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Spatiotemporal Analysis of Covid-19 in Turkey

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ABSTRACT

The Covid-19 pandemic continues to threaten public health around the world. Understanding the spatial dimension of this impact is very important in terms of controlling and reducing the spread of the pandemic. This study measures the spatial association of the Covid-19 outbreak in Turkey between February 8 and May 28, 2021 and reveals its spatiotemporal pattern. In this context, global and local spatial autocorrelation was used to determine whether there is a spatial association of Covid-19 infections, while the spatial regression model was employed to reveal the geographical relationship of the potential factors affecting the number of Covid-19 cases. As a result of the analyzes made in this context, it has been observed that there are spatial associations and distinct spatial clusters in Covid-19 cases at the provincial level in Turkey. The results of the spatial regression model showed that population density and elderly dependency ratio are very important in explaining the model of Covid-19 case numbers. Additionally, it has been revealed that Covid-19 is affected by the Covid-19 numbers of neighboring provinces, apart from the said explanatory variables. The findings of the study revealed that spatial analysis is helpful in understanding the spread of the pandemic in Turkey. It has been determined that geographical location is an important factor to be considered in the investigation of the factors affecting Covid-19.

1. Introduction

Covid-19, which first appeared in Wuhan, China in December 2019, has affected millions of people. It has become a global health problem with the World Health Organization (WHO) announcing that it is a global pandemic (Alcântara et al., 2020; Ramírez-Aldana et al., 2020). On January 30, 2020, the World Health Organization declared a "Public Health Emergency of International Concern". Covid-19 was initially announced as an epidemic, while the developments led to the confirmation of this process as a pandemic on March 12, 2020. The number of Covid-19 cases detected since the first case was seen in 2019 has exceeded 170 million (172,173,283). Approximately 3.7 million (3,695, 990) of these cases resulted in death, while the number of recovering patients approached 155 million (154,794,033) (WHO, 2021). At this point, many countries have taken various measures to fight the virus. In this direction, cities were closed, production was stopped, schools were suspended, and restrictions were imposed on community activities. Therefore, as the epidemic affected people's health and threatened their lives, economic problems have also emerged (Liu et al., 2021; Xiong et al., 2020). As a matter of fact, as underlined by the United Nations, this pandemic is beyond a health crisis. This crisis is a humanitarian, economic and social crisis (UN, 2020).

The spread of Covid-19 and its consequences have led the societies to face health-related problems such as fear, panic, uneasiness, depression and intolerance (Al-Rahimi et al., 2021; Y. Sun et al., 2021). While vaccination efforts continue, mutated forms of the virus continue to be a problem for several countries. Along with the vaccination efforts, social measures such as isolation, quarantine, social distance, interruption of education and curfew, aiming at controlling the spread of the virus, have been put forward (Chen et al., 2021). These measures focus on preventing the spread of the virus among people. At this point, the importance of space in the spread of the virus among people stands out. Spatial analyses allow policy makers and other decision makers to formulate measures such as curfews, isolation, effective planning and control for the protection of vulnerable people. It is believed that it will be possible to minimize and control the spread of the epidemic via these

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methods (Alkhamis et al., 2020; Rahman et al., 2020). It is stated that the spatial information obtained will benefit public institutions and their representatives in making effective decisions and will help them develop important strategies to prevent further spread of Covid-19 (Sarkar et al., 2021). However, while these drastic measures, which are a necessity, have significant social and economic impact, it is obvious that these policies are unsustainable in the long run (Alkhamis et al., 2020).

Based on all this information, this study deals with the spread of the pandemic considering the spatial effects and is structured as follows: The next section summarizes the literature on Covid-19. The third section explains the data set and the method. In the fourth section, the spatial association between the main socio-demographic variables and Covid-19 cases in Turkish cities is presented using spatial regression models. The fifth section explains the results and the sixth section offers a general evaluation.

2. Literature review on the spatial spread of Covid-19

Understanding the factors influencing the Covid-19 outbreak will help contain its spread. With the emergence of this disease, several questions were raised about the spread of the pandemic, and it was concluded that the pandemic was affected by ecological, biological and social factors. At this point, it is mentioned that many social and economic factors such as population density, urban/rural environment, urbanization, population growth, land use affect the spread of this pandemic. Thus, it has been stated that these social, economic and ecological factors will be effective in controlling the pandemic (You et al., 2020). Moreover, many of these factors affecting the spread of Covid-19 are determinants of sustainable development.

Previous studies that associated factors such as income in cities (Ferreira et al., 2020; Ramírez & Lee, 2020; Sannigrahi et al.), population density (Alcântara et al., 2020; Eryando et al., 2020; Ghosh & Cartone, 2020; Hafner, 2020; Han et al., 2021; Kang et al., 2020; Kim & Castro, 2020; Paez et al., 2020; Rahman et al., 2020; Rahmani et al., 2020; Ramírez & Lee, 2020; Sannigrahi et al., 2020; Sarkar et al., 2021; Selcuk et al., 2021; Xiong et al., 2020; You et al., 2020), population movement (Eryando et al., 2020; Kang et al., 2020; Kim & Castro, 2020; Liu et al., 2021; Q. Wang et al., 2021; Xie et al., 2020) and elderly population (Paez et al., 2020; Ramírez-Aldana et al., 2020; Sannigrahi et al., 2020) with the number of cases/death rates are important in terms of determining the variables affecting the pandemic. It is also possible to come across various studies in the related literature that associate meteorological parameters such as air quality (Benchrif et al., 2021; Islam et al., 2021; Liu et al., 2021; Q. Wang et al., 2021), mean temperatures (Liu et al., 2021; Ramírez-Aldana et al., 2020; Q. Wang et al., 2021; Xie et al., 2020), humidity (Liu et al., 2021) and sunlight (Paez et al., 2020) with the spread of the pandemic. Furthermore, it was observed that factors such as urbanization (Ramírez-Aldana et al., 2020), traffic (Xie et al., 2020), living environment deprivation (Das et al., 2021), noise pollution (Basu et al., 2021), education (Ramírez-Aldana et al., 2020) number of hospitals (You et al., 2020), number of hospital beds (Alcântara et al., 2020; Mansour et al., 2021), number of physicians (Kang et al., 2020; Ramírez-Aldana et al., 2020) and even internet access (Ramírez & Lee, 2020) were included in the analyses. Again, in some of these studies, the distribution of risks posed by Covid-19 based on age and gender (Rahman et al., 2020) was discussed, and it was underlined that proximity, connectivity and neighborhood between cities/regions also affected the spread of the pandemic (Eryando et al., 2020; Ghosh & Cartone, 2020; Giuliani et al., 2020; Hafner, 2020).

As a matter of fact, the high death rates caused by Covid-19 reveal the importance of the need to understand the causes of the pandemic. Analyzing the spatial spread of the pandemic will also be important for the development of public health policies. In this context, researchers aimed to reveal the factors affecting the spread of the pandemic by applying spatial analysis tools. Spatial analyses have also been applied in previous studies to study and analyze the spread of various diseases such as tuberculosis, dengue, cholera, H1N1 influenza, diabetes, cancer, SARS, and flu viruses (Ali et al., 2002; Atique et al., 2018; Glick, 1979; Hipp & Chalise, 2015; Lai et al., 2004; Meng et al., 2005; Roth et al., 2016; Souris et al., 2010; Stark et al., 2012; J. F. Wang et al., 2008). For instance, Wang et al. (2008) reported that local response strategies were highly effective in combating SARS, and that effective local control reduced the spread of the disease. These studies, conducted at different scales and for different diseases, partly explain the spatial heterogeneity of the spread of diseases, highlighting the effects of spatial interdependence between regions (Bourdin et al., 2021). Based on the findings of such studies, many researchers today have investigated the existence of spatial effects for Covid-19 (Adegboye et al., 2021; Al-Kindi et al., 2020; Alcântara et al., 2020; Bag et al., 2020; Castro et al., 2021; Coşkun et al., 2021; Desjardins et al., 2020; Dickson et al., 2020; El Deeb, 2021; Ferreira et al., 2020; Kim & Castro, 2020; Lak et al., 2021; Li et al., 2020; Maiti et al., 2021; Murugesan et al., 2020; Rahman et al., 2020; Ramírez-Aldana et al., 2020; Saha et al., 2020; Shariati et al., 2020; F. Sun et al., 2020; Zhang et al., 2020). In this respect, understanding the spatial distribution of Covid-19 is critical for the prediction of the epidemic and for the development of public health policies related to the spread of early Covid-19 (Kang et al., 2020). The determination of associations can assist policy makers and public health experts about the measures to be taken. Although there is agreement that socioeconomic factors influence Covid-19, studies on spatial patterns of Covid-19 vary widely depending on the country or region studied (Cos et al., 2020). This study discusses various factors related to the spread of Covid-19 in Turkey in the context of provinces and in the light of studies conducted for different countries. It can be suggested that the local data produced in the study will contribute to Turkey's fight against the pandemic.

3. Material and method

3.1. Data sources

In Turkey, data related to the Covid-19 pandemic started to be published weekly as of February 15, 2021, (including the week of February 8-14) as the number of cases per population of 100,000 in each province. From this date on, the number of cases per week continues to be announced at the beginning of each week. The present study was conducted with the Covid-19 data for 16 weeks between February 8th and May 28th, 2021.[1] Covid-19 case data were obtained from the Ministry of Health website (https://covid19.saglik.gov.tr/). The selected socio-economic indicators were obtained from the Turkish Statistical Institute website (https://www.tuik.gov.tr/). The most recent elderly dependency ratio and population density datasets include 2020 data, GDP per capita and literacy rate variables include 2019 data, hospital beds per population of 100.000 and number of physicians per population of 1000 include 2018 data. The descriptive statistics for the study variables are presented in Table 1 and the correlations among variables are presented in Table 2.

In response to the increase in cases, public authorities took nationwide measures in late April, and enforced a complete lockdown, which lasted from Thursday, April 29, 2021 until Monday, May 17, 2021. Therefore, the course of the number of cases by province in the selected study period can also be examined. Accordingly, the study period offers the opportunity to compare the spatial distribution of Covid-19 in

[1] Week1 (8th to 14th February), week 2 (15th to 21st February), week 3 (20th to 26th February), week 4 (27th February to 5th March), week 5 (6th to 12th March), week 6 (13th to 19th March), week 7 (20th to 27th March), week 8 (27th March to 2nd April), week 9 (3rd to 9th April), week 10 (10th to 16th April), week 11 (17th to 23th April), week 12 (24th to 30th April), week 13 (1st to 7th May), week14 (8th to 14th May), week15 (15th to 21st May), week 16 (22nd to 28th May).

Table 1
Descriptive statistics of variables.

Variables	Mean	Min	Max	Std. Dev.
Covid-19 mean	171,5261	23,37	353,19	78,05766
Covid-19 february	68,8146	4,95	251,21	56,06496
Covid-19 march	158,8731	12,41	558,29	104,95767
Covid-19 april	347,3060	45,23	778,08	161,56589
Covid-19 may	111,1107	30,46	189,66	41,22737
Population density	132,8186	11,23	2975,84	332,52983
Elderly dependency ratio	16,5300	5,34	31,02	5,53216
Log GDP per capita	4,5741	4,22	4,94	0,14406
Literacy rate	94,9500	87,57	98,67	2,82000
Hospital beds per 100.000	276,1852	120,00	502,00	82,35018
Number of physicians per 1000	1,5062	1,00	3,00	0,57279

Source: The authors' calculations.

Turkey's cities. Based on the data, the spread of the pandemic in Turkish provinces could be analyzed in four periods (February, March, April and May). February was the initial phase of the Covid-19, the number of cases increased in March, the number of cases peaked in April, and the number of cases decreased in May (post-quarantine), when the pandemic was partially under control.

3.2. Research method

The study was carried out primarily by describing the data, investigating the distribution, and then estimating empirical models in order to make inferences. Within the scope of describing spatial data, global spatial autocorrelation and local spatial autocorrelation were utilized, and regression model estimation methods were applied in the estimation of empirical models. Diagram showing key study design elements is presented in Figure 1.

3.2.1. Exploratory spatial data analysis

Provincial differences in Covid-19 were identified via Exploratory Spatial Data Analysis (ESDA). ESDA includes techniques that allow the visualization and explanation of distribution of data, exploration of spatial clusters, and identification of outliers (Anselin, 1988b). Various methods of ESDA help in the preliminary modeling phase of empirical research to reveal possible clustering trends of data (Varga, 1998).

In spatial data analysis, spatial weight matrices are used to determine the interactions of the locations studied in the analysis. The following weight matrix was used to demonstrate the spatial association of 81 provinces:

$$W = \begin{bmatrix} \omega_{1,1} & \cdots & \omega_{1,81} \\ \vdots & \ddots & \vdots \\ \omega_{81,1} & \cdots & \omega_{81,81} \end{bmatrix}$$

$\omega_{i,j}$ represents the relationship between the provinces i and j, $i, j = 1, 2, \ldots, 81$.

There are different ways to determine the spatial weight matrix (Anselin, 1988b, 1996). The study employs queen contiguity based on common borders to determine the interactions between the analyzed provinces in Turkey and to investigate the distribution of Covid-19. The adjacency binary matrix for this study is:

$$\omega_{i,j} = \begin{cases} 1, & \text{i is adjacent to j} \\ 0, & \text{otherwise} \end{cases} \quad i, j = 1, 2, \ldots, \; 81 \; i \neq j$$

$\omega_{i,i}$ is assumed to be zero ($\omega_{i,i} = 0$) (Anselin, 1996).

Spatial autocorrelation, which is among the above-mentioned techniques, gives the correlation between observations at a particular location and is associated with the geographical proximity of these observations. Spatial autocorrelation measures are divided into two categories as global scales and local scales based on the scope or scale of the analysis. Moran's I measure, which is commonly used in global spatial autocorrelation measurements, is calculated as follows (Anselin, 1988b; Moran, 1948, 1950):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - x_j)^2}$$

n represents the number of areas in the sample; i and j, two of the areal units; W_{ij}, the matrix of spatial weight (the similarity of i's and j's positions);$x_i$the value of the variable at position i; $(x_i - \bar{x})(x_j - \bar{x})$, the similarity of the variable at i and j positions.

Moran's I value varies in the range of [-1 +1], similar to the correlation coefficient. A Moran's I score of 0 indicates that there is no spatial autocorrelation. In this case, all provinces included in the analysis have a random distribution, meaning that there are no clusters in the relevant space. If Moran's I shows a value of 1, it indicates a perfectly positive correlation where similar values cluster or interact with their neighbors. In this case, high value provinces or low value provinces are clustered together. If Moran's I shows a value of -1, it indicates a perfect negative correlation where dissimilar observations are clustered together. In this case, high and low value observations are clustered together. The greater the absolute value of Moran's I, the stronger the spatial autocorrelation (Anselin, 1996).

While the global spatial autocorrelation provides data about all the

Table 2
Scatterplot matrix of Pearson's correlation among variables.

	Covid-19 mean	Covid-19 february	Covid-19 march	Covid-19 april	Covid-19 may	Population density	Elderly dependency	LogGDP per capita	Literacy rate	Hospital beds
Covid-19 february	,672***									
Covid-19 march	,920***	,777***								
Covid-19 april	,937***	,395***	,766**							
Covid-19 may	,647***	,201	,361***	,691***						
Population density	,284**	,062	,243**	,324***	,177					
Elderly dependency	,522***	,420***	,474***	,456***	,383***	-,194				
LogGDP per capita	,475***	,125	,337***	,564***	,361***	,374***	,292***			
Literacy rate	,503***	,296***	,427***	,518***	,295***	,173	,455***	,795***		
Hospital beds	,276**	,190	,201	,262**	,296***	-,031	,281**	,150	,312***	
Number of physicians	,203	,063	,145	,234**	,166	,166	,069	,425***	,397***	,512***

Notes: **, and *** denote significance at the 5%, and 1% level, respectively.
Source: The authors' calculations.

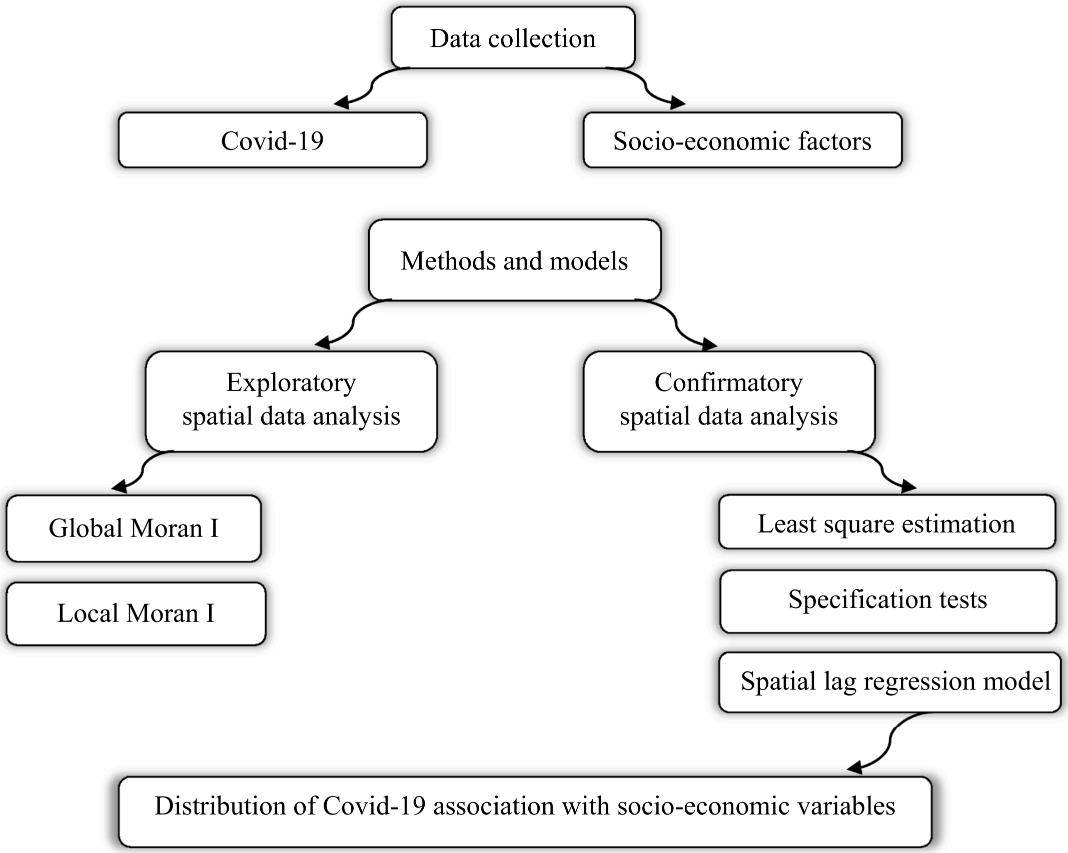

Figure 1. Research workflow
Source: The authors' elaboration.

variables, Local Indicators of Spatial Association (LISA) is employed to determine the spatial clusters of similar values around the observation of a variable. Local spatial autocorrelation determines the spatial clusters of similar values around the observation of a variable. It indicates the presence of hot and cold spots with local clustering of high observation values or local clustering of low observation values. Along with classification into four types of associations, this demonstrates significant local clusters (high-high or low-low) or local spatial outliers (high-low or low-high) (Anselin, 1995; Anselin et al., 2007). Local Moran's I statistics as expressed by Anselin (1995) is as follows:

$$I_i = (x_i - \bar{x}).\sum_{j\in J_i}^{n} W_{ij}(x_j - \bar{x})$$

J_i represents the neighborhood in i region; j, only the areas neighboring J_i; and $\bar{x}$the mean of neighboring observations.

3.2.2. *Confirmatory spatial data analysis*

Confirmatory spatial data analysis was employed to determine the effects of the variables thought to affect Covid-19. Confirmatory spatial data analysis covers a wide range of activities, including model estimation, specification testing, diagnostics and spatial estimations (Anselin, 1988b; Anselin et al., 2007; Anselin & Bera, 1998; Cressie, 1993). In this context, diagnostic tests for spatial dependence were used to detect the presence of spatial dependence in the model estimation process. The most common method used to test spatial autocorrelation is Moran's I statistic applied to regression residuals. Zero hypothesis indicates the lack of spatial dependence in the Moran's I test, while the alternative hypothesis does not specify the type of dependence. Lagrange Multiplier (LM) tests are conducted to determine the type of dependence. If the LM-Error and LM-lag tests are statistically insignificant, it can be deduced that there is no spatial dependence and the results obtained from the classical regression model are employed. If the LM-Error test, which analyzes the spatial error dependence is statistically significant, the spatial error model is valid; however, if the LM-Lag test analyzing the spatial lag dependence is statistically significant, the spatial lag model is predicted. If both LM-Error and LM-Lag tests are statistically significant, robust transformations (Robust LM-Error and Robust LM-Lag) are used to determine which model the spatial dependence originates from. If the Robust LM-Error test is significant, the spatial error model is used, and if the Robust LM-lag test is significant, the spatial lag model is used (Anselin, 1988a, 2005; Anselin et al., 1996).

The following general specification was used to examine the relationship between Covid-19 and socio-economic variables:

$$y = \rho W_1 y + X\beta + \varepsilon$$

$$\varepsilon = \lambda W_2 \varepsilon + u$$

$$u = \mathrm{N}(0, \sigma^2 I)$$

where y is an *nx1* vector of city-specific Covid-19, β is a *kx1* vector of parameters associated with exogenous variables. X is an *nxk* vector of exogenous variables. W_1 and W_2 are matrices of spatial weights; ρ is the coefficient of the spatially lagged dependent variable; λ is the coefficient in a spatial autoregressive structure for the disturbance ε (Anselin, 1988b).

Ordinary Least Square (OLS), under the assumptions $\rho = 0$, $\lambda = 0$:

$$y = X\beta + \varepsilon$$

A Spatial Lag Model (SLM), under the assumption $\lambda = 0$:

$$y = \rho W_1 y + X\beta + \varepsilon$$

A Spatial Error Model (SEM), under the assumption $\rho = 0$:

$$\varepsilon = \lambda W_2 \varepsilon + u$$

$$y = X\beta + \varepsilon$$

The SLM emphasizes the relevance of the observations of the dependent variable in neighboring areas, while the SEM emphasizes the association of residuals observed in the OLS estimation from neighboring areas. As Anselin (1992) points out, spatial errors indicate a violation of the assumption of uncorrelated errors in linear regression analysis. This indicates that relevant and spatially related variables are neglected. In the case of SLM, the statistical significance of spatial lag is that they indicate the presence of propagation processes, that is, events in one place increase the probability of similar events in neighboring locations. The usefulness of the SLM is that it allows a clear distinction to be made between spatial similarity in the dependent variable and spatial similarity in the explanatory variables. The SLM in our study will try to explain the distribution of the Covid-19 variable by adding the prevalence observed in the surrounding provinces (Mourao & Bento, 2021). The study uses the GeoDa software, which provides data visualization, and allows global and local spatial autocorrelation calculations and spatial regression estimations (Anselin, 1995, 1996).

4. Findings

This study examined whether there is a spatial association in Covid-19 cases in Turkey. In order to examine the relationship between the number of Covid-19 cases in any province and the number of cases in neighboring provinces, Moran scatter plots were created for the related periods. Figure 2 shows the relationship between the number of Covid-19 cases in each province shown on the x-axis and the average number of Covid-19 cases in the contiguous provinces shown on the y-axis for February, March, April and May and for the entire period. Accordingly, the Moran's I for the number of Covid-19 cases is 0.448312 for February; 0.501184 for March; 0.676001 for April; 0.512254 for May and 0.653518 for the entire period, and it was found to be significant at 5% significance level. The Moran scatter plots given in Figure 2 reveal that the values are concentrated in regions with positive autocorrelation and are not randomly distributed. This result demonstrates positive spatial autocorrelation in Covid-19 cases across the country. Thus, there is spatial correlation between any province and contiguous provinces based on cases of Covid-19. Furthermore, Moran's I statistics tended to increase by month but decreased during the full lockdown (in May). In this context, April may be a turning point. Although the degree of clustering in May was lower than the previous month, global spatial correlation still shows clustering characteristics.

Local spatial autocorrelation conducted on Covid-19 case data for Turkish provinces for the period between February 8th and May 28th. The findings are presented in Figure 3. High-high is presented in red and represents the high-value aggregation class, low-low is presented in dark blue and represents the low-value cluster class, high-low is shown in pink and represents high-value regions surrounded by low-value regions, and low-high is shown in light blue and represents low-value regions surrounded by high-value regions.

Using LISA analysis, spatial clusters with main low-low patterns were observed in eastern and southeastern Anatolia provinces. During the entire period, low-low clusters were observed in Eastern and Southeastern regions and high-high clusters were observed in Marmara and Black Sea regions. In the Eastern and Southeastern Anatolian regions of the country, there was a continuous distribution trend in the "low-low" cluster regions. While the main high-high clusters were observed in the northern provinces in February, the northern cluster continued, and high-value observations clustered in the Marmara region as well in

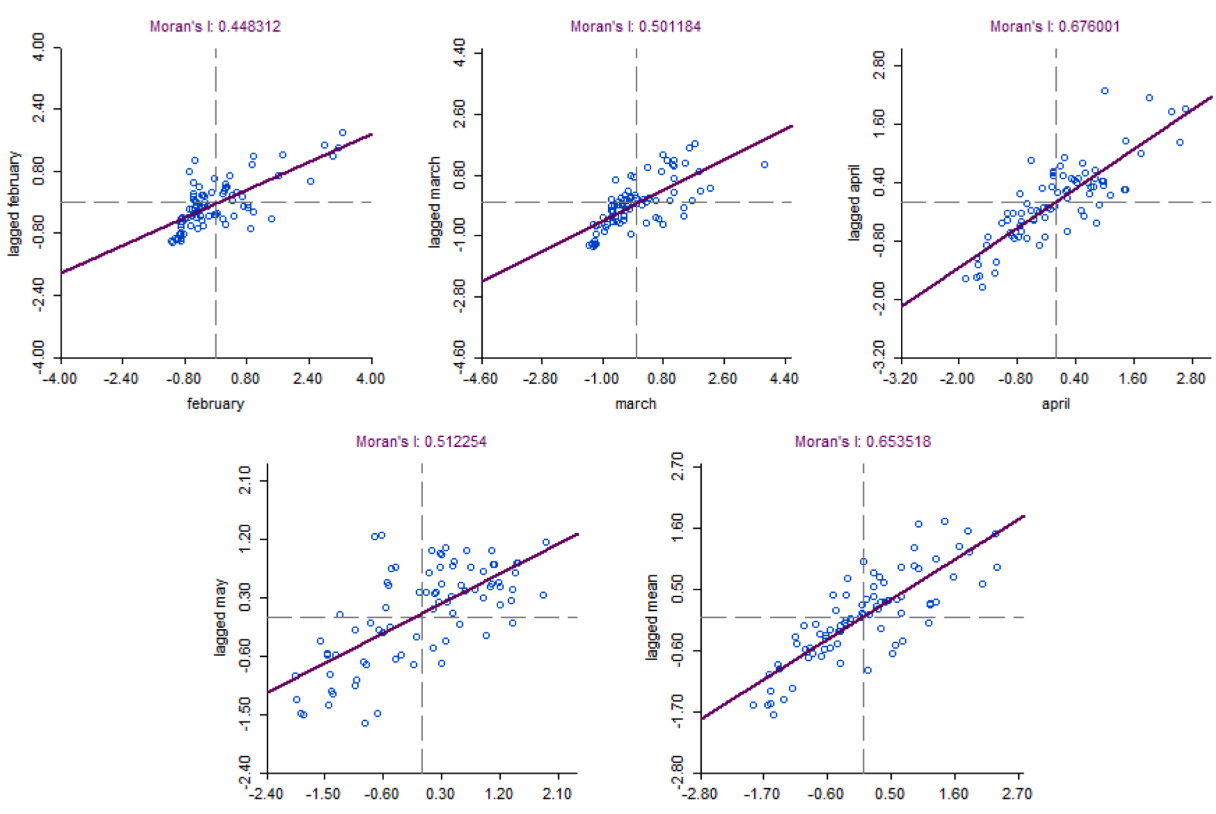

Figure 2. Moran scatter plots of Covid-19 for February, March, April, May and the entire period
Source: The authors' elaboration.

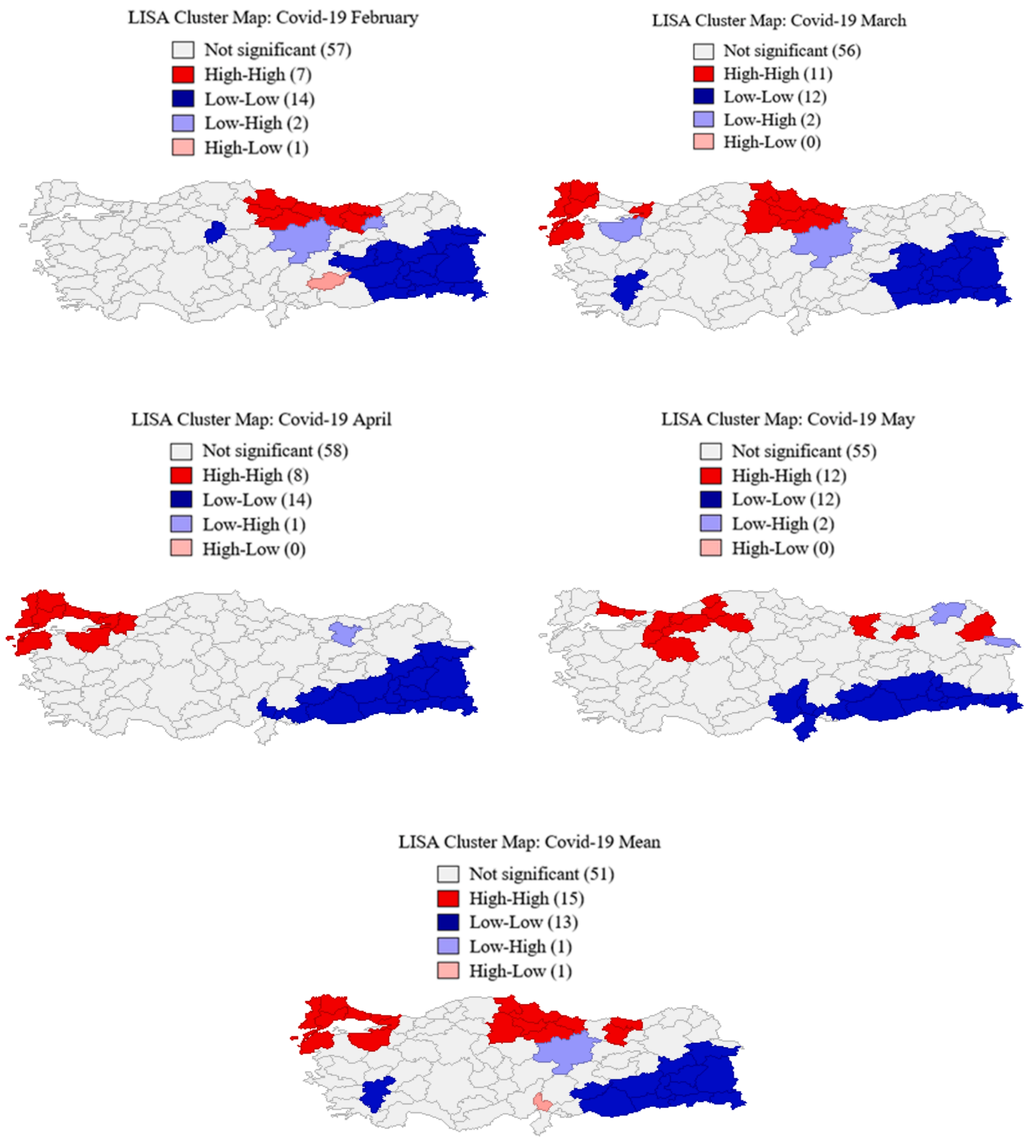

Figure 3. Regional level spatial clustering of Covid-19 for February, March, April, May and the entire period.
Source: The authors' elaboration.

March. In April, the clustering in the north disappeared, while these observations concentrated in Marmara region provinces. In May, the concentration was lower in the Marmara region but spread to neighboring regions. Although the degree of clustering decreased in May, the clustering characteristic continued.

While the clusters observed tended to increase and spread to other regions, they decreased during the full lockdown (in May). In this context, it is possible to observe the positive effects of the measures taken in this period. Similarly, the positive effects of complete lockdown procedures have been demonstrated in studies conducted in different countries. For example, Bourdin et al. (2021) showed that the lockdown imposed in Italy at the beginning of March 2020 was a very important and effective approach to slow the spread of the virus. Analysis of the Italy case is crucial, as Italy was the first country to experience an out-of-control spread of the Covid-19 virus, providing a good basis for evaluating lockdown strategies. Kim and Castro (2020), revealed how government policies can affect the spread of Covid-19 in their study, which evaluated how Covid-19 clustered among districts in South Korea and investigated whether the pattern and duration of clusters had changed following the country's containment strategies. The results showed that the containment strategies against the spread of Covid-19 have been highly effective in both early detection and mitigation.

OLS regression models were estimated for the periods (February, March, April, May and the entire period) to determine the effects of the variables thought to have an effect on Covid-19 cases in Turkey. Furthermore, diagnostic tests for spatial dependence were applied to determine whether the analyzed provinces were affected by contiguity. OLS regression models and spatial dependence test results are given in Table 3.

For the period under review, Moran's I (p=0.00) suggests a problem with spatial autocorrelation. LM test statistics were examined to determine which alternative specification should be employed. The LM-Lag and LM-Error statistics are highly significant. Thus, the use of robust forms of LM statistics allows for discrimination between alternative models (Anselin, 2005). The Robust LM-Lag statistics is significant, while the Robust LM-error statistics are not. These test statistics suggest a SLM. In this context, the estimated results of SLM are presented in Table 4. The highest AIC and SWC were recorded in April in SLM and OLS models, while the lowest values were determined in May. AIC values are lower in SLM when compared to the OLS in all models. The decrease in AIC demonstrates that the SLM provided more effective results when compared to OLS. SLM explains the distribution of the

Table 3
OLS model estimation results for Covid-19 in Turkey.

	Dependent Variable Covid-19 February	Covid-19 March	Covid-19 April	Covid-19 May	Covid-19 Entire
Population density	0,03527	0,10527	0,13316	0,01991	0,07340
	(0,08)	(0,00)***	(0,01)**	(0,16)	(0,00)***
Elderly dependency ratio	4,00271	8,58625	10,8006	2,55671	6,48657
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
GDP per capita	-133,2230	-87,0320	418,277	116,726	78,687
	(0,08)	(0,50)	(0,02)**	(0,03)**	(0,36)
Literacy rate	6,82075	9,31832	-0,748668	-3,77507	2,90383
	(0,07)	(0,15)	(0,93)	(0,16)	(0,50)
Hospital beds per 100.000	0,02264	0,03391	0,28986	0,13647	0,12072
	(0,80)	(0,82)	(0,17)	(0,03)**	(0,24)
Number of physicians per 1000	-0,56964	-0,76040	-19,04660	-6,92248	-6,82479
	(0,97)	(0,97)	(0,54)	(0,46)	(0,65)
Moran's I (error)	4,9420	4,1495	5,1891	4,7241	5,1725
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
LM-Lag	20,5686	15,6320	33,4537	24,2732	29,9135
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
Robust LM-Lag	3,4265	4,2200	16,6976	12,4078	11,9551
	(0,06)	(0,04)**	(0,00)***	(0,00)***	(0,00)***
LM-Error	17,257	11,6738	19,2220	15,6144	19,0866
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
Robust LM-Error	0,1156	0,2617	2,4659	3,7490	1,1282
	(0,73)	(0,61)	(0,12)	(0,05)	(0,29)
LM-SARMA	20,6842	15,8937	35,9196	28,0222	31,0417
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
Jarque-Bera	45,355	46,9491	0,9080	0,7674	1,5754
	(0,00)***	(0,00)***	(0,64)	(0,68)	(0,45)
Breusch-Pagan test	16,927	17,9093	10,5066	4,2189	7,2994
	(0,01)**	(0,00)***	(0,10)	(0,65)	(0,29)
Log likelihood	-429,299	-472,845	-499,504	-401,48	-441,238
Akaike Information Criterion-AIC	872,598	959,690	1013,01	816,96	896,477
Schwarz Information Criterion-SWC	889,359	976,451	1029,77	833,721	913,238
Adjusted R-squared	0,18	0,32	0,48	0,24	0,43

Notes: **, and *** denote significance at the 5%, and 1% level, respectively.
Source: The authors' calculations.

Covid-19 variable by adding the prevalence observed in the surrounding provinces. Overall, the SLM can better explain the spatial distribution of Covid-19 cases. It was determined that the independent variables explained 67% of the variation in Covid-19 cases in SLM and 43% in OLS in the entire period. The highest R^2 was observed in April in SLM and OLS, and the lowest was observed in February. In the entire period, R^2 is higher in SLM when compared to OLS.

Among all factors, the regression coefficient for the population density is positive in March, April and the entire period (Table 4). Population density increases the number of Covid-19 cases. This finding is consistent with previous study findings in the literature. Human activity among the independent variables is a key process in the spread of Covid-19. Population density, a valid indicator of the intensity of human activity (Chen et al., 2021; Han et al., 2021), is a key element that explains the spread rate (Xie et al., 2020). As Covid-19 spreads from person to person, the number of cases is expected to be higher in more densely populated areas (Kang et al., 2020; Kim & Castro, 2020; Mansour et al., 2021; Sigler et al., 2021; Urban & Nakada, 2021). On the other hand, Coşkun et al. (2021) revealed that the population density is the most important and first factor in the spread of the virus. Arauzo-Carod (2021) reported that the population density triggers the contagion process. Since the social interaction is high in urban areas with a high population density, contagion risk is also high in these areas. Eryando et al. (2020)) underlined that the provinces with the highest number of cases in Indonesia are the provinces with the highest population density and the highest mobility. As the virus spreads among people in close contact, it will spread just as quickly in places of high population density and mobility. As emphasized in previous studies, the spread of the virus is effective in highly populated regions, and this accelerates the spread of the epidemic by affecting other regions (Kang et al., 2020). Sigler et al. (2021) stated that human mobility is significantly effective in the spread of the epidemic, therefore, the spread of the pandemic can be prevented by human mobility.

It is seen that the elderly dependency ratio also plays a role in the intensity of Covid-19. The regression coefficient for the elderly dependency ratio is positive in February, March and the entire period. As the elderly dependency ratio increases, the number of Covid-19 cases increases. SARS-CoV-2 is known to target older people or others with pre-existing conditions, however the reason for this age dependence is unclear. Despite some reports characterizing Covid-19 as an age-related disease, the association with advanced age may mean different things depending on the number of comorbidities. This negative effect on the elderly and age-related diseases are both considered as the main risk factors (Santesmasses et al., 2020). In this context, it is possible to observe in the literature, different effects of Covid-19 on the elderly population (Arauzo-Carod, 2021; Mansour et al., 2021; Paez et al., 2020; Sarkar et al., 2021; You et al., 2020).

Furthermore, the lag coefficient for Covid-19 (Rho) is statistically significant at 1% significance level in the entire period. Thus, the number of Covid-19 cases in a province depends on the cases in neighboring provinces. This result is consistent with the findings of studies investigating the existence of spatial effects for Covid-19 (Bourdin et al., 2021; Ramírez-Aldana et al., 2020; Sarkar et al., 2021; Y. Sun et al., 2021; Tao et al., 2020; Vaz, 2021; You et al., 2020). It was underlined in related studies (Eryando et al., 2020; Ghosh & Cartone, 2020; Giuliani et al., 2020; Hafner, 2020; Han et al., 2021; Perles et al., 2021) that proximity between cities and contiguity affect the spread of the pandemic. These studies underline the importance of spatial dimension in explaining Covid-19 cases.

Table 4
SLM estimation results for Covid-19 in Turkey.

	Dependent Variable Covid-19 February	Covid-19 March	Covid-19 April	Covid-19 May	Covid-19 Entire
Rho	0,63570	0,51301	0,64468	0,55378	0,63360
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
Population density	0,02198	0,07714	0,06900	0,01301	0,04367
	(0,16)	(0,01)**	(0,04)**	(0,25)	(0,01)**
Elderly dependency ratio	2,19597	4,92348	3,26373	0,749987	2,53681
	(0,03)**	(0,01)**	(0,15)	(0,31)	(0,03)**
GDP per capita	-107,02100	-98,916300	204,55200	68,35430	15,19730
	(0,07)	(0,36)	(0,13)	(0,11)	(0,82)
Literacy rate	4,20161	6,45409	-0,43530	-1,99376	1,95334
	(0,15)	(0,23)	(0,95)	(0,35)	(0,57)
Hospital beds per 100.000	0,00784	0,00851	0,20456	0,12843	0,08592
	(0,91)	(0,95)	(0,18)	(0,01)**	(0,26)
Number of physicians per 1000	0,62570	1,91598	-17,20860	6,83399	-5,22365
	(0,95)	(0,92)	(0,45)	(0,36)	(0,65)
Likelihood Ratio	22,1264	15,0034	31,6612	20,3275	28,8743
	(0,00)***	(0,00)***	(0,00)***	(0,00)***	(0,00)***
Breusch-Pagan test	10,4084	17,1749	6,5904	2,2391	6,2659
	(0,11)	(0,09)	(0,36)	(0,90)	(0,39)
Log likelihood	-418,236	-465,343	-483,674	-391,316	-426,801
AIC	852,472	946,686	983,347	798,633	869,602
SWC	871,62	965,842	1002,500	817,788	888,758
R-squared	0,48	0,51	0,69	0,50	0,67

Notes: **, and *** denote significance at the 5%, and 1% level, respectively.
Source: The authors' calculations.

5. Discussion

Shortly after the outbreak of the Covid-19 pandemic, academic interest in the subject increased rapidly, and emerging research was built on either diagnosis and treatment or prevention and control of the spread of the disease. Moreover, some universities, research institutes and online platforms share daily data on the pandemic, informing governments and the public about the rate of spread of the pandemic. However, despite these developments, it has been stated that the spatiotemporal part of the subject is missing and at this point, determining the factors affecting the spread of the virus and taking the necessary precautions will contribute to the control of the pandemic (Xiong et al., 2020).

Currently, Turkey ranks fifth in the world in total number of cases (5,263,697). It is very important to control the pandemic in Turkey, where the number of daily cases exceeds seven thousand (7.181) and where more than a hundred (112) virus-related deaths are recorded daily. At this point, the spatial data will be useful in controlling the pandemic and reducing its impact. This could lead to faster and more effective solutions.

This study, which analyzes the cases of Covid-19 in Turkey at the provincial level, aims to add a dimension that includes spatial associations to the growing literature on Covid-19 cases. In this context, it is shown that the spatial association between provinces and socio-economic factors should be considered to model the disease, and the study also highlights the socio-economic factors that may lead to inequalities in the spread of Covid-19. As a result of the analyses made in this direction, it has been determined that there is a positive spatial autocorrelation throughout the country, and that any province has spatial association with its neighboring provinces. It has been observed that there are spatially distinct clusters in Covid-19 cases. These findings show the potential trend of infection spreading from one province to other regions and provide evidence that interprovincial human mobility may exacerbate the spread of the disease. Since the interaction of people in contiguous regions has led to the spread of the disease, geographical proximity is effective in the spread of the pandemic. This reveals the significance of spatial association in the fight against the pandemic. Thus, the existence of the local spatial associations will allow policy makers to achieve effective results in response to the pandemic. It will prevent the spread of the disease once the provincial and regional measures are taken where the number of cases is high. It was also determined in the present study that the full quarantine implemented in Turkey helped control the spread of the virus. As a matter of fact, it is another finding of the study that the complete lockdown enforced in our country has helped in controlling the spread of the virus.

Furthermore, it has been revealed in the research that population density and elderly dependency ratio positively affect the number of Covid-19 cases. The association of the number of Covid-19 cases and the population with the elderly population is vital in terms of highlighting the places to be prioritized in the fight against the pandemic. Provinces with high population density and high elderly population should be closely monitored and should be listed among the prioritized areas of intervention. You et al. (2020) underlined that it will be possible to control infectious diseases such as Covid-19 by regulating social and economic factors. They even expressed how important it is to manage urban development in order to improve human health. For this reason, as a result of spatial analysis, the effect of social and economic factors on the spread of Covid-19 will be analyzed and important information will be obtained on the prevention of the spread of the pandemic. In this way, both healthy and sustainable cities will be created.

6. Conclusion

As the Covid-19 pandemic affects nations, its spread continues, and various measures are implemented between countries to prevent this spread. Similarly, Covid-19 spreads between provinces/regions in countries. This study has revealed the spread of Covid-19 in Turkish provinces based on spatial analyses of interregional relations. Detection of the spatial spread of the virus leads to the conclusion that further spread of the epidemic can be prevented by taking the necessary precautions. The prevalence of Covid-19 in Turkey exhibits spatial variation and spatiotemporal aggregation. This means that the distribution of Covid-19 cases is heterogeneous among Turkish cities. This uneven distribution may be due to many related factors, including demographic, socio-cultural and socio-economic differences between cities in Turkey.

For instance, this study has shown that the elderly dependency ratio and population density positively affect the spread of Covid-19. Considering the decrease in the number of cases following the complete lockdown, it can be suggested that local lockdowns will also prevent the spread of the disease. Therefore, in this study, it is underlined that local lockdowns with lighter social and economic costs will also contribute to the decline in the number of cases.

Although this study was conducted to reveal the socio-economic factors affecting the spread of the Covid-19 virus by analyzing the spatial behavior of the pandemic, it has several limitations. One of the limitations is that the dataset reported for 81 provinces in Turkey was used. The dataset did not include the number of patients and deaths, preventing the analysis of the spatial-temporal impact of Covid-19 based on these variables. Furthermore, as data began to be published from February 2021, the spatial and temporal characteristics of the Covid-19 outbreak could not be investigated at its early stage. Secondly, the study was carried out at the provincial level, and the data were not analyzed for urban-rural differences or based on districts. Thirdly, the variables used are not contemporary as the data on social and economic factors predate the emergence of Covid-19. The biggest difficulty encountered in the study was access to the data. Although there are many factors affecting Covid-19, the socio-economic variables discussed in this study are limited. More variables are needed to get a better idea of Covid-19. In this study, the effects of other controlling factors such as environmental conditions, seasonal variation and climate change were not considered. This may be the scope of future research. Future studies may examine a larger dataset to identify factors that influence death and recovery from Covid-19. Studies that will reveal psychological factors and adherence to quarantine measures will provide an important opportunity for researchers in this field. Therefore, these studies will contribute to the control of the disease, and the spread will be prevented with the precautions to be taken.

Declaration of Competing Interest

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Adegboye, O. A., Adekunle, A. I., Pak, A., Gayawan, E., Leung, D. H., Rojas, D. P., Elfaki, F., McBryde, E. S., & Eisen, D. P. (2021). Change in outbreak epicentre and its impact on the importation risks of COVID-19 progression: A modelling study. *Travel Medicine and Infectious Disease, 40*(January), Article 101988. https://doi.org/10.1016/j.tmaid.2021.101988

Al-Kindi, K. M., Alkharusi, A., Alshukaili, D., Al Nasiri, N., Al-Awadhi, T., Charabi, Y., & El Kenawy, A. M (2020). Spatiotemporal Assessment of COVID-19 Spread over Oman Using GIS Techniques. *Earth Systems and Environment, 4*(4), 797–811. https://doi.org/10.1007/s41748-020-00194-2

Al-Rahimi, J. S., Nass, N. M., Hassoubah, S. A., Wazqar, D. Y., & Alamoudi, S. A. (2021). Levels and predictors of fear and health anxiety during the current outbreak of COVID-19 in immunocompromised and chronic disease patients in Saudi Arabia: A cross-sectional correlational study. *PLOS ONE, 16*(4), Article e0250554. https://doi.org/10.1371/journal.pone.0250554

Alcântara, E., Mantovani, J., Rotta, L., Park, E., Rodrigues, T., Carvalho, F. C., & Filho, C. R. S. (2020). Investigating spatiotemporal patterns of the covid-19 in São Paulo state. Brazil. *Geospatial Health, 15*(2), 201–209. https://doi.org/10.4081/gh.2020.925

Ali, M., Emch, M., Donnay, J. P., Yunus, M., & Sack, R. B. (2002). The spatial epidemiology of cholera in an endemic area of Bangladesh. *Social Science & Medicine, 55*(6), 1015–1024. https://doi.org/10.1016/S0277-9536(01)00230-1

Alkhamis, M. A., Al Youha, S., Khajah, M. M., Ben Haider, N., Alhardan, S., Nabeel, A., Al Mazeedi, S., & Al-Sabah, S. K (2020). Spatiotemporal dynamics of the COVID-19 pandemic in the State of Kuwait. *International Journal of Infectious Diseases, 98*, 153–160. https://doi.org/10.1016/j.ijid.2020.06.078

Anselin, L. (1988a). Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity. *Geographical Analysis, 20*(1), 1–17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x

Anselin, L. (1988b). *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1992). Spatial data analysis with GIS: An introduction to application in the social sciences. *Transactions of the Indian Institute of Metals* (Issue Technical Report 92-10) http://ncgia.ucsb.edu/technical-reports/PDF/92-10.pdf.

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis, 27*(Issue 2). https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L. (1996). The Moran Scatter Plot as an ESDA Tool to Assess Local Instability in Spatial Association. In H. J. Fischer, & M. M Scholten (Eds.), *Spatial Analytical Perspectives on GIS: GISDATA* (4th ed., pp. 111–125). CRC Press.

Anselin, L. (2005). Exploring Spatial Data with GeoDa: A Workbook. *Center for Spatially Integrated Social Science*. http://sal.uiuc.edu/http://www.csiss.org/.

Anselin, L., & Bera, A. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In D. E. Ullah, & Aman Giles (Eds.), *Handbook of Applied Economic Statistics* (pp. 237–289). New York: Marcel Dekker.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics, 26*(1), 77–104. https://doi.org/10.1016/0166-0462(95)02111-6

Anselin, L., Sridharan, S., & Gholston, S. (2007). Using exploratory spatial data analysis to leverage social indicator databases: The discovery of interesting patterns. *Social Indicators Research, 82*(2), 287–309. https://doi.org/10.1007/s11205-006-9034-x

Arauzo-Carod, J. M. (2021). A first insight about spatial dimension of COVID-19: analysis at municipality level. *Journal of Public Health (Oxford, England), 43*(1), 98–106. https://doi.org/10.1093/pubmed/fdaa140

Atique, S., Chan, T.-C., Chen, C.-C., Hsu, C.-Y., Iqtidar, S., Louis, V. R., Shabbir, S. A., & Chuang, T.-W. (2018). Investigating spatio-temporal distribution and diffusion patterns of the dengue outbreak in Swat, Pakistan. *Journal of Infection and Public Health, 11*(4), 550–557. https://doi.org/10.1016/j.jiph.2017.12.003

Bag, R., Ghosh, M., Biswas, B., & Chatterjee, M. (2020). Understanding the spatio-temporal pattern of COVID-19 outbreak in India using GIS and India's response in managing the pandemic. *Regional Science Policy and Practice, 12*(6), 1063–1103. https://doi.org/10.1111/rsp3.12359

Basu, B., Murphy, E., Molter, A., Sarkar Basu, A., Sannigrahi, S., Belmonte, M., & Pilla, F (2021). Investigating changes in noise pollution due to the COVID-19 lockdown: The case of Dublin, Ireland. *Sustainable Cities and Society, 65*, Article 102597. https://doi.org/10.1016/j.scs.2020.102597

Benchrif, A., Wheida, A., Tahri, M., Shubbar, R. M., & Biswas, B. (2021). Air quality during three covid-19 lockdown phases: AQI, PM2.5 and NO2 assessment in cities with more than 1 million inhabitants. *Sustainable Cities and Society, 74*, Article 103170. https://doi.org/10.1016/j.scs.2021.103170

Bourdin, S., Jeanne, L., Nadou, F., & Noiret, G. (2021). Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy. *Regional Studies, 55*(7), 1182–1193. https://doi.org/10.1080/00343404.2021.1887471

Castro, R. R., Santos, R. S. C., Sousa, G. J. B., Pinheiro, Y. T., Martins, I. M., Pereira, M. L. D., & Silva, R. A. R. (2021). Spatial dynamics of the COVID-19 pandemic in Brazil. *Epidemiology and Infection, 149*(e60), 1–9. https://doi.org/10.1017/S0950268821000479

Chen, Y., Li, Q., Karimian, H., Chen, X., & Li, X. (2021). Spatio-temporal distribution characteristics and influencing factors of COVID-19 in China. *Scientific Reports, 11*(1), 1–12. https://doi.org/10.1038/s41598-021-83166-4

Cos, O. De, Castillo, V., & Cantarero, D (2020). Facing a Second Wave from a Regional View: Spatial Patterns of COVID-19 as a Key Determinant for Public Health and Geoprevention Plans. *International Journal of Environmental Research and Public Health, 17*(22), 8468. https://doi.org/10.3390/ijerph17228468

Coşkun, H., Yıldırım, N., & Gündüz, S. (2021). The spread of COVID-19 virus through population density and wind in Turkey cities. *Science of the Total Environment, 751*, Article 141663. https://doi.org/10.1016/j.scitotenv.2020.141663

Cressie, N. (1993). *Statistics for Spatial Data*. New York: Wiley.

Das, A., Ghosh, S., Das, K., Basu, T., Dutta, I., & Das, M. (2021). Living environment matters: Unravelling the spatial clustering of COVID-19 hotspots in Kolkata megacity, India. *Sustainable Cities and Society, 65*, Article 102577. https://doi.org/10.1016/j.scs.2020.102577

Desjardins, M. R., Hohl, A., & Delmelle, E. M. (2020). Rapid surveillance of COVID-19 in the United States using a prospective space-time scan statistic: Detecting and evaluating emerging clusters. *Applied Geography, 118*(January), Article 102202. https://doi.org/10.1016/j.apgeog.2020.102202

Dickson, M. M., Espa, G., Giuliani, D., Santi, F., & Savadori, L. (2020). Assessing the effect of containment measures on the spatio-temporal dynamic of COVID-19 in Italy. *Nonlinear Dynamics, 101*(3), 1833–1846. https://doi.org/10.1007/s11071-020-05853-7

El Deeb, O. (2021). Spatial Autocorrelation and the Dynamics of the Mean Center of COVID-19 Infections in Lebanon. *Frontiers in Applied Mathematics and Statistics, 6*, 1–15. https://doi.org/10.3389/fams.2020.620064

Eryando, T., Sipahutar, T., & Rahardiantoro, S. (2020). The Risk Distribution of COVID-19 in Indonesia: A Spatial Analysis. *Asia-Pacific Journal of Public Health, 32*(8), 450–452. https://doi.org/10.1177/1010539520962940

Ferreira, D., Ferreira, P., Oliveira, P., Ribeiro, J., Goncalves, E., & Papa, A. (2020). Temporal and spatial characteristics of the spread of COVID-19 in Rio de Janeiro state and city. *MedRxiv*. https://doi.org/10.1101/2020.05.13.20101113

Ghosh, P., & Cartone, A. (2020). A Spatio-temporal analysis of COVID-19 outbreak in Italy. *Regional Science Policy and Practice, 12*(6), 1047–1062. https://doi.org/10.1111/rsp3.12376

Giuliani, D., Dickson, M. M., Espa, G., & Santi, F. (2020). Modelling and predicting the spatio-temporal spread of COVID-19 in Italy. *BMC Infectious Diseases, 20*(700), 1–10. https://doi.org/10.1186/s12879-020-05415-7

Glick, B. (1979). The spatial autocorrelation of cancer mortality. *Social Science & Medicine. Part D: Medical Geography, 13*(2), 123–130. https://doi.org/10.1016/0160-8002(79)90058-3

Hafner, C. M. (2020). The spread of the Covid-19 pandemic in time and space. *International Journal of Environmental Research and Public Health, 17*(11), 3827. https://doi.org/10.3390/ijerph17113827

Han, Y., Yang, L., Jia, K., Li, J., Feng, S., Chen, W., Zhao, W., & Pereira, P. (2021). Spatial distribution characteristics of the COVID-19 pandemic in Beijing and its relationship with environmental factors. *Science of the Total Environment, 761*(December 2019), Article 144257. https://doi.org/10.1016/j.scitotenv.2020.144257

Hipp, J. A., & Chalise, N. (2015). Spatial Analysis and Correlates of County-Level Diabetes Prevalence, 2009–2010. *Preventing Chronic Disease, 12*(E08), Article 140404. https://doi.org/10.5888/pcd12.140404

Islam, M. S., Tusher, T. R., Roy, S., & Rahman, M. (2021). Impacts of nationwide lockdown due to COVID-19 outbreak on air quality in Bangladesh: a spatiotemporal analysis. *Air Quality, Atmosphere and Health, 14*(3), 351–363. https://doi.org/10.1007/s11869-020-00940-5

Kang, D., Choi, H., Kim, J. H., & Choi, J. (2020). Spatial epidemic dynamics of the COVID-19 outbreak in China. *International Journal of Infectious Diseases, 94*, 96–102. https://doi.org/10.1016/j.ijid.2020.03.076

Kim, S., & Castro, M. C. (2020). Spatiotemporal pattern of COVID-19 and government response in South Korea (as of May 31, 2020). *International Journal of Infectious Diseases, 98*, 328–333. https://doi.org/10.1016/j.ijid.2020.07.004

Lai, P. C., Wong, C. M., Hedley, A. J., Lo, S. V., Leung, P. Y., Kong, J., & Leung, G. M. (2004). Understanding the spatial clustering of severe acute respiratory syndrome (SARS) in Hong Kong. *Environmental Health Perspectives, 112*(15), 1550–1556. https://doi.org/10.1289/ehp.7117

Lak, A., Sharifi, A., Badr, S., Zali, A., Maher, A., Mostafavi, E., & Khalili, D. (2021). Spatio-temporal patterns of the COVID-19 pandemic, and place-based influential factors at the neighborhood scale in Tehran. *Sustainable Cities and Society, 72* (January), Article 103034. https://doi.org/10.1016/j.scs.2021.103034

Li, H., Li, H., Ding, Z., Hu, Z., Chen, F., Wang, K., Peng, Z., & Shen, H. (2020). Spatial statistical analysis of Coronavirus Disease 2019 (Covid-19) in China. *Geospatial Health, 15*(1). https://doi.org/10.4081/gh.2020.867

Liu, M., Liu, M., Li, Z., Zhu, Y., Liu, Y., Wang, X., Tao, L., & Guo, X. (2021). The spatial clustering analysis of COVID-19 and its associated factors in mainland China at the prefecture level. *Science of the Total Environment, 777*, Article 145992. https://doi.org/10.1016/j.scitotenv.2021.145992

Maiti, A., Zhang, Q., Sannigrahi, S., Pramanik, S., Chakraborti, S., Cerda, A., & Pilla, F. (2021). Exploring spatiotemporal effects of the driving factors on COVID-19 incidences in the contiguous United States. *Sustainable Cities and Society, 68*, Article 102784. https://doi.org/10.1016/j.scs.2021.102784

Mansour, S., Al Kindi, A., Al-Said, A., Al-Said, A., & Atkinson, P. (2021). Sociodemographic determinants of COVID-19 incidence rates in Oman: Geospatial modelling using multiscale geographically weighted regression (MGWR). *Sustainable Cities and Society, 65*, Article 102627. https://doi.org/10.1016/j.scs.2020.102627

Meng, B., Wang, J., Liu, J., Wu, J., & Zhong, E. (2005). Understanding the spatial diffusion process of severe acute respiratory syndrome in Beijing. *Public Health, 119* (12), 1080–1087. https://doi.org/10.1016/j.puhe.2005.02.003

Moran, P. A. P. (1948). The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society: Series B (Methodological), 10*(2), 243–251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x

Moran, P. A. P. (1950). Notes on Continuous Stochastic Phenomena. *Biometrika, 37*(1/2), 17–23. https://doi.org/10.2307/2332142

Mourao, P., & Bento, R. (2021). Explaining COVID-19 contagion in Portuguese municipalities using spatial autocorrelation models. *Revista Galega de Economía, 30* (1), 1–12. https://doi.org/10.15304/rge.30.1.6984

Murugesan, B., Karuppannan, S., Mengistie, A. T., Ranganathan, M., & Gopalakrishnan, G. (2020). Distribution and Trend Analysis of COVID-19 in India: Geospatial Approach. *Journal of Geographical Studies, 4*(1), 1–9. https://doi.org/10.21523/gcj5.20040101

Paez, A., Lopez, F. A., Menezes, T., Cavalcanti, R., Pitta, M. G., & da, R. (2020). A Spatio-Temporal Analysis of the Environmental Correlates of COVID-19 Incidence in Spain. *Geographical Analysis, 0*, 1–25. https://doi.org/10.1111/gean.12241

Perles, M.-J., Sortino, J. F., & Mérida, M. F. (2021). The Neighborhood Contagion Focus as a Spatial Unit for Diagnosis and Epidemiological Action against COVID-19 Contagion in Urban Spaces: A Methodological Proposal for Its Detection and Delimitation. *International Journal of Environmental Research and Public Health, 18*(6), 3145. https://doi.org/10.3390/ijerph18063145

Rahman, M. R., Islam, A. H. M. H., & Islam, M. N. (2020). Geospatial modelling on the spread and dynamics of 154 day outbreak of the novel coronavirus (COVID-19) pandemic in Bangladesh towards vulnerability zoning and management approaches. *Modeling Earth Systems and Environment*, 1–29. https://doi.org/10.1007/s40808-020-00962-z

Rahmani, S. E. A., Chibane, B., Hallouz, F., & Benamar, N. (2020). Spatial distribution of Covid-19, a modeling approach: case of Algeria. *Research Square, 1–11*. https://doi.org/10.21203/rs.3.rs-40447/v1

Ramírez-Aldana, R., Gomez-Verjan, J. C., Bello-Chavolla, O. Y., & Peterson, T. (2020). Spatial analysis of COVID-19 spread in Iran: Insights into geographical and structural transmission determinants at a province level. *PLoS Neglected Tropical Diseases, 14* (11), Article e0008875. https://doi.org/10.1371/journal.pntd.0008875

Ramírez, I. J., & Lee, J. (2020). COVID-19 emergence and social and health determinants in Colorado: A rapid spatial analysis. *International Journal of Environmental Research and Public Health, 17*(11), 3856. https://doi.org/10.3390/ijerph17113856

Roth, D., Otterstatter, M., Wong, J., Cook, V., Johnston, J., & Mak, S. (2016). Identification of spatial and cohort clustering of tuberculosis using surveillance data from British Columbia, Canada, 1990–2013. *Social Science & Medicine, 168*, 214–222. https://doi.org/10.1016/j.socscimed.2016.06.047

Saha, A., Gupta, K., Patil, M., & Urvashi. (2020). Monitoring and epidemiological trends of coronavirus disease (COVID-19) around the world. *Matrix Science Medica, 4*(4), 121. https://doi.org/10.4103/mtsm.mtsm_16_20

Sannigrahi, S., Pilla, F., Basu, B., Basu, A. S., & Molter, A.*The overall mortality caused by COVID-19 in the European region is highly associated with demographic composition: A spatial regression-based approach Srikanta*. https://doi.org/10.1016/j.scs.2020.102418.

Sannigrahi, S., Pilla, F., Basu, B., Basu, A. S., & Molter, A. (2020). Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach. *Sustainable Cities and Society, 62*, Article 102418. https://doi.org/10.1016/j.scs.2020.102418

Santesmasses, D., Castro, J. P., Zenin, A. A., Shindyapina, A. V., Gerashchenko, M. V., Zhang, B., Kerepesi, C., Yim, S. H., Fedichev, P. O., & Gladyshev, V. N. (2020). COVID-19 is an emergent disease of aging. *Aging Cell, 19*(10), e13230. https://doi.org/10.1111/acel.13230

Sarkar, S. K., Ekram, K. M. M., & Das, P. C. (2021). Spatial modeling of COVID-19 transmission in Bangladesh. *Spatial Information Research*, 1–12. https://doi.org/10.1007/s41324-021-00387-5

Selcuk, M., Gormus, S., & Guven, M. (2021). Impact of Weather Parameters and Population Density on the COVID-19 Transmission: Evidence from 81 Provinces of Turkey. *Earth Systems and Environment, 5*(1), 87–100. https://doi.org/10.1007/s41748-020-00197-z

Shariati, M., Mesgari, T., Kasraee, M., & Jahangiri-rad, M. (2020). Spatiotemporal analysis and hotspots detection of COVID-19 using geographic information system (March and April, 2020). *Journal of Environmental Health Science and Engineering, 18* (2), 1499–1507. https://doi.org/10.1007/s40201-020-00565-x

Sigler, T., Mahmuda, S., Kimpton, A., Loginova, J., Wohland, P., Charles-Edwards, E., & Corcoran, J. (2021). The socio-spatial determinants of COVID-19 diffusion: the impact of globalisation, settlement characteristics and population. *Globalization and Health, 17*(1), 56. https://doi.org/10.1186/s12992-021-00707-2

Souris, M., Gonzalez, J.-P., Shanmugasundaram, J., Corvest, V., & Kittayapong, P. (2010). Retrospective space-time analysis of H5N1 Avian Influenza emergence in Thailand. *International Journal of Health Geographics, 9*(1), 3. https://doi.org/10.1186/1476-072X-9-3

Stark, J. H., Sharma, R., Ostroff, S., Cummings, D. A. T., Ermentrout, B., Stebbins, S., Burke, D. S., & Wisniewski, S. R. (2012). Local spatial and temporal processes of influenza in pennsylvania, usa: 2003-2009. *PLoS ONE, 7*(3), Article e324245. https://doi.org/10.1371/journal.pone.0034245

Sun, F., Matthews, S. A., Yang, T.-C., & Hu, M.-H. (2020). A spatial analysis of the COVID-19 period prevalence in U.S. counties through June 28, 2020: where geography matters? *Annals of Epidemiology, 52*, 54–59. https://doi.org/10.1016/j.annepidem.2020.07.014

Sun, Y., Huang, Y., Yuan, K., Chan, T. O., & Wang, Y. (2021). Spatial Patterns of COVID-19 Incidence in Relation to Crime Rate Across London. *ISPRS International Journal of Geo-Information, 10*(53). https://doi.org/10.3390/ijgi10020053

Tao, R., Downs, J., Beckie, T. M., Chen, Y., & McNelley, W. (2020). Examining spatial accessibility to COVID-19 testing sites in Florida. *Annals of GIS, 26*(4), 319–327. https://doi.org/10.1080/19475683.2020.1833365

UN, (2020). *United Nations*. https://www.un.org/en/.

Urban, R. C., & Nakada, L. Y. K. (2021). GIS-based spatial modelling of COVID-19 death incidence in São Paulo, Brazil. *Environment and Urbanization, 33*(1), 229–238. https://doi.org/10.1177/0956247820963962

Varga, A. (1998). *University research and regional innovation: A spatial econometric analysis of academic technology transfers*. Springer Science & Business Media.

Vaz, E. (2021). Covid-19 in Toronto: A spatial exploratory analysis. In *Sustainability (Switzerland), 13* p. 498). https://doi.org/10.3390/su13020498

Wang, J. F., Christakos, G., Han, W. G., & Meng, B. (2008). Data-driven exploration of "spatial pattern-time process-driving forces" associations of SARS epidemic in Beijing, China. *Journal of Public Health, 30*(3), 234–244. https://doi.org/10.1093/pubmed/fdn023

Wang, Q., Dong, W., Yang, K., Ren, Z., Huang, D., Zhang, P., & Wang, J. (2021). Temporal and spatial analysis of COVID-19 transmission in China and its influencing factors. *International Journal of Infectious Diseases, 105*, 675–685. https://doi.org/10.1016/j.ijid.2021.03.014

WHO. (2021). *WHO Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data*. https://covid19.who.int/.

Xie, Z., Qin, Y., Li, Y., Shen, W., Zheng, Z., & Liu, S. (2020). Spatial and temporal differentiation of COVID-19 epidemic spread in mainland China and its influencing factors. *Science of The Total Environment, 744*, Article 140929. https://doi.org/10.1016/j.scitotenv.2020.140929

Xiong, Y., Wang, Y., Chen, F., & Zhu, M. (2020). Spatial Statistics and Influencing Factors of the COVID-19 Epidemic at Both Prefecture and County Levels in Hubei Province, China. *International Journal of Environmental Research and Public Health, 17*(11), 3903. https://doi.org/10.3390/ijerph17113903

You, H., Wu, X., & Guo, X. (2020). Distribution of COVID-19 Morbidity Rate in Association with Social and Economic Factors in Wuhan, China: Implications for Urban Development. *International Journal of Environmental Research and Public Health, 17*(10), 3417. https://doi.org/10.3390/ijerph17103417

Zhang, X., Rao, H., Wu, Y., Huang, Y., & Dai, H. (2020). Comparison of spatiotemporal characteristics of the COVID-19 and SARS outbreaks in mainland China. *BMC Infectious Diseases, 20*(805), 1–7. https://doi.org/10.1186/s12879-020-05537-y