Al-Qadisiyah Journal of Pure Science
ISSN(Printed): 1997-2490 ISSN(Online): 2411-3514
DOI: 10.29350/jops
Al-Qadisiyah Journal of Pure Science

Mapping and Spatial Determinants of COVID-19 at the Neighborhood Level in Al-Diwaniyah City, Iraq

Aqeel Thamer Almayahi[1], Salwan Ali Abed[2]

[1] M.Sc. in Environmental Sciences, College of Science, University of Al-Qadisiyah, Al-Diwaniyah, Iraq, https://orcid.org/0009-0003-1010-5455

[2] Professor of Environmental Science, College of Science, University of Al-Qadisiyah, Al-Diwaniyah, Iraq. https://orcid.org/0000-0001-7347-3843

Abstract

Background: The spatial distribution of outbreaks of infectious diseases in urban settings is affected by complex interactions of demographic, built environment, and socioeconomic determinants.

Background: The aim of this study is to map the epidemiological patterns of COVID-19 at micro-scale and to identify its spatial determinants in the neighbourhoods of Al-Diwaniyah City, Iraq.

Methodology: Spatial clustering was performed using Geographic Information Systems (GIS) and spatial statistics applying Global Spatial Autocorrelation (Moran's I) and Hotspot Analysis (Getis-Ord G_i^*). The relationships between the COVID-19 incidence rates and the key environmental/demographic predictors were modelled by Geographically Weighted Regression (GWR) with spatial variation.Results: Spatial analysis identified significant non-random spatial clustering ($p < 0.05$) of COVID-19 cases, with high-risk hotspots concentrated in high-density, mixed-use central neighbourhoods. Strong positive associations were found for population density, household overcrowding and proximity to commercial hubs.In conclusion, the results show how spatial epidemiology can be useful for urban health planning and provide practical information to local health authorities to implement targeted interventions in future health crises.Keywords: Spatial Epidemiology, GIS, COVID-19, Moran's I, Geographically Weighted Regression, Urban Health, Al-Diwaniyah, Iraq.

1. Introduction

The COVID-19 pandemic has shown how important geography is in the spread of disease. At the intra-urban scale, the epidemic does not affect all places with the same intensity. Urban environments are characterised by different population density, socio-spatial segregation and heterogeneous infrastructure (Bhadra et al., 2021; Fallah-Aliabadi et al., 2022; Geng et al., 2021; Kuang & Chen, 2025).

In Iraq, macro-level studies have been done at governorate or district level, but micro-scale studies on neighborhood-level dynamics are still limited. Al-Diwaniyah City is a special case study due to its unique spatial structure from dense historic commercial cores to sprawling modern residential layouts and informal peripheral settlements (Bilal et al., 2020; Huang et al., 2020; Paixão et al., 2023; Smail et al., 2023).

This study attempts to fill this empirical gap by:

Geospatial mapping of COVID-19 cases and clustering in the neighbourhoods of Al-Diwaniyah City (Ahasan et al., 2022; Soni et al., 2023a).

Quantifying the spatial determinants (demographic, socio-economic and structural) driving the disease vulnerability using local spatial regression techniques(Chandra & Sharma, 2024; Kala et al., 2017).

2. Materials and Methods

2.1 Study Area

The study includes the urban administrative limits of Al-Diwaniyah City, the capital of Al-Qadisiyyah Governorate, Iraq. The unit of analysis is the residential sector

(Mahallah/Residential Sector).2.2 Data GatheringEpidemiological Data: Anonymised and geo-coded records of COVID-19 positive cases aggregated at the neighbourhood level, from the Al-Qadisiyyah Health Directorate.Spatial and Demographic Data: Neighbourhood boundary layers (Shapefiles), population estimates, household counts and land-use data from Directorate of Urban Planning in Al-Diwaniyah.2.3 Spatial Analysis MethodsGlobal Spatial Autocorrelation (Moran's I)Determines if the incidence rate of COVID-19 is clustered, dispersed or random throughout the city:

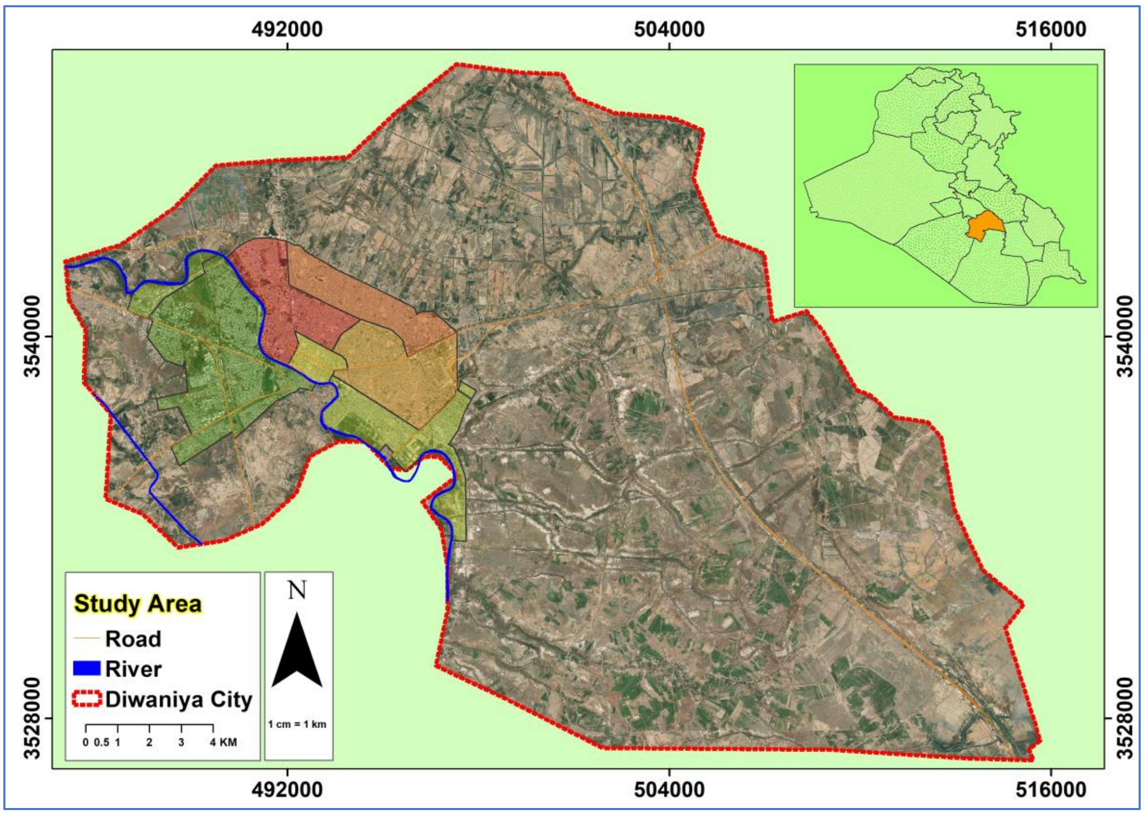

Fig. 1. Spatial pattern of COVID-19 incidence rates across Al-Diwaniyah neighborhoods (2020).

Source: Prepared by the researcher using Al-Diwaniyah Health Directorate COVID-19 records (2020), neighborhood population data, and the Al-Diwaniyah 55-neighborhood GIS polygon layer.

2.2 Data AcquisitionEpidemiological Data:

Anonymised and geo-coded records of COVID-19 positive cases aggregated at the neighbourhood level, from the Al-Qadisiyyah Health Directorate.Spatial and Demographic Data: Neighbourhood boundary layers (Shapefiles), population estimates, household counts and land-use data from Directorate of Urban Planning in Al-Diwaniyah.

2.3 Spatial Analysis Methods

1- Global Spatial Autocorrelation (Moran's I)Determines whether the COVID-19 incidence rate is clustered, dispersed or random across the city:

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

2- Hotspot Analysis (Getis-Ord G_i^*).): Detects statistically significant spatial clusters of high values (hotspots) and low values (coldspots)

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2}{n-1}}}$$

3- Geographically Weighted Regression (GWR):

Accounts for spatial non-stationarity by allowing local estimates of parameters to vary across neighbourhoods:

$$y_i = \beta_0 (u_i , v_i) + \sum_k \beta_k (u_i , v_i) x_{ik} + \varepsilon_i$$

Variable Category	Variable Name	Conceptual Framework / Expected Effect

Dependent Variable	COVID-19 Incidence Rate	Total confirmed cases per 10,000 residents per neighborhood.
Demographic	Population Density	Higher density facilitates higher contact rates (+).
Socioeconomic	Household Overcrowding Index	Average number of occupants per residential unit (+).
Built Environment	Proximity to Central Business District (CBD)	Distance to major commercial and market zones (−).
Healthcare Infrastructure	Healthcare Accessibility	Distance to primary health centers/hospitals (−).

4. Expected Results and Structural Layout

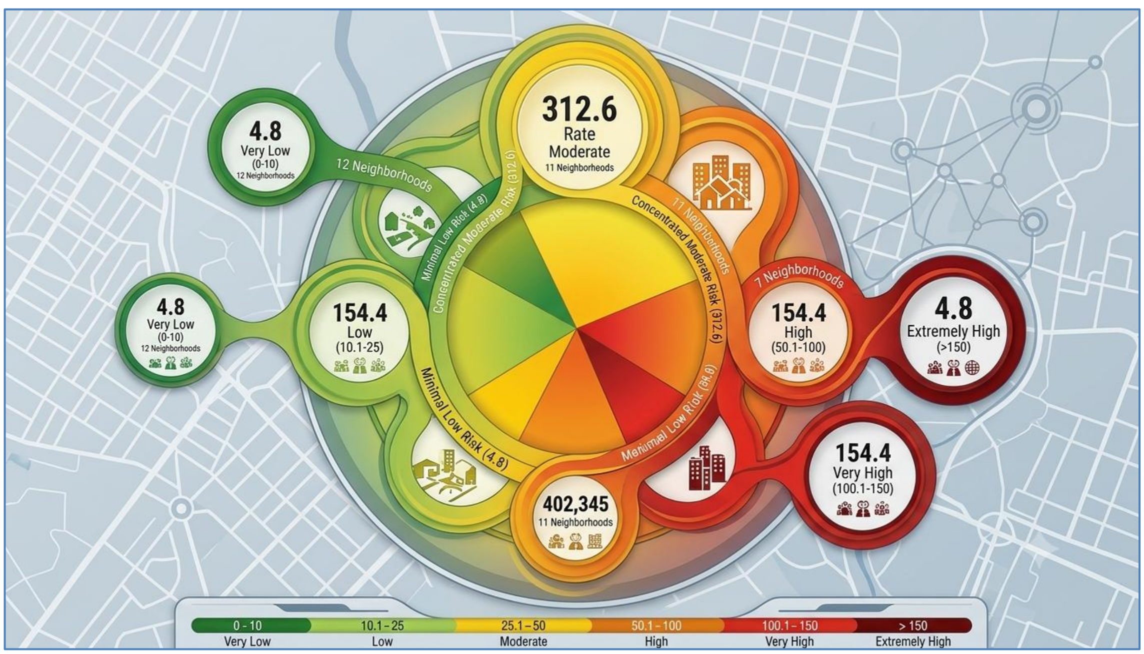

Fig. 2. Frequency distribution of Al-Diwaniyah neighborhoods by COVID-19 incidence-rate classes (2020).

Source: Prepared by the researcher from neighborhood-level COVID-19 incidence-rate classes calculated from confirmed cases and population data, Al-Diwaniyah City, 2020.

4.1 Spatial Distribution and Hotspot Mapping

- **Clustering Analysis:** Moran's I results indicating spatial dependence (z-score and p-value).
- **Hotspot Identification:** Visualization of high-risk neighborhoods (e.g., central commercial districts, high-density residential blocks like *Al-Orouba* or *Al-Iskan*) versus low-risk neighborhoods on the periphery (Adesina & Chukwu, 2025; Das & Ghosh, 2025; Jiao et al., 2021; Soni et al., 2023b).

4.2Spatial Determinants (GWR Findings)

- **Model Performance:** Comparison between Global Ordinary Least Squares (OLS) and GWR (R^2) improvement and Akaike Information Criterion / AICc).
- **Local Coefficient Variation:** Spatial maps displaying how variables like *Population Density* and *Market Proximity* have varying impacts across different zones of Al-Diwaniyah (Afroj & Haque, 2026; Ge et al., 2016; Kianfar & Mesgari, 2022).

5. Discussion

1. **Intra-Urban Vulnerability:** Explanation of why core urban neighborhoods exhibited higher vulnerability due to dense social interactions, mixed commercial activities, and informal transit hubs.
2. **Built Environment Impact:** Discussion on how spatial layout, lack of open/green space, and high building coverage contributed to localized outbreaks.
3. **Policy Implications:**
    - Transitioning from blanket municipal lockdowns to **targeted, spatial interventions** focused on identified hotspot neighborhoods.
    - Enhancing healthcare resource allocation based on GIS-derived risk maps rather than uniform distribution.

6. Conclusion

This study provides a spatial empirical assessment of COVID-19 determinants at the neighborhood level in Al-Diwaniyah City. By integrating GIS mapping with local spatial regression models, the research highlights the necessity of incorporating geographic frameworks into public health responses. The methodologies used here offer a scalable blueprint for managing future epidemic risks in Iraqi cities.

Referances:

Adesina, E. A., & Chukwu, S. (2025). *Geospatial Multi-Criteria Decision Analysis for Hotel Site Suitability Assessment in Minna Metropolis, Nigeria: Integrating Remote Sensing and GIS*.

Afroj, S., & Haque, A. (2026). Comparing the spatial factors responsible for multiple waves of COVID-19 in Bangladesh: A GIS-based approach. *Heliyon*, *12*(7).

Ahasan, R., Alam, M. S., Chakraborty, T., & Hossain, M. M. (2022). Applications of GIS and geospatial analyses in COVID-19 research: A systematic review. *F1000Research*, *9*, 1379.

Bhadra, A., Mukherjee, A., & Sarkar, K. (2021). Impact of population density on Covid-19 infected and mortality rate in India. *Modeling Earth Systems and Environment*, *7*(1), 623–629.

Bilal, U., Barber, S., Tabb, L., & Diez-Roux, A. V. (2020). Spatial inequities in COVID-19 testing, positivity, incidence and mortality in 3 US cities: a longitudinal ecological study. *MedRxiv*, 2020–2025.

Chandra, S., & Sharma, M. (2024). Addressing Multicollinearity in Spatial Modelling: A District Level Spatial Analysis of Pandemic COVID-19 in India. *Indonesian Journal of Statistics & Its Applications*, *8*(1).

Das, S., & Ghosh, T. (2025). Identifying the gaps in cyclone vulnerability mitigation in the Indian Sundarban using AHP based multi criteria decision analysis (MCDA) and GIS techniques: tool for the policy makers. *Earth Systems and Environment*, *9*(4), 3365–3383.

Fallah-Aliabadi, S., Fatemi, F., Heydari, A., Khajehaminian, M. R., Lotfi, M. H., Mirzaei, M., & Sarsangi, A. (2022). Social vulnerability indicators in pandemics focusing on COVID-19: A systematic literature review. *Public Health Nursing*, *39*(5), 1142–1155.

Ge, L., Zhao, Y., Sheng, Z., Wang, N., Zhou, K., Mu, X., Guo, L., Wang, T., Yang, Z., & Huo, X. (2016). Construction of a seasonal difference-geographically and temporally weighted regression (SD-GTWR) model and comparative analysis with GWR-based models for hemorrhagic fever with renal syndrome (HFRS) in Hubei Province (China). *International Journal of Environmental Research and Public Health*, *13*(11), 1062.

Geng, S., Ma, M., Hu, X., & Yu, H. (2021). Multi-scale geographically weighted regression modeling of urban and rural construction land fragmentation–a case study of the Yangtze River Delta Region. *IEEE Access*, *10*, 7639–7652.

Huang, I., Pranata, R., Lim, M. A., Oehadian, A., & Alisjahbana, B. (2020). C-reactive protein, procalcitonin, D-dimer, and ferritin in severe coronavirus disease-2019: a meta-analysis. *Therapeutic Advances in Respiratory Disease*, *14*, 1753466620937175.

Jiao, J., Chen, Y., & Azimian, A. (2021). Exploring temporal varying demographic and economic disparities in COVID-19 infections in four US areas: Based on OLS, GWR, and random forest models. *Computational Urban Science*, *1*(1), 27.

Kala, A. K., Tiwari, C., Mikler, A. R., & Atkinson, S. F. (2017). A comparison of least squares regression and geographically weighted regression modeling of West Nile virus risk based on environmental parameters. *PeerJ*, *5*, e3070.

Kianfar, N., & Mesgari, M. S. (2022). GIS-based spatio-temporal analysis and modeling of COVID-19 incidence rates in Europe. *Spatial and Spatio-Temporal Epidemiology*, *41*, 100498.

Kuang, Y., & Chen, X. (2025). Spatial heterogeneity of forest carbon stocks in the Xiangjiang river Basin urban agglomeration: analysis and assessment based on the multiscale geographically weighted regression (MGWR) model. *Frontiers in Environmental Science*, *13*, 1573438.

Paixão, J. T. R., Santos, C. de J. S. e, França, A. P. F. de M., Lima, S. S., Laurentino, R. V., Fonseca, R. R. de S., Vallinoto, A. C. R., Oliveira-Filho, A. B., & Machado, L. F. A. (2023). Association of D-dimer, C-reactive protein, and ferritin with COVID-19 severity in pregnant women: Important findings of a cross-sectional study in Northern

Brazil. *International Journal of Environmental Research and Public Health*, *20*(14), 6415.

Smail, S. W., Babaei, E., & Amin, K. (2023). Hematological, inflammatory, coagulation, and oxidative/antioxidant biomarkers as predictors for severity and mortality in COVID-19: a prospective cohort-study. *International Journal of General Medicine*, 565–580.

Soni, P., Gupta, I., Singh, P., Porte, D. S., & Kumar, D. (2023a). GIS-based AHP analysis to recognize the COVID-19 concern zone in India. *GeoJournal*, *88*(1), 451–463.

Soni, P., Gupta, I., Singh, P., Porte, D. S., & Kumar, D. (2023b). GIS-based AHP analysis to recognize the COVID-19 concern zone in India. *GeoJournal*, *88*(1), 451–463.