

The influence of sociocultural variables on COVID-19 fatalities has been studied from various perspectives, including housing conditions, public opinion, and adherence to public health regulations[41,42]. Varshney et al.[42] found that household overcrowding was positively associated with COVID-19 mortality rates, further highlighting the influence of sociocultural factors on mortality rates. Abbasi et al.[41] examined sociocultural factors including political ideology, individualism, fatalism, health literacy, and prosociality indirectly affecting adherence to COVID-19 emergency measures and thus incidence rates.

Methodologically, many attempts (e.g[43–45].,) have emphasised that large sample sizes are better and more effective when the Geographically Weighted Regression (GWR) is utilised mainly to diminish the influence of multicollinearity, improve the inference process, and recapture vigorous and reliable parametric estimates. In addition, the inferences of spatial heterogeneity may be affected by the small sample size, and thus, the possibility of pseudo-correlations between coefficients increases[43]. Using GWR, preliminary work on modelling the demographic, social, and environmental determinants of the COVID-19 pandemic across Polish counties was conducted[46]. The findings indicated that demographic factors were powerful predictors of COVID-19 incidence and social determinants were significant to a medium degree, while environmental variables were lowest in explaining the spatial heterogeneity of disease cases.

Within the broader literature, several studies beyond the context of Oman have used a wide range of geospatial modelling approaches to explore the spatial dynamics of COVID-19 incidence or mortality. For instance, Kang et al.'s[11]study in China and Arauzo-Carod's[14]study in Spain used local indicators of spatial associations and Global Moran's I index to explore the spatial patterns of COVID-19 infections. Another study[13] in China employed spatial panel data models to investigate the associations among incidence, mortality, and cases recovered due to treatment. Likewise, Desjardins et al.[16]used space-time clustering to detect clusters of COVID-19 infections in the USA. Some of these studies are limited to country- or cross-country-level analyses, mainly due to the data limitations. Moreover, most studies surveyed in the literature adopted a range of regression models where parameters were assumed to be fixed and, as such, did not capture spatial heterogeneity when examining the relationship between COVID-19 mortality and sociodemographic and health correlates. Other studies that employed ecological approaches overlooked the possibility that spatial variations in the relationships between COVID-19 and sociodemographic and health factors may vary geographically[47].

GWR creates local regression models at each point in space using a scale of weights that considers the features of nearby sites when building the model. GWR derives a local weight matrix from a kernel function, assigning more weight to proximate locations[48]. GWR has been used across several research disciplines to model geographical data, especially within the health sector (e.g[10,49–51]). In other areas, Cahill and Mulligan[53] used GWR to support the idea that crime is a localised phenomenon, so local settings must be considered when exploring crime rates.

Additionally, Jendryke and McClure[54] investigated the impact of proximity by employing a co-location map, a GWR for count data, and a Spatial Lag Model at various scales to determine the extent to which the size of the aggregation units influenced the relationship between hate groups and hate crimes. Fotheringham et al.[55]investigated the geographical context of school performance by employing GWR to analyse various socioeconomic factors in northern England. Spatial disparities occur between educational zones and socioeconomic groupings. Additional uses for GWR encompass the analysis of spatial disparities in residential property values in London[12]and the investigation of geographical factors influencing rental housing prices in Hefei, China[56].

This study uses non-parametric methods including GWPR to analyse the spatial dimensions and correlates of COVID-19 mortality within the subregions of Oman. This captures the spatially varying relationships between COVID-19 mortality and multiple demographic and health variables. The adoption of GWPR for disease association mapping reveals geographic variations in the relationships between health outcomes and various explanatory variables. Moreover, GWPR has the added benefit of revealing meaningful geographical drifts and spatial clusters in the association between outcome and explanatory variables[47]. Despite increasing research on COVID-19 epidemics in numerous countries, the spatial modelling of disease mortality is uncommon in the GCC states. Thus, this study seeks to bridge this gap by developing a local geographic model of Oman's mortality rates. We used several sociodemographic factors, one global model (ordinary least squares) and two local models (GWR and GWPR) to forecast geographical disparities in COVID-19 mortality across Omani subnational zones. Using innovative spatial techniques such as GWPR to examine the patterns and correlates of COVID-19 mortality in Oman fills a methodological void in COVID-19 mortality literature by informing spatially targeted population health policy interventions. Therefore, this research outcome may be crucial for health governance and could provide critical insights into mitigating the hazards of disease mortality.

Study area and dataset
Study area
Located in the far southeastern corner of the Arabian Peninsula, the Sultanate of Oman has a total land area of nearly 309,500 km[2], including several islands in the Arabian Sea and the Gulf of Oman. This research covers the entire country, extending from latitudes 16.40–26.20° north and longitudes 51.50–59.40° east. Oman borders the

Republic of Yemen in the south, the Kingdom of Saudi Arabia in the west, and the United Arab Emirates (UAE) in the north and west (Fig. 1).

Its long coastlines stretch to around 3165 km from the far north to the east and south on the Gulf of Oman, the Arabian Sea, and the Indian Ocean. The country has a subtropical climate, with hot summers and warm winters. The humidity ranges from 60 to 80%, while the annual average precipitation ranges from 150 mm to 300 mm in the north and from 50 mm to 150 mm in the south.

In 2023, Oman was the third most populous country among the members of the GCC (Saudi Arabia, UAE, Oman, Kuwait, Qatar, and Bahrain) with approximately 5,432,422 inhabitants (including both locals and non-Omani migrants), with a population density averaging 16 per km[257]. Administratively, the country is divided into 11 governorates and 61 subnational administrative boundaries called Wilayats (states). Muscat

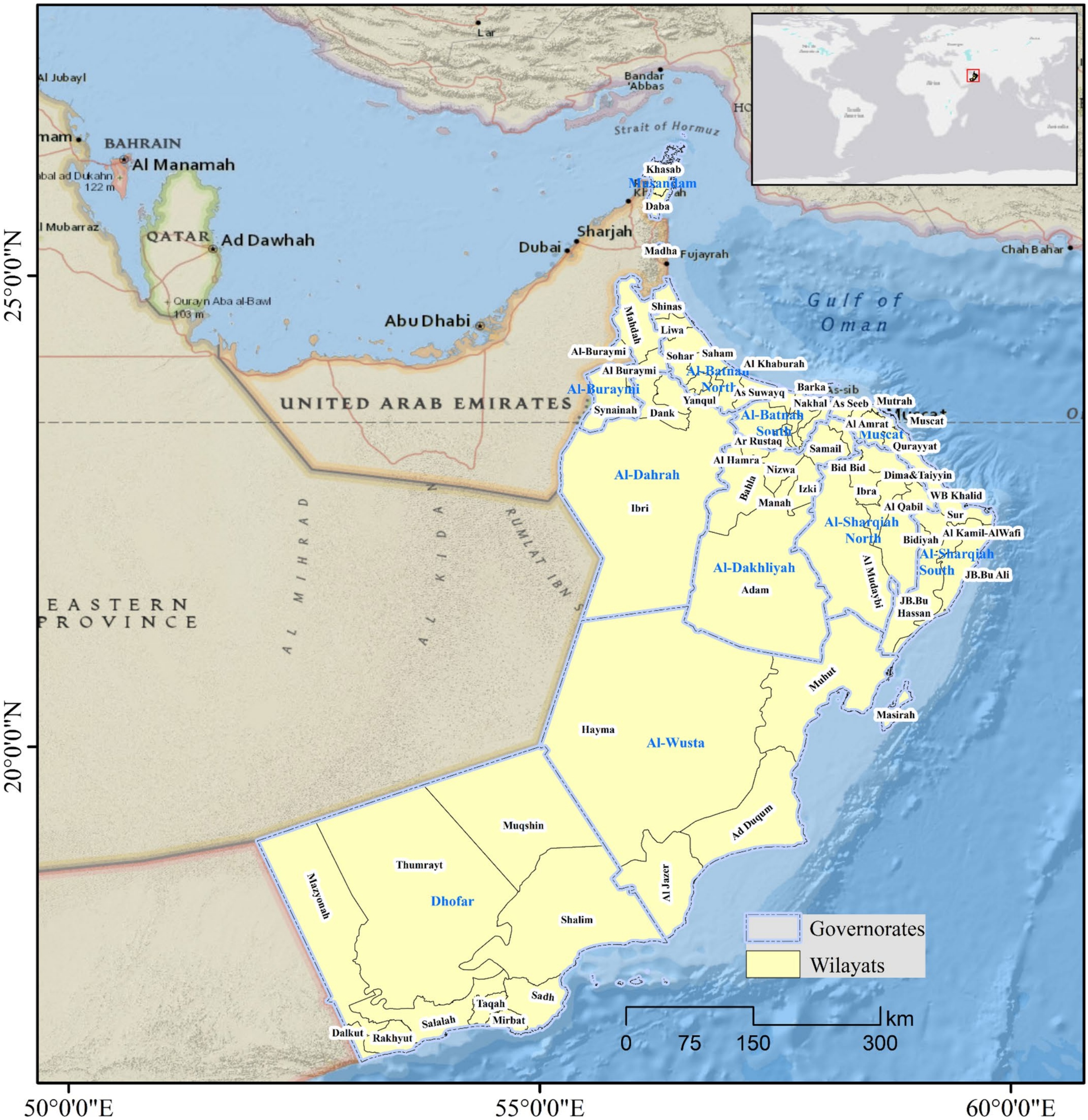

Fig. 1. The location of the study area. (Created using Arc GIS version 10. https://www.esri.com/news/arcnews/spring12articles/introducing-arcgis-101.html)

has the largest population and other socioeconomic activities. Approximately 87% of the population lives in urban agglomerations, particularly in the northern region where the Muscat governorate and the Al-Batinah coastal plain are located; in the south, the population is mostly concentrated in the southwest of the Dhofar governorate. The age composition of Oman's population is comparatively youthful, with approximately 26% of the population (including children and adolescents) falling within the age range of 0–14 years. Working-age individuals between 15 and 64 represent nearly 72% of the population. In contrast, the elderly population, consisting of individuals aged 65 and over, represents a relatively small proportion, comprising only 2% of the total population. Approximately 58% of the population are Omani nationals, while the remaining 42% are expatriates and non-Omani individuals. The population in Oman lives predominantly in urban areas along the coast, with specific governorates including Muscat comprising 30% of the population; Musandam has the smallest share at 1%.

In Oman from January 2020 to January 2023, approximately 399,154 cases and 4,628 deaths due to COVID-19 were documented (WHO, 2022d). Spatial variations of incidence rates were reported[10], with the Wilayats of Muscat and South Al-Batinah governorates suffering the most infections. In contrast, the Wilayats of South Al-Sharqiyah, Al-Buraymi, and Dhofar showed lower infection rates. Regarding COVID-19 mortality from 16 March to 16 August 2020, a 15% overall increase in all-cause mortality (excess mortality) occurred in Oman[8]. This includes excess mortality due to respiratory diseases, infectious diseases, and unclassified deaths, which increased by 9%, 2% and 9%, respectively. From a sociocultural perspective, Omani society is characterised by its generosity and deep connection to family values. Likewise, local communities usually value prosociality, collectivism, and communal well-being over individualism. These collective mindsets influenced by cultural values are likely to increase the infection rates of any communicable diseases and thus mortality rates, particularly among extended families.

Dataset

Using the COVID-19 mortality data from the Omani Ministry of Health, this research investigates and models the effects of the socioeconomic, demographic and health factors underlying spatial heterogeneity in mortality outcomes at subnational administrative boundaries. The total number of COVID-19 deaths from the start date of the pandemic to the end of 2021 was acquired, and the count Poisson dependent variable was created and mapped at a subnational scale (Fig. 2). Table 1 displays the descriptive statistics of all explanatory variables included in the modelling process.

In addition, a geodatabase involving all the explanatory variables was constructed, and ArcGIS software linked the attributes dataset to the spatial Omani administrative boundaries. The selection of explanatory variables included in the fitted GWPR models was based on the literature review, theory and conceptual framework (Table 2).

We collected the spatial boundaries and demographic datasets from the National Center for Statistics and Information. The modelling process of global and local GWPR was employed to examine the non-stationary relationships between the response (COVID-19 mortality) and the predictors and to identify the driving forces that are more influential in explaining spatial variations of the dependent variable.

Methods

The GWPR is a non-linear regression model commonly used to model counted response variables. The model incorporates spatially weighting schema and likelihood into the general regression. In this research, the GWPR was fitted to model the influences of demographic and epidemiological determinants on COVID-19 mortality across subnational zones. The model is computed as follows (Nakaya et al., 2005):

$$\mathrm{p_i} = \beta_{\,0}(\mu_{\,\mathrm{i}}, \mathrm{v_i}) + \sum\nolimits_{\mathrm{k=1}}^{\mathrm{n}} \beta_{\,\mathrm{k}}(\mu_{\,\mathrm{i}}, \mathrm{v_i})\,\mathrm{x_{ik}} + \epsilon_{\,\mathrm{i}} \tag{1}$$

where p_i indicates the predicted number of COVID-19 mortality in subnational boundaries i, while (u_i, v_i) signifies the centroid coordinates of that zone. $\beta_0(u_i, v_i)$ represents the intercept, $\beta_k(u_i, v_i)$ refers to the coefficient of the explanatory variable x_{ik}, n denotes the total number of explanatory variables, and ε_i states the error term.

The weighted least square technique is applied to estimate the coefficients in the GWPR. This technique requires local smoothing and can be calculated as follows:

$$\widehat{\beta}\;(\mu_{\,\mathrm{i}}, \mathrm{v_i}) = \left(\mathrm{x^T W}(\mu_{\,\mathrm{i}}, \mathrm{v_i})\,\mathrm{X}\right)^{-1} \mathrm{x^T W}(\mu_{\,\mathrm{i}}, \mathrm{v_i})\,\mathrm{Y} \tag{2}$$

where $\widehat{\beta}\;(\mu_{\,i}, v_i)$ indicates a row vector calculated by coefficient estimates in zone i, x represents the matrix of the predictors, Y refers to the column vector of the responses and $\mathrm{W}(\mu_{\,\mathrm{i}}, \mathrm{v_i})$specifies the spatial weight matrix, which is computed as follows[48]:

$$\mathrm{W}(\mu_{\,\mathrm{i}}, \mathrm{v_i}) = \begin{bmatrix} w_{i1} & \cdots & 0 \\ 0 & w_{i2} & 0 \\ 0 & \cdots & w_{in} \end{bmatrix} \tag{3}$$

where wij (j = 1, 2…, n) shows the weight of subnational zone j when predicting coefficients in zone i.

In applying the GWPR, we assumed that the COVID-19 mortality in zone $_{\mathbf{n}}$ when it is closer to zone $_{\mathbf{I}}$ has more influence and thus a larger weight. The weight function is a relationship between distance and the assigned weight value. Common weight functions are the Gaussian and bi-square functions. Fixed bandwidths characterise the Gaussian function, while adaptive bandwidths describe the bi-square function.

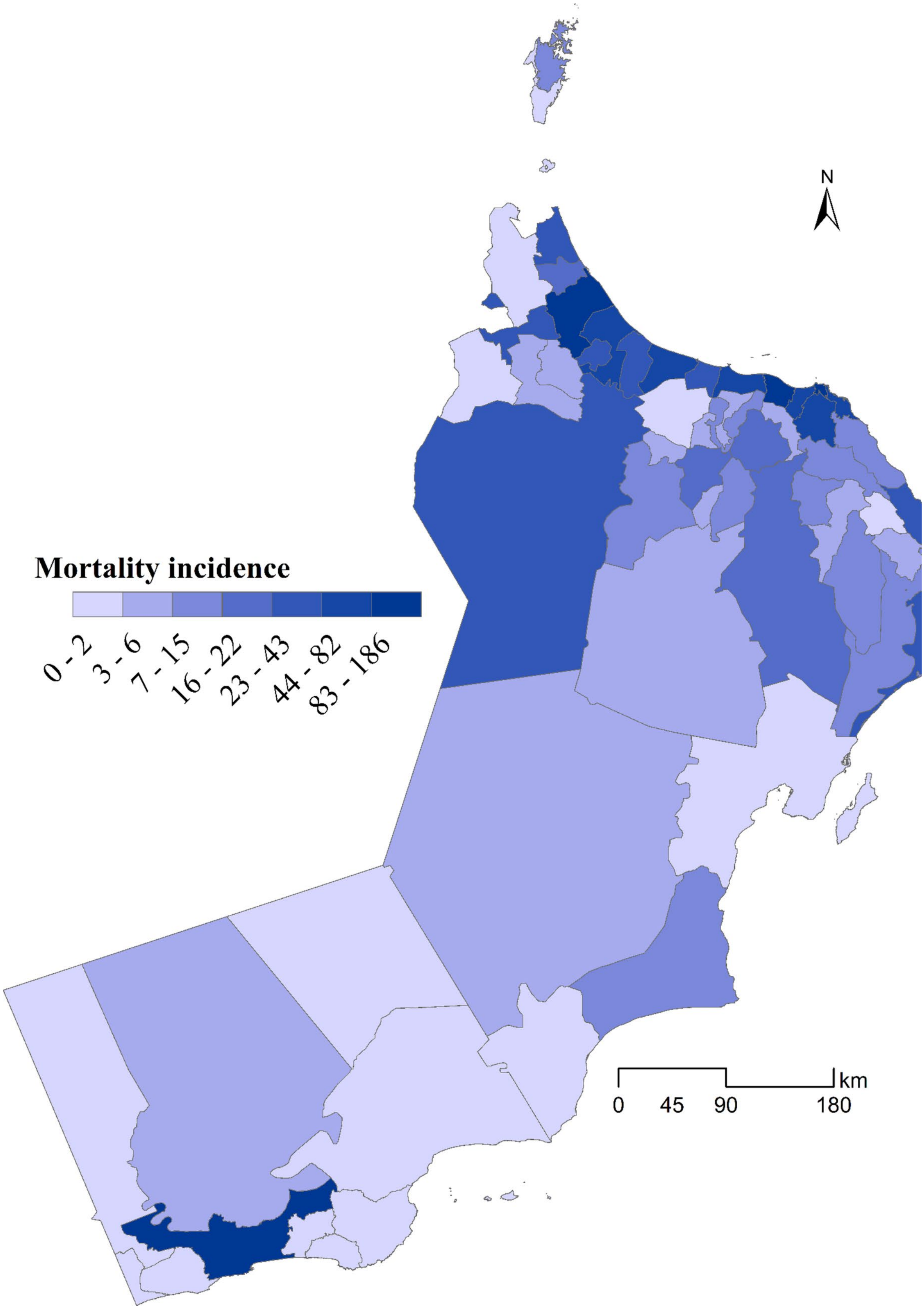

Fig. 2. COVID-19 mortality (the dependent variable) across Omani subnational boundaries.

Variables	Minimum	Maximum	Mean	Median	Std. Deviation
Blood diseases	0	4626	1210.85	864.00	1224.243
Respiratory disease	239	70,677	13569.84	8174.00	13230.111
Diabetes	15	8732	1655.43	946.00	1839.958
Population density	1	2574	120.33	32.00	372.557
Elderly population	24	15,278	2524.02	1219.00	3221.296
Hospital beds (Public)	0	738	82.41	18.00	157.484
Physicians and nurses	5	441	105.75	70.00	89.513
Dependent variable	1	186	23.86	8	36.93

Table 1. Summaries of primarily descriptive statistics for dependent and independent variables.

Variables	Definition	Data Source	The rationale for COVID-19 mortality
Blood diseases	Number of persons with reported blood diseases	Ministry of Health	Blood diseases including sickle cell disease and other abnormal haemoglobins (Hb) have generally been associated with an increased risk of severe illness and death from respiratory infections including COVID-19[58] .
Respiratory disease	Number of persons with a disease that affects the lungs and respiratory system	Ministry of Health	The increased risk of COVID-19 mortality has been evident among populations with chronic respiratory diseases, i.e., chronic obstructive pulmonary disease, interstitial lung diseases, lung cancer, and severe asthma[29,39,59] .
Diabetes	Number of persons who are diabetic (type 1 and type 2 diabetes)	Ministry of Health	Studies have revealed that populations infected with diabetes have a higher rate of hospital admission, severe pneumonia, and risk of COVID-19 mortality than non-diabetic populations[29,60]
Population density	Number of inhabitants per square kilometre	National Center for Statistics and Information	The contagion of COVID-19 spreads rapidly in areas of high population density. Chang et al.'s[17]and Bhadra et al.'s[35] studies showing a positive significant relationship between population density and COVID-19 infection and mortality affirm this. Hamidi et al.[36] demonstrate contrasting findings and attribute the negative causation to better access to the healthcare system in denser metropolitan counties.
Elderly population	Population aged 65 and over	National Center for Statistics and Information	The age structure of COVID-19 cases has largely explained the disparities in COVID-19 mortality rates[19]. Significant positive associations between increasing age and COVID-19 mortality are documented by Caramel et al.[61], Karmakar et al.[40], and Kulu and Dorey[22].
Hospital beds	Number of hospital beds	National Center for Statistics and Information	Prior literature has linked hospital resource availability, defined as hospital bed occupancy, as a risk factor for inpatient COVID-19 mortality[62]. Janke et al.[62], for instance, indicate that geographies with greater intensive care unit beds were significantly associated with a reduced incidence of COVID-19 mortality. The authors, however, argue that the benefit of hospital bed availability may be limited due to insufficient numbers of physicians and nurses.
Physicians and nurses	Number of physicians and nurses	Ministry of Health	Hospital resource and infrastructure variables such as an increased number of physicians and nurses have been significantly associated with fewer COVID-19-related deaths[62]

Table 2. Explanation of the selected independent variables and their rationale associations to mortality.

The Gaussian function with a fixed bandwidth involves fewer points in the regression and leads to greater standard errors. In contrast, the bi-square function considers the density of data points, assigning 0 to all points outside the bandwidth, nullifying their influences on regression points and thus optimising the bandwidth. Adopting the GWPR, the bi-square function with adaptive bandwidth was selected and is calculated as follows:

$$w_{ij} = \begin{cases} (1 - \frac{d_{ij}^2}{b_i^2})^2 \; d_{ij} \leq \; b_i \\ 0 \; d_{ij} > \; b_i \end{cases} \tag{4}$$

where d_{ij} is the distance between the centroid of zone i and zone j and b_i is the bandwidth used in zone i. The optimal bandwidth can be determined by the corrected Akaike information criterion (AICc) (Burnum & Anderson,2002; Hurvich et al.,1998) which can be expressed as follows:

$$AIC_c = AIC\,(m) + \frac{2k^2 \; + 2k}{n - k - 1} \tag{5}$$

where AIC(m) depicts the Akaike information criterion, k represents the number of free parameters in m, and n is the number of data points (zones).

We used the Breusch-Pagan test to determine whether spatial variability exists in the model. The null hypothesis holds that the error variance is constant across all data points, whereas the alternative hypothesis posits heteroscedasticity in the error variance due to variability among data points.

$BP = N^*R^2$ (K) (6).

where N denotes the number of observations, R^2 is the regression coefficient, and k specifies the number of explanatory variables. The test statistics follow a Chi-squared distribution:

$$\sigma^2 = \sum_{k=1}^{n} \mu_i^2 / n \tag{7}$$

Variable	Estimate	Std.	Z value	Pr(>|z|)	VIF
Intercept	2.71882	0.03519	77.26	0.0000	
Elderly population	0.46537	0.03373	13.797	0.0000	6.874
Population density	0.11887	0.0245	4.851	0.0000	3.891
Respiratory disease	0.30433	0.02892	10.524	0.0000	3.838

Table 3. The coefficient estimates of the global model. AIC: 806.1 R-square = 0.687 Null deviance: 2550.8 (60 df) Residual deviance: 798.1 (57 df).

Variable	Min.	1stQu.	Median	3rdQu.	Max.
Intercept	−2.20544	2.41406	2.71969	2.93934	3.6309
Elderly population	−1.17958	0.25536	0.80214	1.13826	1.7591
Population density	−13.898	−0.21736	0.10647	0.52888	3.8139
Respiratory disease	−0.35669	0.21051	0.44999	0.65769	1.5253

Table 4. Results of GWPR coefficient estimates. AICc: 363.724 Pseudo-R2: 0.879 GW Deviance: 307.540.

where the μ_i^2 is the squared residuals and n refers to the number of observations.

Results

To examine possible regressors of the dependent variable, a calibrated global regression model was fitted[6364]. Its outcome indicates that three variables were positively associated with and influenced the number of COVID-19 deaths (Table 3). Further, we deployed the variance inflation factor (VIF) to evaluate the extent of multicollinearity in the regression model. A VIF score over 10 for any explanatory variable indicates significant multicollinearity with other predictors, prompting the removal of that variable[10,65,66]. All regressors were standardised: Each variable had a mean of zero and a standard deviation of one. The first explanatory variable represents the number of elderly populations (people aged 65 and over) in each zone (Wilayat).

As the number of elderly people in each Wilayat increases, so does the COVID-19 mortality count. This variable mirrors the ageing factor of population composition, particularly the increasing rate of physical health problems. The power of this variable in explaining the mortality counts was the highest of the three independent variables (0.465). The second predictor is the population density in each Wilayat. Many COVID-19 deaths were mainly associated with zones of high population density. The third significant predictor is respiratory disease, representing the total number of respiratory disease patients in each Wilayat. This variable was influential in explaining the mortality counts and had a higher explanatory power (0.304) than population density (0.12).

The parameter estimates of the global model significantly describe the relationships between COVID-19 mortality and a set of epidemiological and demographical variables. However, these relationships are assumed to be stationary and fixed everywhere in the study area. This assumption should not be accepted without further examination as they might hide local spatial variations of the relationships between COVID-19 mortality and the three predictors. Therefore, fitting a local Poisson regression can show the falsity of this assumption and depict the spatial heterogeneity of the relationships between the dependent and independent variables over space.

The GWPR was adopted to examine spatial heterogeneity and variability of explanatory variables over the study area. The results of the GWPR model indicate that the local model is better than the global one (Table 4). Using the AICc criterion as a proxy to assess the performance of models, the GWPR local model was the best fit with a lower value (363.7) compared to the large AICc of the global model (806.1). Likewise, by comparing the R-square values of both models, the GWPR performed better (Pseudo-R2 = 0.879).

The standardised residuals are a ratio denoting the difference between the observed and estimated counts of pandemic mortality. Figure 3(a) exhibits the spatial distribution of standardised residuals. Light colours indicate low values (underestimation), while dark colours represent high residuals (overestimation). Overall, the spatial distribution of residuals across the study area illustrates a random scatter that specifies no pattern, suggesting that the model structure is appropriate. Examining the model fit can also be checked through a comparison of residuals. Figure 3(b) indicates that the residuals of GWPR are relatively less than the global model across the administrative boundaries. Overall, this result also shows that the local model had higher goodness of fit and robust explanatory power.

In addition, plotting the residuals against predicted values (Fig. 4a) indicates that in most cases values tend to cluster towards the middle of the plot and close to zero. This suggests that the model was a better fit with higher accuracy. Similarly, plotting the predicted versus the observed values (Fig. 4b) confirms a strong association between the model predictions and the actual values of COVID-19 mortality. Figure 4c demonstrates the association of the increasing values of observed COVID-19 mortality cases and residuals with the large leverage values. Leverage refers to influential values of predictors on the regression model where removing any leverage point would change the coefficients. Cook's distance also measures the influence of each observed case on the local model (Fig. 4d).

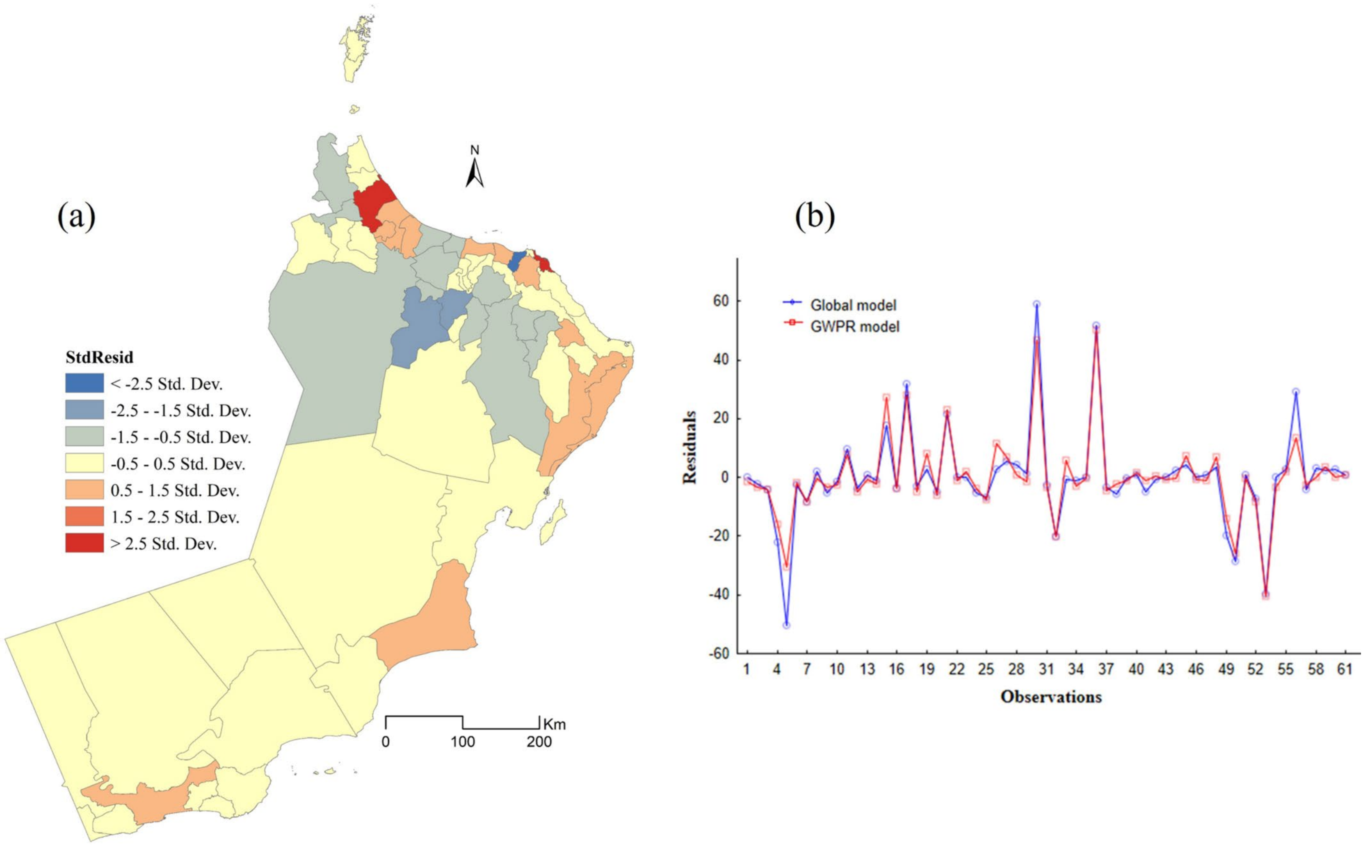

Fig. 3. A comparison between residuals of both the local (GWPR) and global models.

Table 5 reports the results of the geographical variability test. The Breusch-Pagan test was significant, indicating a variability among the observations. Likewise, the values of different criterion parameters are all negative. Additionally, this finding suggests that the existence of spatial variability and selecting the local model to explain spatial variations of relationships was better. Figure 5 illustrates local parameter estimates of the GWPR model. As shown, the effects of explanatory variables on COVID-19 mortality vary spatially, indicating the influence of specific local characteristics on each predictor.

Looking at the intercept coefficients (Fig. 5a) across all Wilayats, lower values of these coefficients are found mainly in the Muscat Governorate and Wilayats along the coastline of the northwest areas. Negative associations were evidenced between population density and COVID-19 mortality, particularly in the southern Wilayats, and positive and large coefficients mainly within the southwest of the Dhofar Governorate and the northern Wilayats of the study area (Fig. 5b). The population concentration in these places is higher than in other Wilayats, as the most densely populated areas of the country are in the north and south. The model outcomes also indicate that positive coefficient estimates of elderly population variables exist in the northern Wilayats (Fig. 5c). On the other hand, the values were negative in the central and southern Wilayats. The coefficient values of respiratory disease are positive and significantly associated with COVID-19 mortality in the southern Wilayats, predominantly within the Dhofar governorate (Fig. 5d). Similarly, the coefficient estimates of this variable were higher in the northwest zones, which may indicate that high rates of respiratory illness were found in these areas.

When examining the reliability of each predictor, the standard errors of local coefficient estimates were mapped (Fig. 6). The values of standard errors of the local intercept were relatively small in the northern Wilayats, mainly in Muscat and the South Al-Batinah governorates (Fig. 6a). In contrast, large values of standard errors were in the southern areas and the Dhofar governorate. Figure 6b shows the spatial distribution of the standard errors associated with the population density. Small errors were concentrated specifically in the northeast zones, indicating that the significance of population density on the dependent variable was higher in these places. On the other hand, large standard error values appeared mostly in the southern areas. In Fig. 6c, despite a clear spatial variation in the standard errors of the elderly population variable, the values are relatively small in the northern zones, particularly the northeastern Wilayats. The standard errors of the respiratory disease variable reached their lowest value in the northern Wilayats (Fig. 6d), which may indicate that the rates of respiratory disease illness in these areas were lower than in other administrative zones.

In addition to the standard errors, the t-values of the GWPR local parameters of each independent variable are crucial measures of significance (Fig. 7). The highest significance of the population density estimator was in the northern areas while the lowest significance was mainly in the southern and southeastern Wilayats (Fig. 7b). Likewise, high t-values of the elderly population variable were found in the northern areas, especially in

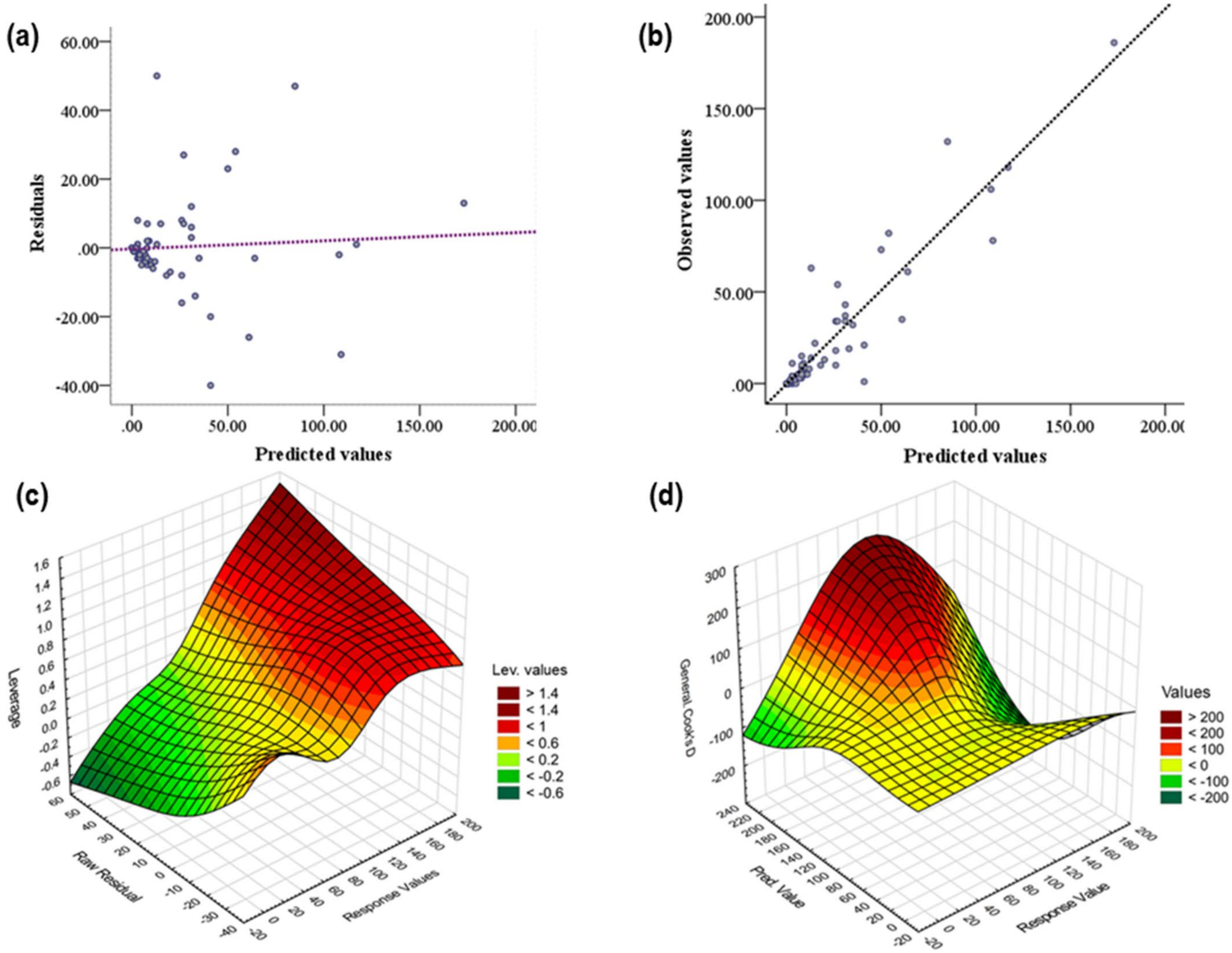

Fig. 4. The distributions of GWPR predicted values versus model residuals (**a**), the actual COVID-19 observations against the predicted values (**b**), the association between actual values, model residuals and leverages (**c**) , and the association between Cook's distance, actual and predicted values of the model (**d**) .

	Diff. of deviance	Diff. of DOF	Diff. of criterion
Intercept	29.76507	0.957265	−27.2184
Elderly population	9.418104	0.455897	−8.19364
Population density	3.932756	0.2263	−3.32228
Respiratory disease	32.59964	1.04713	−29.8186

Table 5. Summary of Spatial variability tests of local coefficient estimates. Breusch-Pagan test: 23.4122 Degree of freedom = 4 P- value = 0.00010*. (*) Significant at a = 5%.

Al-Dakhalya and the Muscat governorates (Fig. 7c). In contrast, this variable was less significant in the central and southern areas. The impacts of respiratory disease on COVID-19 mortality were highly significant in the northern and northwest Wilayats, predominantly Al-Buraymi and North Al-Batinah (Fig. 7c).

Discussion

The literature search found clear gaps concerning COVID-19 mortality in the GCC countries, particularly in terms of spatial, sociodemographic, and epidemiological drivers associated with death rates and the influences of such factors on spatial mortality patterns. To bridge these gaps, this research provides a potential contribution to the current literature on COVID-19 ramifications, particularly enhancing our understanding of the

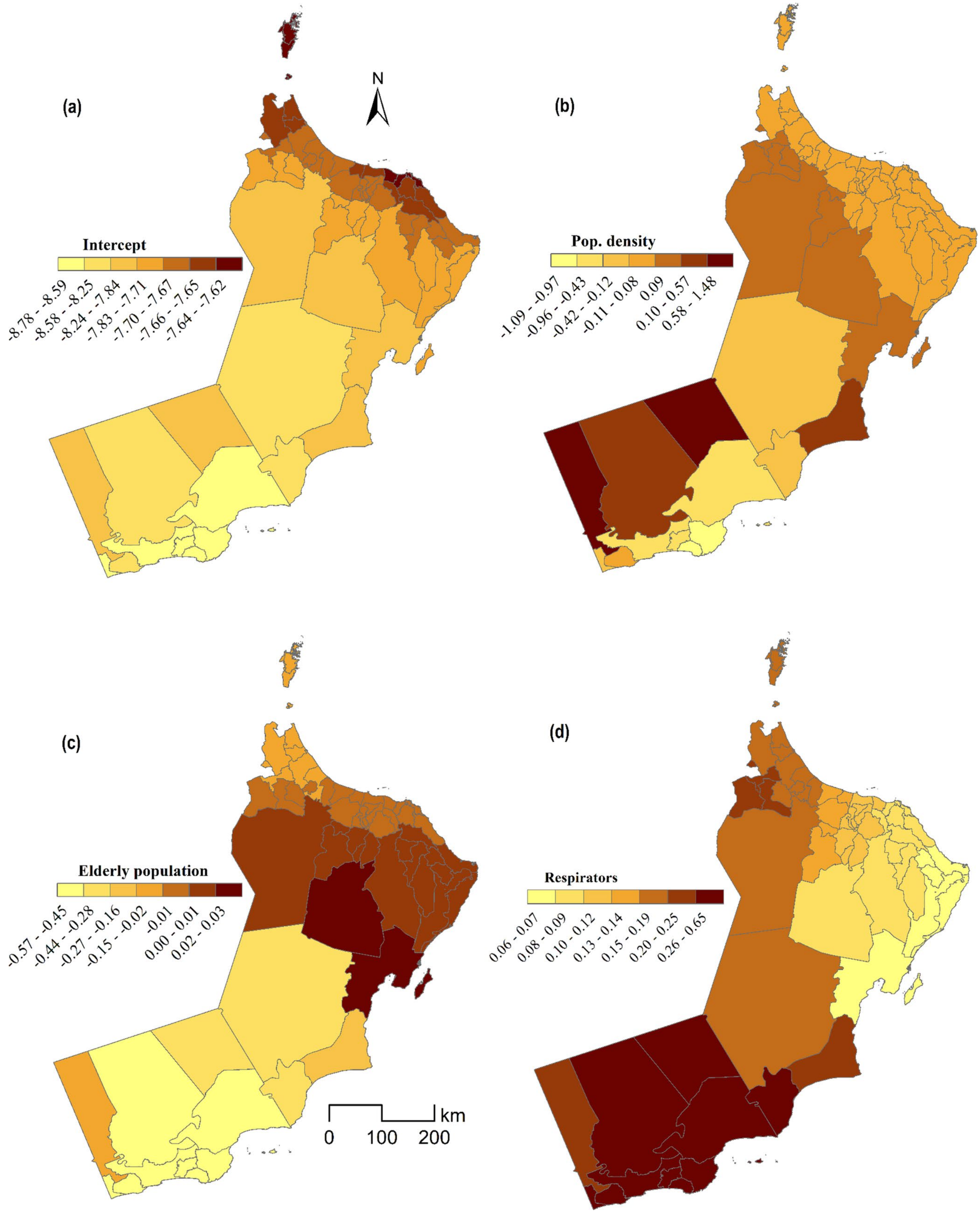

Fig. 5. Parameters of GWPR local estimates: intercept (**a**), population density (**b**), elderly populations (**c**), and respiratory disease (**d**).

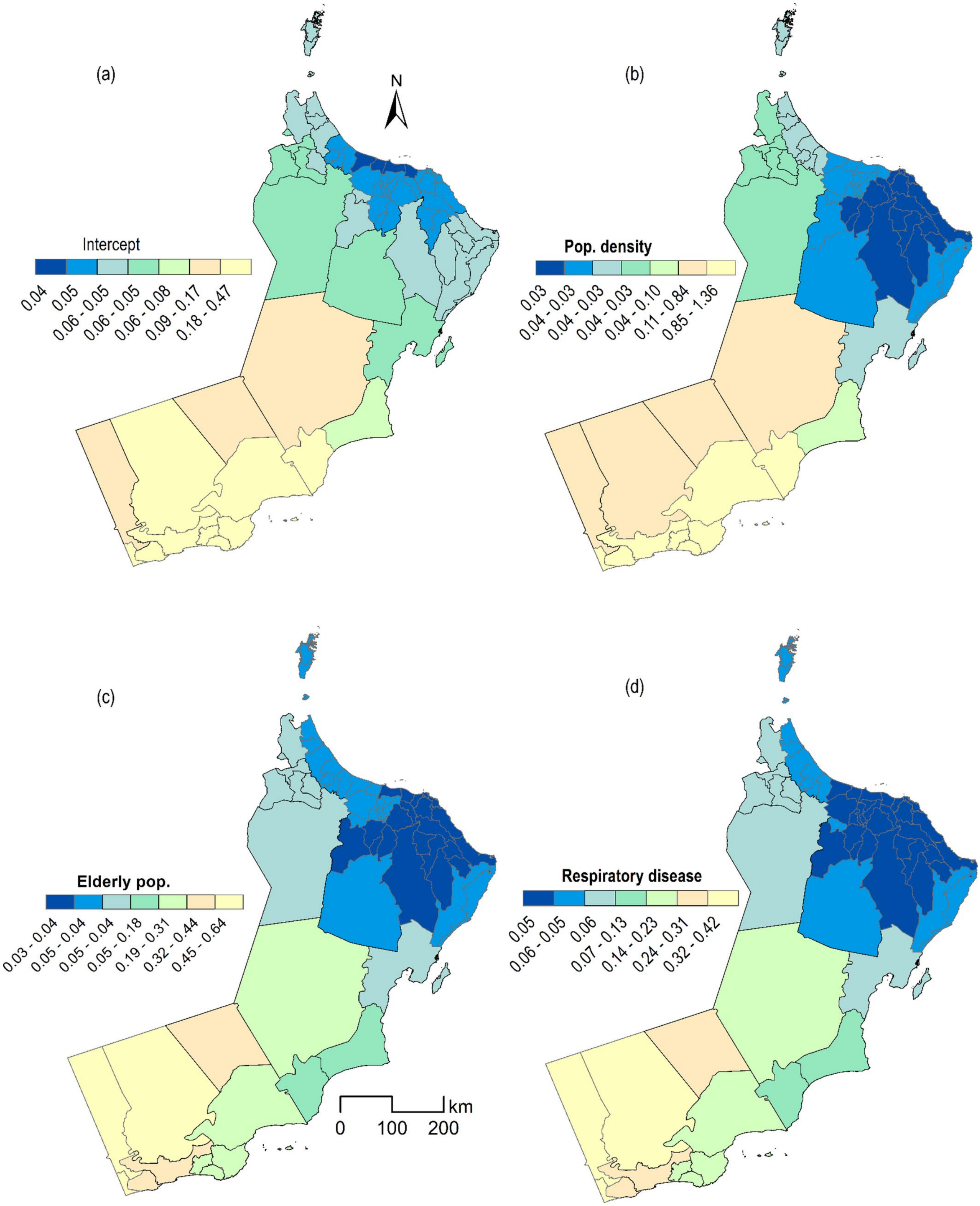

Fig. 6. Spatial distribution of standard error parameters in the GWPR: intercept (**a**), population density (**b**), elderly populations (**c**), and respiratory disease (**d**).

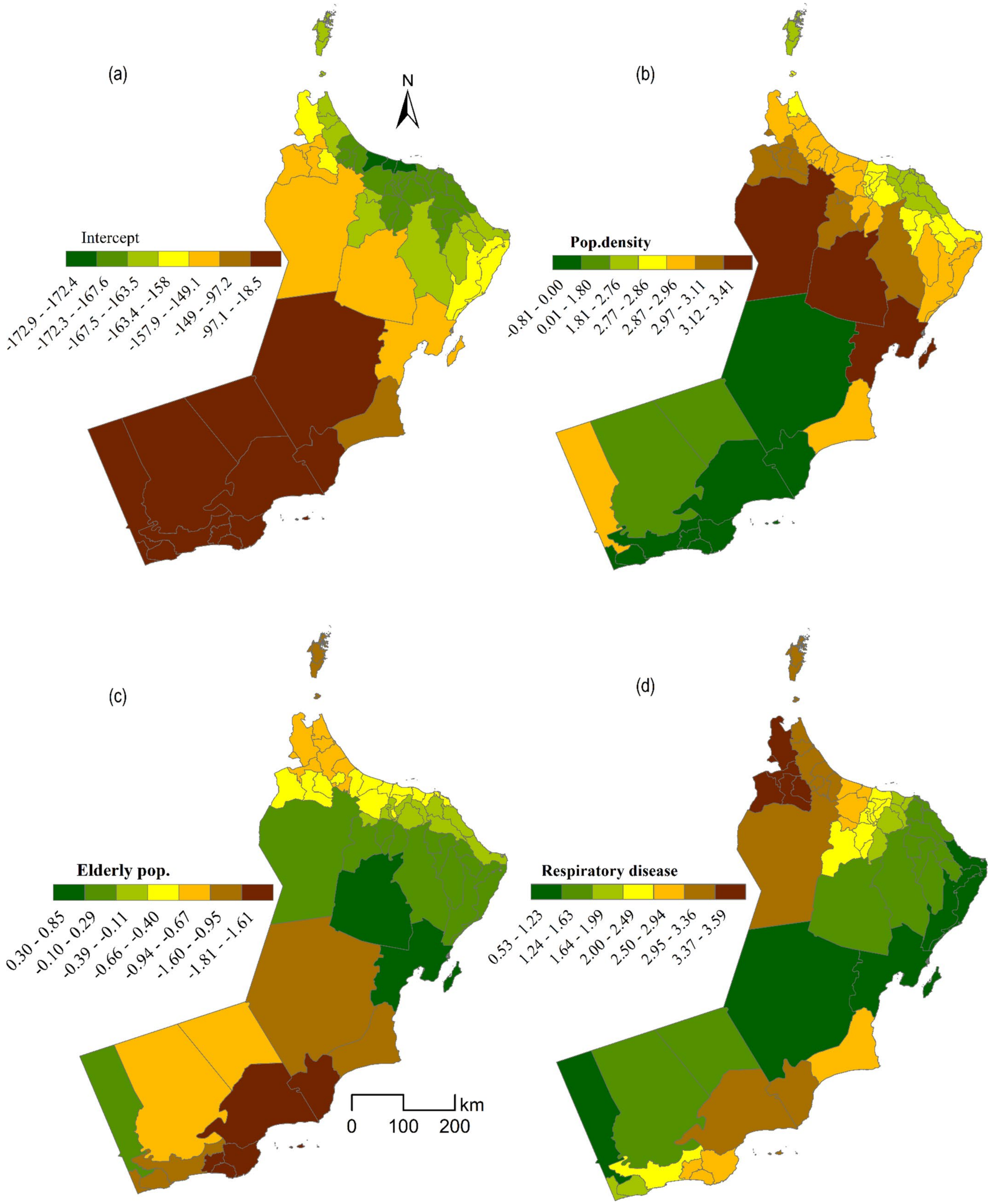

Fig. 7. Spatial distribution of t-values parameters in the GWPR: intercept (**a**), population density (**b**), elderly populations (**c**), and respiratory disease (**d**).

sociodemographic and epidemiological factors that primarily impacted COVID-19 mortality in Oman and neighbouring nations.

Accordingly, this research aimed to develop a geospatial model for synthesising COVID-19 data and capturing local spatial patterns of driving forces that impacted the pandemic mortality. Furthermore, the GWPR model was implemented to assess the non-stationary relationships between COVID-19 mortality and significant explanatory variables. Likewise, the model successfully computed the spatially varying parameter estimates across the study area. Accordingly, applying the GWPR to examine the cause-and-effect relationships between the dependent and independent variables had several advantages. First, and through local modelling, the analysis captured the associations between the response and predictors correctly and accurately considering their spatial heterogeneity and the non-stationarity relationships. Second, the spatial modelling of this research was mainly based on subnational administrative boundaries. Thus, it provided clear identifications of the local spatial patterns behind the variations of COVID mortality across Oman. Third, we fitted a local model including an epidemiological dataset to project the effects of chronic illness on COVID-19 mortality.

Our analysis demonstrates significant associations between COVID-19 mortality and population density, particularly in the northern and southern areas of Oman. This can be attributed specifically to the higher concentration of populations in these places. Indeed, most of these Wilayats also demonstrate high rates of migrant workers living in overcrowded housing units. The pandemic infection, transmission, and mortality rates increased overall in these housing circumstances. Our results, incorporating spatial heterogeneity, concur with other studies[9,10,17,20,51,39,40] in the same vein of literature regarding the influential driving forces on COVID-19 mortality. Nevertheless, other explanatory variables, such as the number of physicians, nurses and hospital beds, were not significant in explaining spatial variations of mortality across the study area.

The analysis indicated that multiple sociodemographic, epidemiological, and health risk factors substantially shape COVID-19 mortality. Research on the spatial dimensions and correlates of COVID-19 mortality is scarce, specifically in the context of Oman. Most studies examining COVID-19 in Oman and beyond[9–13,16,67,68] have relied on geospatial modelling and GIS techniques to capture the spatial heterogeneity and spatial varying relationships between COVID-19 incidence rates and socioeconomic and demographic determinants.

Our findings filled this gap and painted a broad picture of the spatial effects of epidemiological and demographical factors on COVID-19 mortality, particularly the rates of respiratory disease and elderly population size. The spatial distribution of these associations and impacts follows a broad pattern of demographic characteristics and structure. More importantly, the outcomes of the GWPR model proved valid the assumption that relationships exist between mortality and population density and structure and epidemiological factors and that such relationships are heterogeneous over places. Overall, the COVID-19 mortality rates varied spatially at the subnational scale. The highest mortality rates were found across the northern region, particularly in the Muscat and Al-Batinah governorates, followed by the eastern Wilayats of Dhofar governorate in the southern regions. In addition, the local model suggests that a positive relationship exists between population density and COVID-19 mortality across these areas. These findings can be attributed to various reasons, mainly the probability of the high prolonged exposure to disease infection. Correspondingly, living in densely populated areas increases individuals' contacts and thus the risk of disease transmission.

The demographic coefficient estimates from the GWPR model varied spatially. The outcomes of the local model also revealed strong positive relationships between COVID-19 mortality and elderly populations, mainly in the Wilayats of Al-Sharqiyah North and South, Al-Dakhliyah, and Al-Dahrah governorates. This relationship was also strong in the urban Wilayats of the Muscat governorate compared to other Wilayats in the middle and southern parts of the country (Wilayats of Al-Wusta and Dhofar). This pattern of local relationships suggests that numerous infected elderly people increased the number of COVID-19 deaths during the first wave of the pandemic in these places. Furthermore, the findings of the local model pointed to the considerable effects of respiratory diseases on COVID-19 mortality. Positive and stronger relationships between COVID-19 mortality and respiratory diseases occurred particularly in the southern regions. Large coefficient estimates were found in all Dhofar Wilayats, while small coefficients were found in the Wilayats of Muscat and Al-Sharqiyah governorates. Indeed, these findings are consistent with the existing literature that reported population density[17,35,36], elderly populations (e.g[27]). , and respiratory diseases[2969] as the most influential factors for COVID-19 mortality.

Regarding the modelling process, although the variables of health facility (e.g., number of physicians, nurses, and hospital beds) and medical infrastructure (e.g., number of public hospitals, private hospitals, and clinics) were insignificant in predicting COVID-19 deaths, the number of chronic disease cases was statistically significant in predicting mortality, particularly across the south-central areas. In Oman, the preventive measures during the pandemic were effective compared to surrounding countries in reducing the incidence rates and thus the number of deaths. Nonetheless, the relative mortality was considerably higher in urban areas, where demographic factors such as the ageing population influenced the number of COVID-19 deaths. The epidemiological drivers in these areas also significantly shaped the mortality risks. Overall, the finding of the modelling process has implications for informing spatially targeted population health policy interventions that could better position Oman's public health system for future possible waves of COVID-19 triggered by new variants. The Omani government implemented strategies to mitigate COVID-19 mortality rates during the pandemic. However, given the fundamental finding of local mortality patterns in this research, local policies of disease prevention and mortality reduction should be adopted. More speculatively and according to the modelling outcome, a spatial strategy using geographical variations of mortality drivers may be important in identifying the unmeasured facets of future pandemic mortality in the country. Furthermore, given the excess mortality among old populations, protective factors (e.g., regarding elderly populations and migrants) may be required in densely populated areas, particularly major urban areas.

Conclusion

The full recovery from COVID-19 has shed a glaring light on the socioeconomic and demographic inequalities among countries globally and the spatial variations of the devastating effects of the pandemic locally. For instance, the high risks of mortality were more noticeable in elderly populations with long-term illness in the developed countries; across the developing nations, the fragile healthcare infrastructures increased the reported cases of deaths. This research provides insights into the determinants of COVID-19 mortality across Oman, delving more deeply into where and how higher or lower rates occurred. To identify the key risk factors associated with mortality, we employed the GWPR model. Sociodemographic characteristics were key determinants of mortality cases, with a positive relationship between population density, elderly people and COVID-19 fatalities in all Wilayats. Nevertheless, particularly high impacts of respiratory diseases on mortality were found in the south and rural communities, and high risks of death were associated with household overcrowding, old populations in the north, and urban zones.

Although the strength of this research is predominately in filling the gap in modelling COVID-19 mortality in the GCC region and Oman, some limitations are associated with spatial and non-spatial data. One limitation, for example, was the absence of an ancillary economic dataset. Including additional economic variables is therefore useful if the research is to be built on in the future. In addition, the geospatial modelling of this study was based on subnational administrative boundaries across the entirety of Oman. This is considered the finest available geographic scale, and the spatial distribution of mortality and its explanatory variables have been impacted by the modifiable areal unit problem and aggregation level. Given this limitation, to our knowledge, this is the first study that adopts the GWPR to investigate COVID-19 mortality in Oman and the surrounding countries. The geographical scope of this research focuses on Oman and may provide more accurate and vital spatial guidelines about the influential demographic and epidemiological drivers of mortality during similar crises. The reproducibility of our research would allow a similar analysis and may also be relevant for other developing nations surrounding Oman and elsewhere. Adopting the local model of GWPR identified the spatial variability of the coefficient estimates of different predictors of disease mortality. Understanding factors associated with COVID-19 mortality at a subnational spatial scale can be useful to policymakers and public health planners designing effective protection plans to control the spread of disease and reduce mortality. Therefore, future research on modelling the spreading of disease should consider spatial varying associations between spatial, sociodemographic, and epidemiological determinants. Applying the same methodology should consider including further ancillary data at a finer spatial scale to gain more robust insights into the spatial variations of mortality determinants and enrich the outcomes of the modelling process.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

SM: Conceptualization, Methodology, Visualization, Original draft preparation, Writing- Reviewing and Editing. Mohammed Alahmadi: Writing-Reviewing and Editing, Investigation. AM: Data curation, Visualization, Investigation. KS: Data curation, Visualization, Investigation. MA: Data curation, Investigation.WA: Original draft preparation, Writing- Reviewing and Editing.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to S.M.

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