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Spatial Analysis of Tuberculosis (TB) Disease in Iraq, 2019–2021: Using a Geographical Information Systems Approach

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ABSTRACT

Spatial analysis involves examining global and local spatial autocorrelation using statistical measures such as Moran's I and +Getis-Ord. We used Arc GIS 10.8 to analyze the data. The autocorrelation coefficient results revealed a specific pattern in the tuberculosis (TB) incidence distribution across different provinces in 2019 The Moran's I value is 0.188 with a corresponding p-value of (0.0.52) was statistically significant clustering. In four provinces (Diyala, Baghdad, Babil, and Wasit districts), BT incidence was clustered overall study area. The findings from the spatial examination of tuberculosis prevalence in the northeastern region of the country indicate the presence of four high-prevalence hotspot clusters (H-H) and one low-prevalence spatial outlier (L-H) in the year 2019. In 2020 (Moran's I: 0.109, P = 0.165), distribution of TB overall country was random. Cluster analysis shows that one is a spatial cluster (H-H) hotspot located in Baghdad and the other randomness overall of the country. In 2021 (Moran's I: 0.237, P = 0.016) spatial analysis of TB for all countries was clustered. The analysis identifies four spatial groupings (H-H) and one spatial anomaly (L-H). The results showed that there are four groups of spatial hotspots located in different regions of Iraq, which can be identified as follows: Diyala, Baghdad, Diwaniyah, and Wasit, while the Karbala region is the least hotspot.

Keywords: Geographic Information System (GIS), spatial analysis, Tuberculosis (TB), Moran's I, and Getis-Ord.

INTRODUCTION

Epidemiologists use certain systems that perform spatial analysis well and give accurate details on a large scale, and one of those systems is the geographic information system, which is abbreviated by the symbol (GIS) (Musa *et al*., 2013; Clarke *et al*., 1996). Through geographic information systems (GIS) and spatial analysis, epidemiologists were able to identify and monitor the distribution of various diseases, find out the places where they spread, and identify them in order to be controlled. There are many examples of these diseases, for example, *Mycobacterium tuberculosis* (TB) (Rosli *et al*., 2018; Moonan *et al*., 2004). When someone infected with tuberculosis coughs or sneezes, they release airborne particles responsible for the disease's transmission. Tuberculosis, also known as TB, is a communicable, contagious disease. Inhaled particles, containing the infectious agent, infiltrate the upper respiratory tract, bronchi, and alveoli, leading to the rapid degeneration of the pulmonary tissue (Adom Agyeman and Ofori-Asenso, 2017). The clinical manifestation of tuberculosis involves a wide range of symptoms and not only affects the pulmonary system, but also extends its influence to other parts of the body, including the spine, kidneys, and brain. The initial infection will appear within two to eight weeks, the body's immune system activates, leading to a significant reduction in tubercle bacilli (Adom Agyeman and Ofori-Asenso, 2017). Tuberculosis (TB) is a significant contributor to illness and death in numerous nations and remains a prominent global public health issue (Schluger, 2005). It is classified as the ninth leading cause of mortality on a worldwide scale and stands as the predominant cause within the category of infectious diseases, surpassing HIV/AIDS. Despite being a treatable condition, almost nine million individuals contract the disease annually, resulting in two million fatalities (Karadakhy *et al*., 2016). Tuberculosis (TB) is considered one of the sources of concern for Iraqis' lives and affects the work of public health, as it is in other countries in the Middle East. In the Eastern Mediterranean region, the incidence of pulmonary tuberculosis is about 3%, and when calculating the incidence rates of this disease, it is about 43 cases per 100,000 people, and the detection rate is about 54% (Karadakhy *et al*., 2016; WHO, 2016). In 2014, the number of new and recurrent cases of tuberculosis (TB) was 8268. In 1989, Iraq implemented a nationwide tuberculosis (TB) control program. in 2008, Scientists have created centers whose task is to be a tool in determining places in public health research, so they resorted to the establishment of short-term treatment clinics, which are subject to direct monitoring in their work, which are named after (DOTS), also known as TB-DOTS centers, where geographic information systems have recently appeared for this purpose, which is common to work on mapping diseases and identifying locations with the most deadly injuries and the highest danger to human life (Ibrahim, 2013; Zulu *et al*., 2014). These modern systems or technologies will directly contribute to understanding the dynamics of tuberculosis infection in areas with high incidence and therefore be controlled because they are easily identified (Kulldorff and Nagarwalla, 1995). This will facilitate the identification of data and changes that contributed to the spread of the disease, as well as the determination of its location with high accuracy. Researchers have conducted prior research to determine whether tuberculosis occurs in a clustered or random manner (Ibrahim, 2015; Tiwari *et al*., 2006; Ratovonirina *et al*., 2015). The concept originated from Tobler's first law of geography, which asserts that "everything is interconnected, but objects in close proximity have stronger relationships than those that are far apart" (Ibrahim, 2015). Consequently, various nations, including India, Portugal, Japan, and South Africa, have carried out numerous geographical surveillance studies and spatial analyses to identify regions with a high incidence or concentration of a particular occurrence, known as hot spot locations. These investigations revealed a notable prevalence of tuberculosis infection and concentrated pockets of illness in the investigated locations (Tiwari, 2010; Couceiro *et al*., 2011; Onozuka *et al*., 2007; Randremanana *et al*., 2009; Nunes *et al*., 2007; Munch *et al*., 2003). To our knowledge, no previous studies have used GIS technology to examine the spread of verified tuberculosis cases and pinpoint the specific region in Iraq with a high prevalence of the disease. If this is the case, it will simplify the identification of populations at high risk and, as a result, improve TB control strategies. The aim of this research was to determine specific geographic locations with a high incidence of tuberculosis (TB) and assess the spatial global autocorrelation using Geographic Information System (GIS) technology.

MATERIALS AND METHODS

The study is undertaken in the 18 counties that make up the geographic region under investigation, this list comprises Ninawa, Dahuk, Karbala, Tammim, Najaf, Baghdad, Muthanna, Babil, Diwaniyah, Dhe Qar, Basrah, Salah Ad Din, Anbar, Arbil, Diyala, Sulaymaniyah, Wasit, and Maysan. The tuberculosis (TB) data for all 18 provinces of Iraq was provided by the Department of Health and Life Statistics, a subsidiary of the Ministry of Health and Environment see table (1). The Ministry of Planning's Central Bureau of Statistics has released population projections for all 18 provinces of Iraq, spanning from 2019 to 2021. In the geographic information systems section, the water resources directorate in Najaf has provided the shape file for each province's geographic region. Using both global and local Moran I techniques, a geographical study was conducted on tuberculosis (TB), and the aim was to identify spatial clusters. To describe the spatial correlation or determine the cluster pattern in the monitored area (the affected area), a combination of height (H) and low (L) criteria will be used. It is clear that the combination of HH indicates an area of great observational value, in addition to the area adjacent to it. While the LL group represents an area characterized by lower monitoring values than the higher values found in the surrounding monitoring area (Samphutthanon et al., 2013).While the LH group represents an area with a lower monitoring value, at the same time, the HL group refers to an area characterized by high spatial monitoring values within its borders, while the surrounding area appears to contain lower spatial monitoring values (Ferreira, 2020) .The H and L groups can be used to examine the distribution patterns of cancerous diseases in the cervix to determine their locations. Through these H and L groups and their adjacent areas, the sites can be detected with high accuracy in the surveillance area for diseases affected by cervical cancer. Therefore, the use of the Moran I index is considered. In determining the spatial differences in all the details of these diseases and their spread. The Moran method, initially introduced by Moran in 1950, has become a prevalent approach for identifying the spatial variability of diseases (Ord and Getis,1995; Espindola et al., 2006). The index value typically ranges from -1 to +1. A value near -1 indicates a significant negative correlation in the disease's spatial distribution, while a value near 1 indicates a strong positive relationship. The equation of interest is:

$$\text{Moran's I} = \frac{\sum_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{ij}^{n} w_{ij}} \qquad \dots\dots\dots (1)$$

The recorded prevalence of the illness row in the area is denoted by x_i . While the illness column in the area is denoted by x_j . The mean is denoted by. ;$\bar{x}$. The matrix of spatial weights is denoted by w_{ij}. The mean square error is denoted by S^2.

$$S^2 = \frac{\sum_{ij}(x_i - \bar{x})^2 (x_j - \bar{x})^2}{N} \qquad \dots\dots\dots (2)$$

The matrix of spatial weights is computed using Geoda program, where a value of 1 is assigned if two regions are adjacent to each other, and a value of 0 is assigned otherwise.

The utilization of Getis-Ord cold and hotspot analysis can improve the detection of specific areas in a locality that have either high or low risks by considering global spatial autocorrelation (Ord and Getis,1992; Ord and Getis,1995). The computation procedure is as follows:

$$G_i^* = \frac{\sum_i w_{ij} x_{j-} \bar{x} \sum_j w_{ij}}{s\sqrt{\frac{\left[n \sum_{ij} w_{ij}^2 - \left(\sum_{ij} w_{ij}\right)^2\right]}{n-1}}} \qquad \dots\dots (3)$$

In general, Gi will be standardized, where n is the total number of samples; $\bar{x}$ denotes the mean; w_{ij} denotes the matrix of spatial weight and S represents the standard deviation.

$$Z(G_i^*) = \frac{G_i^* - E(G_i^*)}{\sqrt{Var\,(G_i^*)}} \qquad \dots\dots\dots\dots\dots (4)$$

The expected value is $E(G_i^*)$ located where the variance is $Var\ (G_i^*)$, and the normalized value of Gi can be utilized to detect cold and hotspots within the research region.

Table 1: Tuberculosis (TB) disease incidence per 100000 in the Iraq 2019 to 2021

ID	Province name	Population	2019 Cases/100000	2020 Cases/100000	2021 Cases/100000
1	Ninawa	3928215.00	8.04	6.01	6.31
2	Dahuk	1361211.00	9.04	7.05	7.93
3	Najaf	1549788.00	11.23	9.81	9.42
4	Karbala	1283484.00	18.62	12.78	12.39
5	Tam'mim	1682809.00	17.29	12.90	12.90
6	Baghdad	8558625.00	23.57	19.10	22.83
7	Muthanna	857652.00	18.77	13.06	14.81
8	Babil	2174783.00	15.31	9.98	20.51
9	Diwaniyah	1359642.00	17.58	12.65	13.61
10	Dha qar	2206514.00	18.76	15.95	21.53
11	Basrah	3063059.00	14.66	10.51	11.59
12	Salah ad din	1680015.00	13.10	10.36	9.82
13	Anbar	1865818.00	11.95	9.00	9.11
14	Arbil	1953341.00	15.46	11.88	12.08
15	Diyala	1724238.00	20.65	13.34	13.51
16	Sulaymaniyah	2277171.00	9.40	9.35	10.54
17	Wasit	1452007.00	20.80	13.84	15.56
18	Maysan	1171802.00	10.41	12.12	14.42

RESULTS

For three years 2019,2020, and 2021, the incidence of the tuberculosis (TB) in the Iraq was 274.63, 209.69, and 238.88 cases per 100,000 for all age and gender respectively (Table1). Fig. (1) depicts the variation in the distribution of TB at the county level.

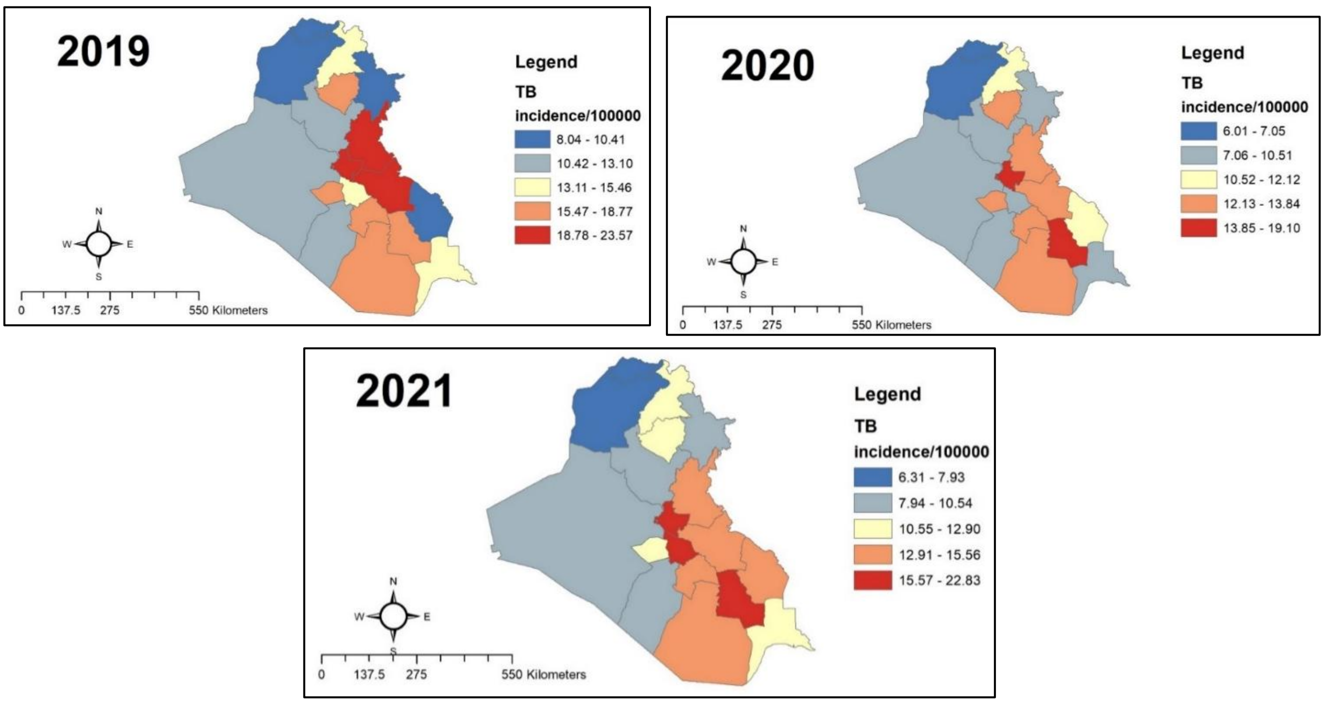

Fig. 1: Spatial distribution of TB incidence in the Iraq 2019-2021.

Based on equation (1), Fig. (2) (top panel), and (Table 2), the global spatial autocorrelation analysis of the cumulative TB incidence in Iraq in 2019 revealed a Moran's I index of 0.188 ($z=1.941$; $p< 0.0522$). This indicates a positive spatial autocorrelation, with a clustering pattern observed. In other words, subdistricts with high TB incidence rates tend to have neighboring subdistricts with similarly high incidence rates. In contrast, subdistricts with low TB incidence rates are likelier to have neighboring subdistricts with similarly low incidence rates. In 2020, Fig. (1) (middle panel) Moran's I index of 0.109 ($z=1.388$; $p<0.165$) the pattern was randomness overall country, while in 2021, Fig. (1) (bottom panel) Moran's I index of 0.237 ($z=2.390$; $p<00.016$) a positive spatial autocorrelation with the pattern was clustering.

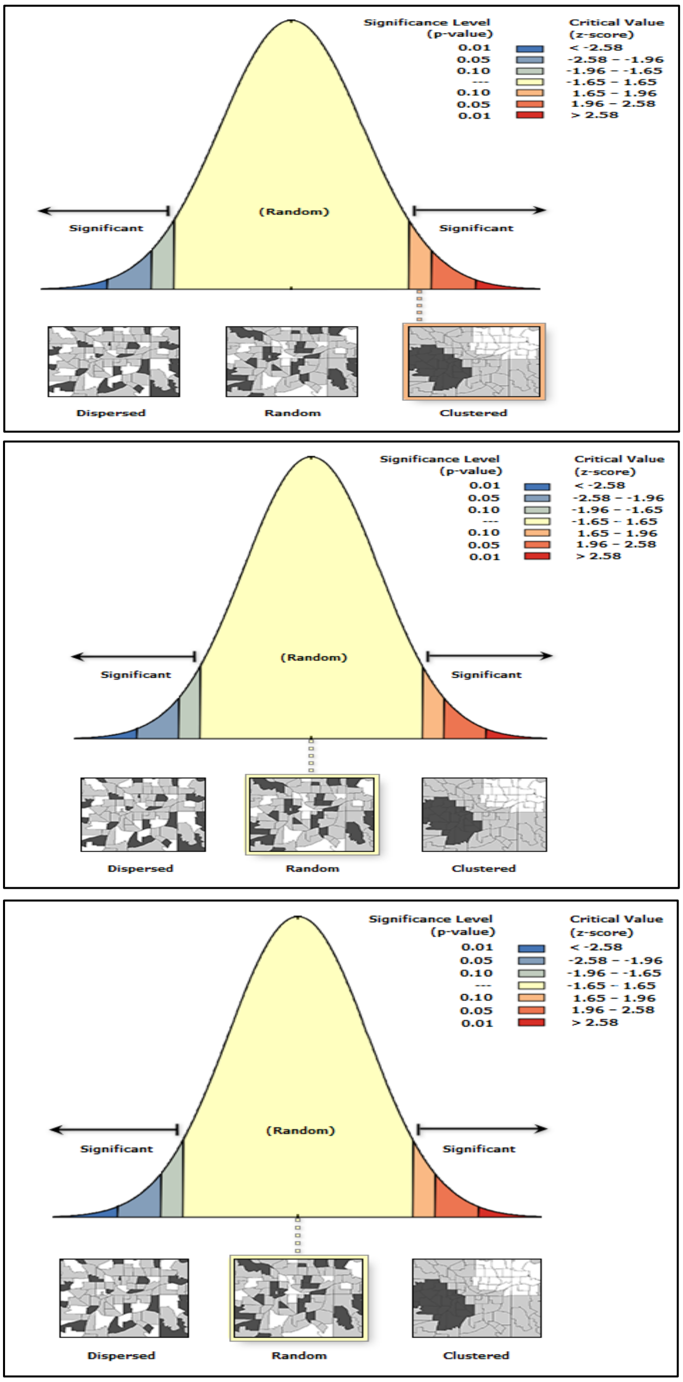

Fig. 2: Result of Spatial autocorrelation Moran's I of TB 2019 (top panel), 2020 (middle panel) and 2021 (bottom panel).

Table 2: Spatial autocorrelation test results of Tuberculosis (TB) incidence in the Iraq 2019 to 2021

Year	Moran's I	Z-score	p-value	Expected index	Variance	Pattern
2019	0.188	1.941	0.0522	-0.058	0.0162	Cluster
2020	0.109	1.388	0.165	-0.058	0.0147	Random
2021	0.237	2.390	0.016	-0.058	0.015	Cluster

Spatial cluster analysis, identification of outliers, and hotspot analysis for TB during 2019-2021 were performed using the local Moran index and Getis-Ord cold and hotspot analysis equations (3, 4). The 2019 cluster analysis revealed four spatial clusters and one spatial outlier for TB. There were four high-high spatial clusters (red) identified as hotspots and one low-high spatial outlier (blue) identified as a cold spot. The spatial hotspots were located in Diyala, Baghdad, Babil, and Wasit districts, while the cold spot was in the Salah ad-Din district. In the 2020 cluster analysis show that one is spatial cluster/ hotspot (Baghdad) and other randomness clusters. While in the 2021 cluster analysis show that four are spatial clusters and one spatial outlier. There are four hotspot (high-high) spatial clusters (red), one cold-spot/low-high spatial outliers (blue). The location of four spatial hotspot groups in Diyala, Baghdad, Diwaniyah. And Wasit districts, one cold spot spatial in Karbala district (low-high) as shown in Fig. (3, 4).

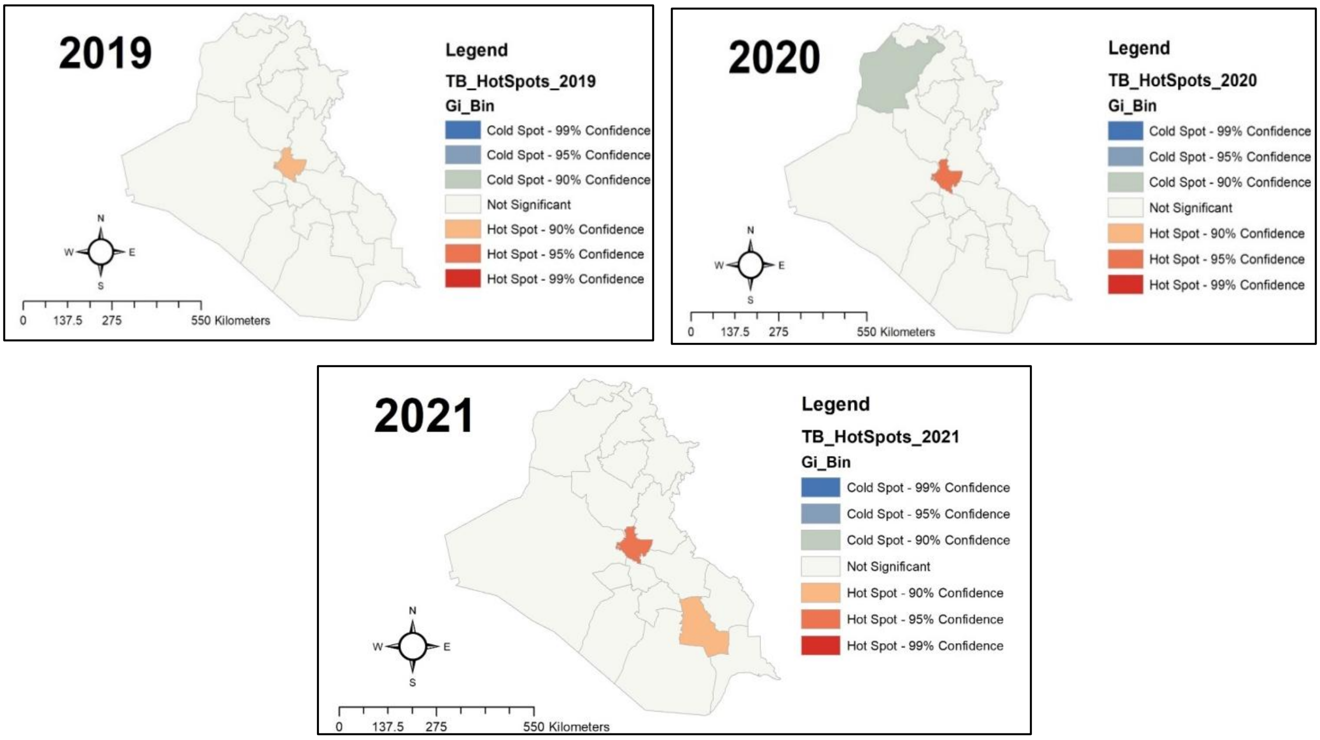

Fig. 3: Spatial distribution of cold and hotspots in TB incidence in the Iraq 2019-2021.

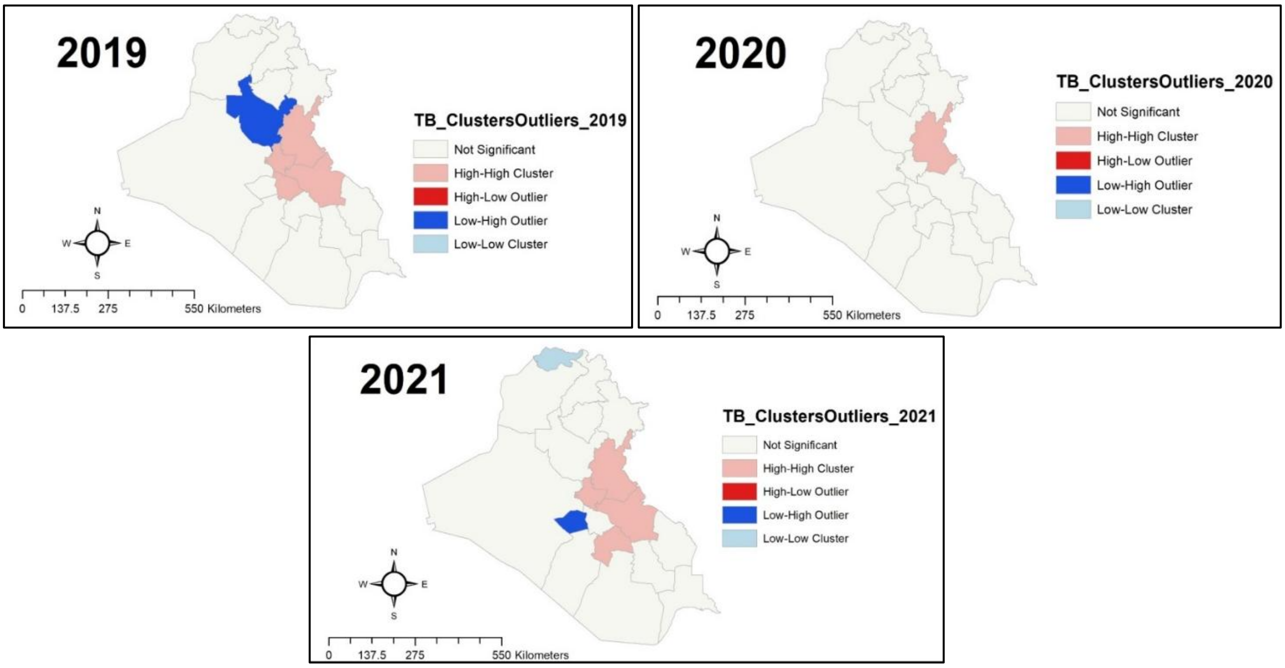

Fig. 4: Spatial distribution of clusters and outliers in TB incidence in the Iraq 2019-2021.

DISCUSSIONS

An increase in tuberculosis has been observed in the center of the country as a result of the increase in population density, especially the capital, Baghdad, as well as in the northeastern parts, perhaps due to poverty factors. There are factors that can increase the risk of infection and transmission of tuberculosis (TB) between communities that have been identified in advance, including malnutrition, promiscuity, poverty, inadequate housing, and unhealthy conditions in which a person lives, which accelerate the transmission of infection between people and are associated with this disease (Hargreaves *et al*., 2011). The incidence of tuberculosis (TB) closely correlates with malnutrition and smoking (Mustafa *et al*., 2018). In order to study the regional distribution of tuberculosis cases in different regions of Iraq, a spatial analysis study was used, through which the most widespread areas of the disease were identified, which may increase infection and injuries for transmission. During the study of spatial analysis, it was also noted that people could still get infected. Because of this, the research suggested using spatial analysis to get a better idea of the epidemiological situation of tuberculosis cases so that it could be better controlled (Mohammed *et al*., 2019). An essential factor to consider is a precise comprehension of the distribution and dissemination of tuberculosis, enabling public health departments to allocate therapeutic and preventive healthcare resources effectively until the disease is managed. An investigation carried out in Duhok demonstrated that individuals who are related to each other had a higher probability of contracting an infection, particularly latent tuberculosis. A thorough examination of individuals who have come into contact with TB patients, as well as those residing in areas with a high number of TB cases, may be considered a measure for effectively managing TB (Hussein *et al*., 2019). In our study, there are many strong points for spatial analysis estimation using global Moran's I statistics were applied, the score ranges from -1 to 1, with a score of zero indicating acceptance of the null hypothesis. Whereas, the positive scores represent the presence of clustering, and the negative score represents no clustering of TB cases (Lai *et al*., 2008). One of the weaknesses in this study is the neglect of age and gender, which unfortunately we did not obtain from the ministry's website.

CONCLUSIONS

GIS usage in studying of Spatial analysis of TB cases reveals useful information about the epidemiological situation of TB cases in the Iraq. The global spatial autocorrelation analysis of the cumulative TB incidence in Iraq in 2019, the result of a Moran's I index indicated a positive spatial autocorrelation, with a clustering pattern observed. In 2020, the pattern was randomness overall country. while in 2021, a positive spatial autocorrelation with the pattern was clustering. The 2019 cluster analysis revealed four spatial clusters and one spatial outlier for TB. There were four high-high spatial clusters (red) identified as hotspots and one low-high spatial outlier (blue) identified as a cold spot in north end east country. In the 2020 cluster analysis show that one is spatial cluster/ hotspot (Baghdad) and other randomness clusters. While in the 2021 cluster analysis show that four are spatial clusters and one spatial outlier. There are four hotspot(high-high) spatial clusters (red), one cold-spot/low-high spatial outliers (blue) were located in west and east country.

REFERENCES

Adom Agyeman, A.; Ofori-Asenso, R. (2017). Tuberculosis-an overview. *J. Pub. Health Emerg.,* 1:7. DOI:10.21037/phe.2016.10.04

Clarke, K.C.; McLafferty, S.L.; Tempalski, BJ. (1996). On epidemiology and geographic information systems: A review and discussion of future directions. *Emerg. Inf. Dis.,* **2**(2), 85-92. DOI:10.3201/eid0202.960202

Couceiro, L.; Santana, P.; Nunes, C. (2011) Pulmonary tuberculosis and risk factors in Portugal: A spatial analysis. *Int. J. Tub. Lung Dis*., **15**, 1445 -54. (n.d.). DOI:10.5588/ijtld.10.0302

Espindola, G.M.; Câmara, G.; Reis, I.A.; Bins, L.S. (2006). Monteiro AM. Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation. *J. Rem. Sens*., **27**(14), 3035–3040. DOI:10.1080/01431160600617194

Ferreira, M.C. (2020). Spatial association between the incidence rate of Covid-19 and poverty in the São Paulo municipality, Brazil. *Geosp. Health*., **15**(2), 194. DOI:10.4081/gh.2020.921

Hargreaves, J.R.; Boccia, D.; Evans, C.A.; Adato, M.; Petticrew, M.; Porter, J.D. (2011). The social determinants of tuberculosis: From evidence to action. *Am. J. Pub. Health*., **101**(4), 654-662. DOI:10.2105/AJPH.2010.199505

Hussein, N.; Balatay, A.A.; Almizori, L.A.; Saifullah, H.H. (2019). A study of the prevalence of latent tuberculosis in household contacts of patients with active tuberculosis in Kurdistan Region of Iraq: A brief report. *Int. J. Inf.,* **6**(2), e90402. DOI:10.5812/iji.90402

Ibrahim, S.A. (2013). Comparing alternative methods of measuring geographic access to health services: An assessment of people's access to specialist hospital in Kebbi state. *Acad. J. Inter. Stud*., **2**, 109. DOI:10.5901/ajis.2013.v2n12p109

Ibrahim, S.A.; Hamisu, I.; Lawal, U. (2015). Spatial pattern of tuberculosis prevalence in Nigeria: A comparative analysis of spatial autocorrelation indices. *Am. J. Geogr. Inf. Syst*., **4**, 87-94. DOI:10.5923/j.ajgis.20150403.01

Karadakhy, K.; Othman, N.; Ibrahim, F.; Saeed, A.A.; Hama Amin, A.A. (2016). Tuberculosis in Sulaymaniyah, Iraqi Kurdistan: A detailed analysis of cases registered in treatment centers. *Tan.,* **15**(4), 197–204.

Kulldorff, M.; Nagar Walla, N. (1995). Spatial disease clusters: Detection and inference. *Stat. Med*., **14**, 799- 810. DOI: 10.1002/sim.4780140809

Lai, P.C.; So, F.M.; Chan, K.W. (2008). Spatial epidemiological approaches in disease mapping and analysis. *Boc. Raton*., **1**, 194, CRC Press. DOI:10.1289/ehp.6735

Li, H.; Ding, Z.; Hu, Z.; Chen, F.; Wan get, K. (2020). Spatial statistics analysis of coronavirus disease 2019 (Covid-19) in China. *Geos. Health*., **15**(1), 12. DOI:10.4081/gh.2020.867

Mohammed, S.H.; Ahmed, M.M.; Mohammed, Z.H.; Adeboye, A. (2019). High risk disease mapping and spatial effect of pulmonary tuberculosis in Kerbala, Iraq. *Biomed. Biotech. Res. J*., **3**, 150–155. DOI:10.4103/bbrj.bbrj_88_19

Moonan, P.K.; Bayona, M.; Quitugua, T.N. (2004). Using GIS technology to identify areas of tuberculosis transmission and incidence. *Int. J. Health. Geo*., **3**(1), 23. DOI:10.1186/1476-072X-3-23

Munch, Z.; Van Lill, S.W.; Booysen, C.N.; Zietsman, H.L.; Enarson, D.A.; Beyers, N. (2003) Tuberculosis transmission patterns in a high incidence area: A spatial analysis. *Int. J. Tub. Lung Dis.*, **7**, 271-277.

Musa, G.J.; Chiang, PH., Sylk, T.; Bavley, R. (2013). Use of GIS mapping as a public health tool-from cholera to cancer. *Health Serv. Ins.,* **6**, 111–116. DOI:10.4137/HSI.S10471

Mustafa, I.; Najib; B.; Al, T.N. (2018) Association between life-style factors and pulmonary tuberculosis in Erbil. *Zanc. J. Med. Sci*., **15**(6–110). DOI:10.15218/zjms.2011.026

Nunes, C. (2007). Tuberculosis incidence in Portugal: Spatiotemporal clustering. *Int. J. Health Geogr*., **6**, 30.

Onozuka, D.; Hagihara, A. (2007). Geographic prediction of tuberculosis clusters in Fukuoka, Japan, using the space time scan statistic. *BMC Inf. Disp*., **7**, 26. DOI:10.1186/1471-2334-7-26

Ord, J.K.; Getis, A. (1992). The analysis of spatial association by use of distance statistics. *Geog. Anal.*, **24**(189–206). DOI:10.1111/j.1538-4632.1992.tb00261.x

Ord, J.K.; Getis, A. (1995). Local spatial autocorrelation statistics: distributional issues and an application. *Geogr. Ana*., **27**(286–306). DOI:10.1111/j.1538-4632.1995.tb00912.x

Randremanana, R.V.; Sabatier, P.; Rakotomanana, F.; Randriamanantena; A., Richard, V. (2009). Spatial clustering of pulmonary tuberculosis and impact of the care factors in Antananarivo city. *Trop. Med. Int. Health*., **14**, 429-370. DOI:10.1111/j.1365-3156.2009.02239.x

Ratovonirina, N.H.; Rakotosamimanana, N.; Razafimahatratra, S.L.; Raherison, M.S.; Refrégier, G.; Sola, C. (2017). Assessment of tuberculosis spatial hotspot areas in Antananarivo, Madagascar, by combining spatial analysis and genotyping. *BMC Inf.*, **17**(1), 562. DOI:10.1186/s12879-017-2653-9

Rosli, N.M.; Azhar Shah, S.; Mahmood, M. (2018). Geographical Information System (GIS) application in tuberculosis spatial clustering studies: A systematic review. *Malays J. Pub. Health Med.,* **18**(1), 70–80.

Samphutthanon, R.; Tripathi, N.; Ninsawat, S.; Duboz, R. (2013). Spatiotemporal distribution and hotspots of hand, foot and mouth disease (HFMD) in Northern Thailand. *Int. J. Env. Res. Pub. Health*., **11**(1), 312-36. DOI:10.1371/journal.pone.0270061

Schluger, N.W. (2005). The pathogenesis of tuberculosis: the first one hundred (and twenty-three) years. *Am. J. Resp. Cell Mol. Bio*., **l32**, 251–256. DOI: 10.1165/rcmb. F293

Tiwari, N.; Adhikari, C.M.; Tewari, A.; Kandpal, V. (2006). Investigation of geo spatial hotspots for the occurrence of tuberculosis in Almora district, India, using GIS and spatial scan statistic. *Int. J. Health Geogr*., **5**, 33. DOI:10.1186/1476-072X-5-33

Tiwari, N.; Kandpal, V.; Tewari, A.; Rao, K.R.; Tolia, V. (2010). Investigation of tuberculosis clusters in Dehradun city of India. *Asian Pac. J. Trop. Med.*, **3**, 486-90. DOI:10.1016/S1995-7645(10)60117-4

WHO Iraq Program Tuberculosis. (2021). Available from: http:// www. emro. WHO. int/ irq/ progr ammes/ tuberculosis. *html*., Accessed16 Jan 2021.

Zulu, L.C.; Kalipeni, E.; Johannes, E. (2014). Analyzing spatial clustering and the spatiotemporal nature and trends of HIV/AIDS prevalence using GIS: The case of Malawi, 1994 2010. *BMC Inf. Dis.*, **14**, 285. DOI:10.1186/1471-2334-14-285

التحليل المكاني لمرض السل في العراق 2019–2021: بأستخدام نهج نظم المعلومات الجغرافية

نبيل عبود كاظم

وزارة التربية / مديرية تربية النجف / النجف / العراق

الملخص

التحليل المكاني يتضمن استخدام المقاييس الإحصائية لفحص الارتباط التلقائي وهي معامل موران المحلي والعالمي وكيدس لفحص النقاط الساخنة والباردة. تم استخدام نظم المعلومات الجغرافية لفحص نمط توزيع مرض السل في عموم العراق. في عام 2019 نتأج معمل الارتباط الذاتي يشيرالى نمط توزيع مرض السل متجمعاً وذو دلالة إحصائية في أربع محافظات (ديالى، بغداد، بابل، وواسط). وفي نفس العام تشير نتائج الفحص المكاني لانتشار مرض السل في المنطقة الشمالية الشرقية من البلاد إلى وجود أربع مجموعات من النقاط الساخنة عالية الانتشار (H-H) ونقطة مكانية واحدة منخفضة الانتشار (L-H). في عام 2020 نتأج معمل الارتباط الذاتي يشيرالى نمط توزيع مرض السل في جميع انحاء البلاد عشوائياً وفي نفس العام تشير نتائج الفحص المكاني لانتشار مرض السل أن أحد المحافظات عبارة عن نقطة ساخنة مكانية (H-H) تقع في بغداد والأخرى عشوائية الاصابات في عموم البلاد. بينما في عام 2021 نتأج معمل الارتباط الذاتي يشيرالى نمط توزيع مرض السل متجمعاً وذو دلالة إحصائية في أربع محافظات وتشير نتائج الفحص المكاني لانتشار مرض السل إلى وجود أربع مجموعات من النقاط الساخنة عالية الانتشار (H-H) وذو دلالة إحصائية وهي (ديالى، بغداد، الديوانية، وواسط) وشذوذ مكاني واحد (L-H) التي تقع في (كربلاء).

الكلمات الدالة: نظام المعلومات الجغرافية (GIS)، التحليل المكاني، مرض السل، معامل موران، كيتيس–أورد.