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SPATIAL DIFFERENTIATION OF COVID-19 IN TURKEY

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Abstract

The sudy aims to focus on spatial transmission of Covid-19 in Turkey, to understand the channels through which it spreads by considering the regional socio-economic dimension. Within this scope, demographic, socioeconomic and healthcare factors associated with the spread of Covid-19 were analyzed in a provincial context. Spatial autocorrelation was used to examine parameters that spatially affect the number of cases. Spatial autocorrelation results reveal spatial differences in the spread of the pandemic. The findings highlight the importance of the space factor in reducing local contamination within the country. The results obtained will enable the discovery of risk factors for disease and will lead policy makers to make effective decisions. In this context, spatial-specific policy strategies will protect public health by reducing the spread of the virus.

Keywords: Covid-19, Turkey, Spatial Data Analysis.

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TÜRKİYE'DE COVID-19'UN MEKÂNSAL FARKLILIKLARI

Öz

Bu çalışma, Türkiye'de Covid-19'un bölgesel dağılımına odaklanmayı, sosyo-ekonomik boyutu da dikkate alarak Covid-19'un yayılımını anlamayı amaçlamaktadır. Bu kapsamda, Covid-19'un yayılmasıyla ilişkili demografik, sosyoekonomik ve sağlık faktörleri il bazında analiz edilmiştir. Vaka sayılarını mekânsal olarak etkileyen parametreleri incelemek için mekânsal otokorelasyon kullanılmıştır. Elde edilen sonuçlar, pandeminin yayılmasındaki mekânsal farklılıkları ortaya koymaktadır. Bulgular, ülke içindeki yerel yayılımı azaltmada mekân faktörünün önemini vurgulamaktadır. Elde edilen sonuçlar risk faktörlerinin keşfedilmesini sağlayarak politika yapıcıların etkin karar almalarına yol açacaktır. Bu bağlamda mekâna özgü uygulanacak politika stratejileri ile virüsün yayılımı azaltılarak kamu sağlığı korunacaktır.

Anahtar Kelimeler: Covid-19, Türkiye, Mekânsal Veri Analizi.

1. INTRODUCTION

With its high rate of contagion, the Covid-19 has affected thousands of people within a short period of time. The world was caught off guard against this pandemic, which killed many people around the world and seriously damaged the economies of all nations. Upon realizing the seriousness of the situation, nations took precautions but failed to prevent the spread of Covid-19. Despite all the measures taken such as travel restrictions, lockdowns and interruption of education, the main problem of our day continues to be the uncontrollable spread of the pandemic. According to official reports, the number of people who have died from Covid-19 worldwide has accounted more than 180 million cases have been diagnosed (WHO, 2021).

Covid-19 has emerged as an extremely serious threat for global health due to its high transmission risk and speedy spread worldwide (Lak et al., 2021). To prevent this spread, communication in public health and preventive precautions have been applied all over the world. Governments have limited the international mobility of people while most countries in the world closed their borders, the number of ships at anchor increased during the Covid-19 crisis, the temporary suspension of activities at various places was ordered, hotels, restaurants and tourist attractions were closed. The events stopped global communication and trade, causing a worldwide recession. For these reasons, Covid-19 has been expressed as a combination of health, economic, social and political crisis (Liang et al., 2021).

During the fight against the pandemic, evaluations made in the spatial context allow public administrators to act quickly and focus on the target. With the results obtained from spatial analysis, an effective health service can be provided for certain areas and the pandemic can be fought without the need for isolation or complete lockdown of the country. In this way, public resources can be quickly shifted to the areas most affected by the pandemic. Therefore,

measures to be taken at the local level to prevent the spread of the pandemic within national borders come to the fore in this context. In conclusion, determination of the spatial spread of the Covid-19 will enable the public administration to respond to the pandemic with more effective and faster decisions (Arauzo-Carod, 2021). Covid-19 has revealed the necessity of a complementary socio-economic perspective beyond clinical risk factors such as understanding the pandemic and taking the necessary precautions. As a matter of fact, it is possible to assess the spread of the virus between contiguous regions in this context (Ehlert, 2021). Therefore, geography plays a crucial role in the spread of the Covid-19 (Kapitsinis, 2020).

It is vital to figure out the geographical distribution of the pandemic and to use the scarce resources of the public to eliminate the negative effects of the virus and to control the pandemic. The identification of local clusters, where the virus spreads rapidly, separates these areas from other areas and leads to the concentration of public resources in these areas. In other words, spatial analysis techniques detect the spatial significance of risk factors of the disease influencing the Covid-19 transmission. Therefore, revealing the geographical connections of the Covid-19 is important for the public authority's success in combating the virus. It is also stated that the spread of the virus can be prevented through effective decision-making and rapid implementation of these decisions via the spatial information obtained (Arauzo-Carod, 2021; Sarkar et al., 2021).

As part of the precautions that can be taken to control the Covid-19, most research has focused on the relationship of Covid-19 with socio-economic factors. Population density (Baser, 2021; Bhadra et al., 2021; A. Das et al., 2021; Ganasegeran et al., 2021; Hafner, 2020; Han et al., 2021; Hou et al., 2021; Kadi & Khelfaoui, 2020; Kodera et al., 2020; Li et al., 2021; C. Liu et al., 2021; Rahmani et al., 2020; Sun et al., 2020; Sy et al., 2021; You et al., 2020), rate of aging population (Amdaoud et al., 2021; Bourdin et al., 2021; M. C. Ferreira, 2020; Hu et al., 2020; Mansour et al., 2021; Paez et al., 2020; Ramírez-Aldana et al., 2020; Raymundo et al., 2021; Sigler et al., 2021), GDP (Amdaoud et al., 2021; Bourdin et al., 2021; D. Ferreira et al., 2020; Martinho, 2021; Paez et al., 2020; Raymundo et al., 2021), literacy rate (Dutta et al., 2021; Ramírez-Aldana et al., 2020), number of physicians (Kang et al., 2020; Ramírez-Aldana et al., 2020) and hospital beds (Alcântara et al., 2020; Mansour et al., 2021) impact on the transmission of Covid-19. Also Ren et al. (2021) emphasized the importance of physical barriers in reducing the spread of this outbreak. Besides, Das and Zang (2021) underlined the relationship between technology, society and covid 19. Many researchers have expressed the importance of spatio-temporal transmission patterns that affect

the spread of the Covid-19 and assessed the spatio-temporal patterns of the novel coronavirus in different contexts. Many of these studies also focused on socio-economic indicators and the essential role of space in the Covid-19 transmission was emphasized and the importance of geographical proximity was underlined (Kapitsinis, 2020; Lak et al., 2021; Y. Liu et al., 2021).

Although there is a consensus that socio-economic factors have influenced the outbreak, studies on Covid-19 distribution vary greatly depending on the countries/regions studied (Alcântara et al., 2020; Bag et al., 2020; Cos et al., 2020; Ghosh & Cartone, 2020; Kapitsinis, 2020). In this study, the relations between socio-economic factors and Covid-19 in Turkey were examined with the help of spatial analysis. This way, the factors to be prioritized in avoiding the spread of Covid-19 can be determined.

2. DATA AND METHODS

Covid-19 case rate corresponds to the number of cases registered as Covid-19-related case per 100,000 population inhabitants for 24 weeks (between 8 February and 23 July 2021) by province. Sources of data include official Ministries of Health and Turkish Statistical Institute websites. The most recent population density and elderly dependency ratio datasets can be found for 2020 data, literacy rate and GDP per capita variables based on 2019 data, hospital beds per 100,000 and the number of physicians per thousand published 2018 data. Table 1 presents summary statistics for the variables used in this study.

Table 1. Description of Data

Variables	Mean	Min	Max	Std. dev.
Covid-19	131.7549	24.99	255.10	52.26877
Population density	132.8186	11.23	2975.84	332.52983
Elderly dependency ratio	16.5300	5.34	31.02	5.53216
GDP per capita	39595.5309	16727.00	86798.00	13645.46379
Literacy rate	94.9500	87.57	98.67	2.82000
Hospital beds per 100,000	276.1852	120.00	502.00	82.35018

Source: The authors' calculations.

Because the relationships studied between Covid-19 and various factors are "spatial" in nature, spatial analyzes were used. Spatial autocorrelation features of Covid-19 were investigated with the Moran scatterplot, Moran's I statistics (Anselin, 1995, 1996, 1999).

Spatial distributions associated with socioeconomic factors were examined with the Bivariate Moran's I. It indicates the association between the value of a variable at one location and the mean of neighboring values for another variable. Bivariate Moran's I can be of two types, Global and Local Bivariate Moran's I (BILISA- Bivariate Local Indicators of Spatial

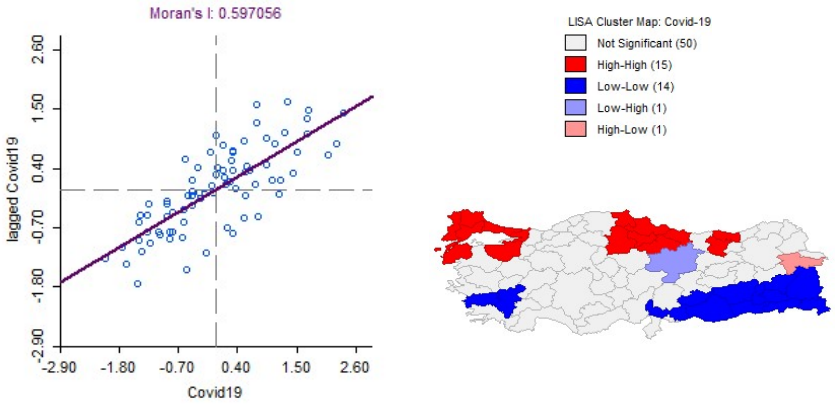
Association). Proposed by Anselin et al. (2002) BILISA was designed to examine the spatial autocorrelation between two geographical variables. BILISA can define positive autocorrelation (high-high HH and low-low LL); or negative spatial autocorrelation (spatial outliers) (high-low HL and low-high LH) (Anselin et al., 2002; Lee, 2001).

G test proposed by Getis and Ord (1992) and further detailed in Ord and Getis (1995) is another indicator of local spatial autocorrelation (Getis & Aldstadt, 2004; Getis & Ord, 2010). Anselin (2019) proposed a multivariate version of the statistics as the sum of the local G statistics for each variable studied. Multivariate Local Geary (MLG) statistic is the weighted average of the distance in the feature space between the observation and its geographic neighbors, summarizing the influence of neighbors in a single statistic (Anselin & Li, 2020).

3. RESULTS

Global spatial autocorrelation features of Covid-19 were investigated with the Moran scatterplot proposed by Anselin (1995, 1996) and local spatial features were examined with the LISA map. Accordingly, the Moran diagram and the LISA map, which show the relationship between Covid-19 in any province and Covid-19 in contiguous provinces and were created using the queen contiguity weight matrix, are given in Figure 1.

Figure 1. Spatial Distribution of Covid-19 in Turkey



Source: The authors' elobration.

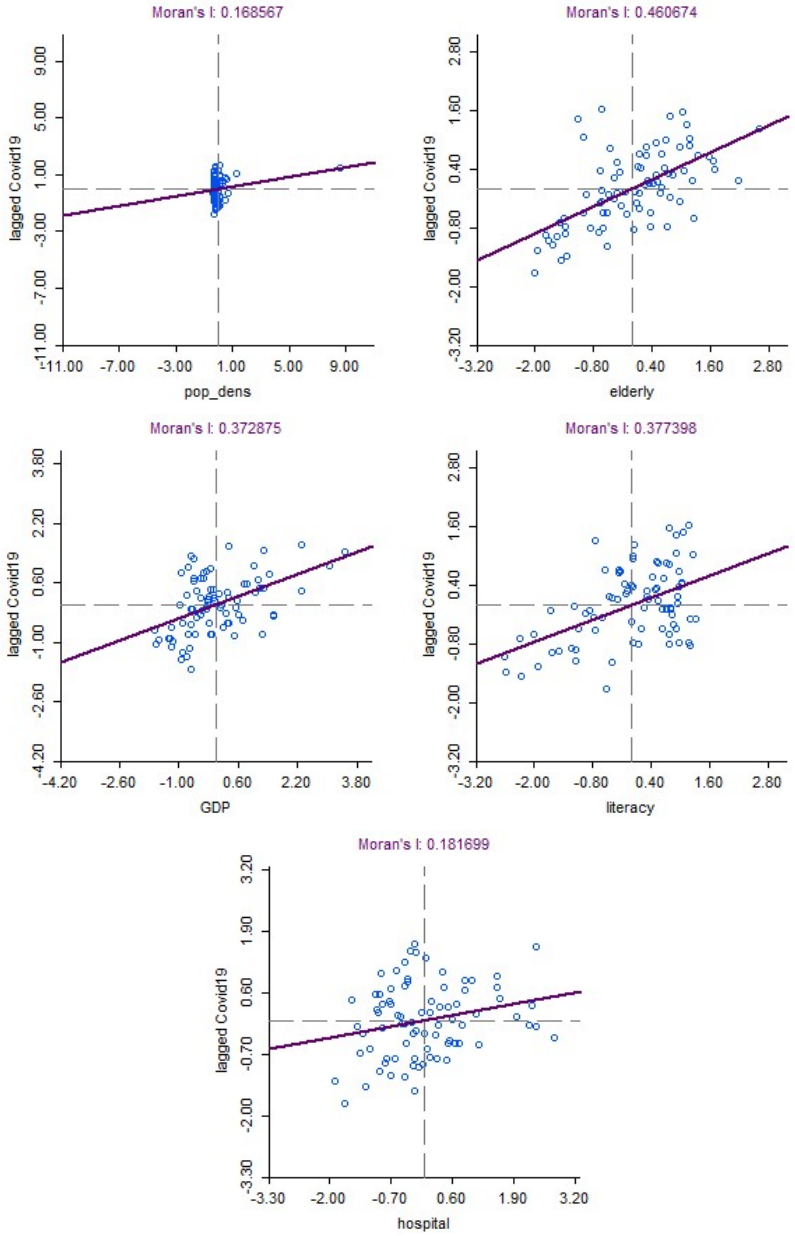
Spatial autocorrelation presents whether Covid-19 cases are related with neighbouring locations. Figure 1 demonstrates spatial autocorrelation in Covid-19 throughout country. Moran's I value (0.597056, p=0.05) calculated for Covid-19 shows the presence of positive autocorrelation, confirming the existence of spatial structure. LISA was used to indicate spatial clusters of Covid-19 in Turkey and reveals the pattern of clusters. HH (red) shows provinces with higher numbers of cases than average and are also surrounded by provinces

with higher numbers of cases. LL (blue) shows provinces with lower numbers than average and are also surrounded by provinces with lower numbers. HL (pink) shows provinces with higher numbers of cases but surrounded by provinces with lower numbers of cases. LH (purple) shows provinces with lower numbers of cases but surrounded by provinces with higher numbers of cases.

The association between the spatial lag of socio-economic variables and Covid-19 were examined with Bivariate Moran's I scatterplots (Anselin et al., 2010). When the Bivariate Moran's I p values given in Figure 2 are examined, at 95% confidence interval, the spatial patterns of Covid-19 are clustered and spatially correlated with the parameters of contiguous provinces.

According to the results of Bivariate Moran's I (Figure 2), there is a positive autocorrelation between the Covid-19 cases and population density. Provinces with higher numbers of Covid-19 and provinces with high population density are similar to areas with high-high and low-low Covid-19 spatial clusters. There is a significant positive spatial autocorrelation between elderly dependency ratio and Covid-19. The positive association between GDP and Covid-19, the positive association between literacy rate and Covid-19, the positive association between the number of hospital beds and Covid-19 cases are also confirmed. Both clusters are almost identical to the spatial cluster for cases. This shows that, in general, variables are spatially correlated with the Covid-19, expressing a direct relationship between them.

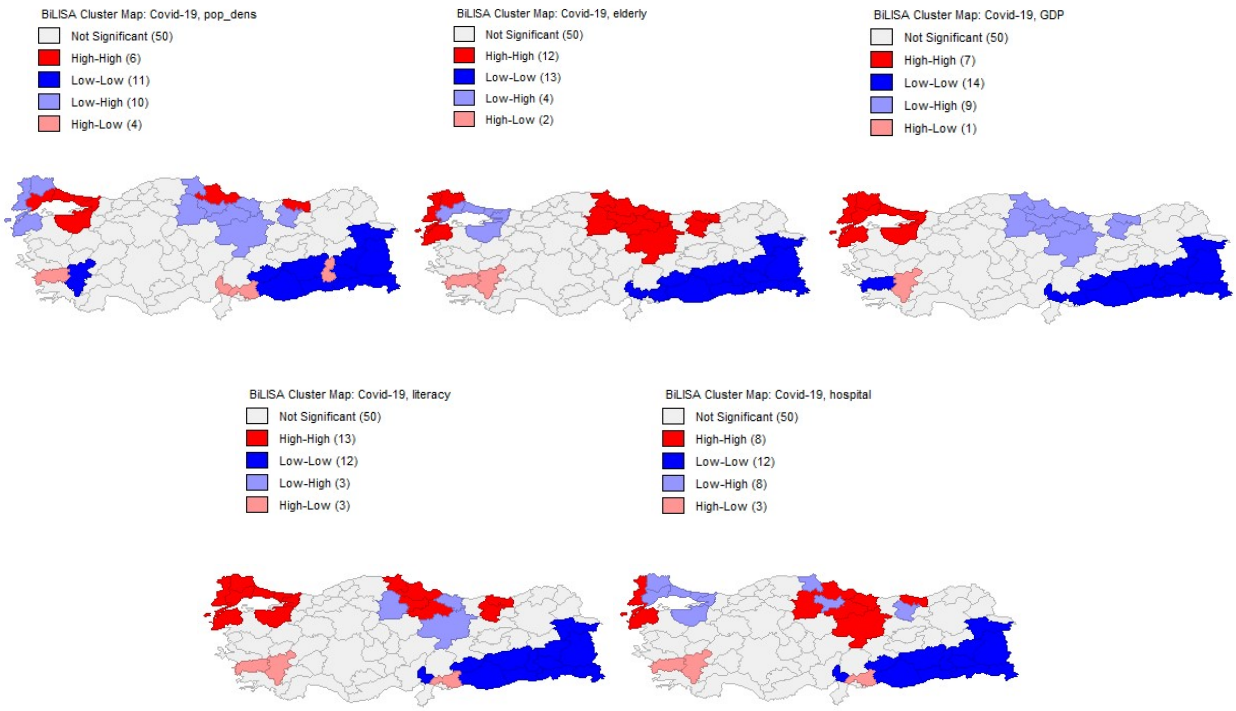
Figure 2. Bivariate Moran's I Scatterplots



Source: The authors' elobration.

According to BILISA maps, in the correlation between population density versus the number of cases, HH shows provinces with high numbers of Covid-19 and high population density (Figure 3). LL shows provinces with low numbers of Covid-19 and low population density. Provinces classified as HL and LH, respectively, show increase in cases and low population density, or low number of coronavirus cases and high population density.

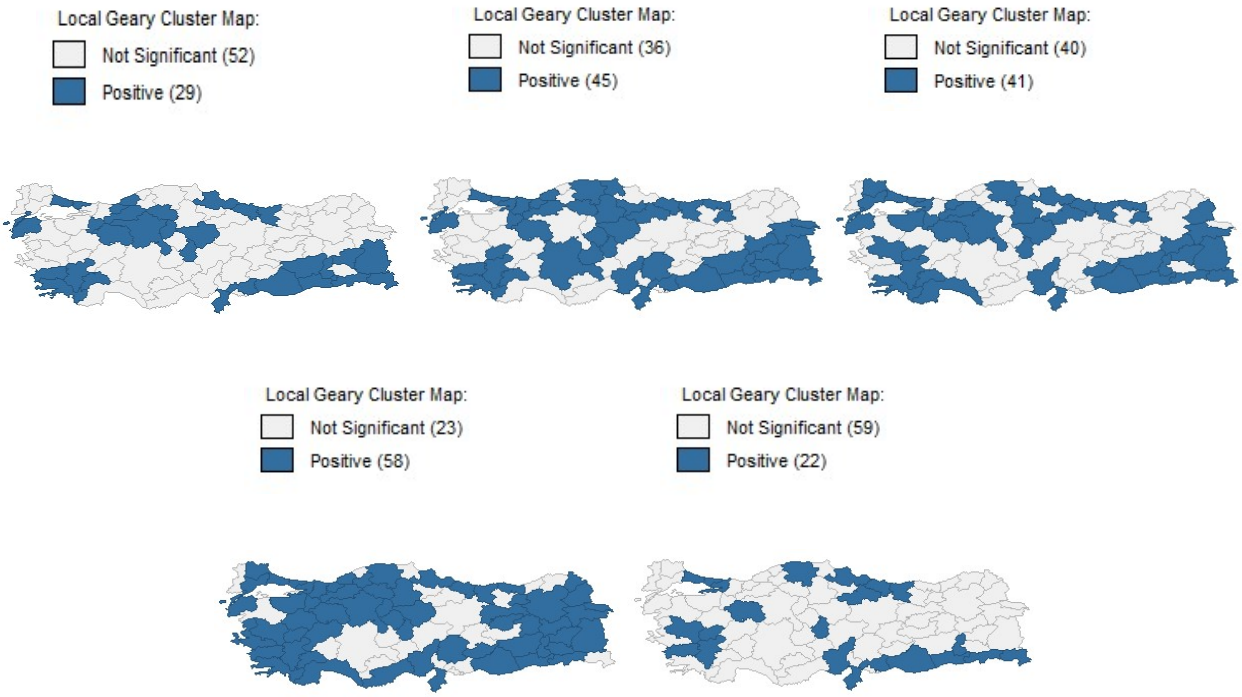
Figure 3 Clustering Tendency of According to BILISA Analysis of the Relationship between Covid-19 and Socioeconomic Variables



Source: The authors' elobration.

Figure 4 demonstrates the clusters obtained from the MLG analysis. According to this, 29 provinces show positive association (smaller distances in one location and values in contiguous locations) between Covid-19 and population density. There are positive associations between Covid-19 and elderly dependency ratio in 45 provinces, between Covid-19 and GDP in 41 provinces, between Covid-19 and literacy rate in 58 provinces, between Covid-19 and hospital beds (100,000 people) in 22 provinces.

Figure 4. Clustering Tendency of According to MLG Analysis of the Relationship between Covid-19 and Socioeconomic Variables



Source: The authors' elobration.

4. DISCUSSION AND CONCLUSIONS

Regarding the measures to be taken, it is very important to look at the developments in Turkey, which ranks sixth in the worldwide in the number of Covid-19 cases, and to determine the course of the pandemic and the risk factors affecting Covid-19 transmission. Because the need to understand the Covid-19 pandemic and to take the necessary precautions went beyond taking medical measures at this point. The necessity of a socio-economic perspective that will affect the virus transmission has been acknowledged, and the public health policies have been expanded in this direction. As a matter of fact, it is possible to evaluate the factors such as population, age and neighborhood-contiguity as effective in the transmission of infectious disease.

Several studies in the literature produced similar results regarding the socio-economic variables associated with Covid-19. The results of the research showed that a positive correlation exists betwen population density and Covid-19 cases. As a matter of fact, provinces with high population density stand out as the provinces that have been most affected by the pandemic. It has become clear how important social distancing measures are.

At this point, the strict measures taken are very effective in decreasing the Covid-19 cases. Dutta et al. (2021) examined the factors triggering the transmission of Covid-19 at the district level in India, and found positive autocorrelation between population density and Covid-19 cases (Moran's I= 0.13, p= 0.002). Arauzo-Carod (2021) underlined that the highest number of positive cases are seen in Barcelona, where the Catalan population is the most dense, and that this is important in terms of showing the number of positive cases-metropolitan cities. Mansour et al. (2021) showed that population density is a statistically significant determinant of the incidence of Covid-19 cases. Human activity is an important process in the transmission of Covid-19. Population density (Chen et al., 2021; Han et al., 2021) as a prevealing indicator that influences of human activity intensity, is a crucial element to explain the rate of transmission of the pandemic (Xie et al., 2020). Since Covid-19 spreads mainly between people, it is expected that the most densely populated areas have recorded high number of Covid-19 cases (Kang et al., 2020; Kim & Castro, 2020).

In many studies, it is possible to observe distinctive effects of the elderly population on Covid-19 (Arauzo-Carod, 2021; Paez et al., 2020; Sarkar et al., 2021; You et al., 2020). Ramírez-Aldana et al. (2020) underlined that the elderly population attributed to the rise in Covid-19. Similarly, Mansour et al. (2021) indicated that the number of older people is one of the significant determinants of Covid-19.

Looking at the scientific researches examing the relation between coronovirus cases and GDP, for example, Raymundo et al. (2021) found that the higher the income level at the local level, the higher the impact of the Covid-19. Again, studies have emphasized the importance of literacy in reducing the cases. Ramírez-Aldana et al. (2020) underlined that literacy is one of the factors that reduce the number of cases. Khavarian-Garmsir et al. (2021) revealed that areas with well educated people showed a higher risk from Covid-19 infection in the early phases of the Covid-19 pandemic, but that this association became negligible over time.

Less educated workers are less likely to have a lower share of remote work occupations and therefore cannot maintain physical distance like those with higher level of educational attainment. Therefore, the risk of contracting Covid-19 may increase for this vulnerable group with lower levels of educational attainment (Finch & Hernández Finch, 2020). It is no surprise that lower educated groups are benefit from public transport, not everyone can work from home, they are not fully aware of infectiousness of the virus, and are also unconscious of taking measures such as social distancing to mitigate the health crisis (A. Das et al., 2021). Studies have also demonstrated that the number of hospital beds has significant effects in

Covid-19 (Mansour et al., 2021). Saffary et al. (2020) found a real but weak spatial dependence between the number of beds in intensive care unit and the number of cases.

The impacts of socio-economic factors on the virus, which have been revealed in studies on the spatial analysis of Covid-19 outbreaks in various countries, can also be observed in the relations between socio-economic factors and Covid-19 in Turkey. Therefore, in this paper, the relationship of socio-economic factors with Covid-19 was examined by spatial analysis techniques. Thus, the aim of the analysis is to reveal the spreading the spreading mechanisms of Covid-19. To this end, the links between regional factors and case density are analyzed and the necessary strategies to contain the pandemic are discussed with an emphasis on the central role of geography.

As Bag et al. (2020) points out, "space-specific" policy strategies are crucial in reducing the spread of the Covid-19. It can be stated that the transmission of the pandemic will be controlled as a result of the measures to be taken for the provinces with a high daily case numbers at the spatial level, and thus the cost to be incurred will be reduced by applying restrictions to the whole country. Therefore, the findings will assist policy makers by facilitating the right decisions in a way that will protect public health against the virus. This will enable a more effective and efficient fight against the pandemic, preventing the transmision of the Covid-19. The results obtained will lead to the discovery of potential hot spots and risk factors, thereby enabling public administrators to take effective decisions in combating the pandemic (Lak et al., 2021).

The high number of daily Covid-19 cases in Turkey has caused the country to rank among the countries most affected by the pandemic. At this point, the analyzes and the results about Turkey are important. Information obtained at the spatial level will lead to effective results in the fight against the pandemic. Furthermore, the strategies to be used as a result of the findings at the spatial level will set an example for other countries in the fight against the pandemic. In this context, this study reveals the spatial relationships of socio-economic factors related to Covid-19 in Turkey. The geographical distribution and the transmission of the virus in Turkey were investigated by using the scatterplots showed a spatial distribution of Covid-19. The bivariate local indicator of spatial association was used to measure the spatial concentrations of covariates between Covid-19 cases and various explanatory variables. The spatiality of how the values of socio-economic factors are surrounded by the values of Covid-19 were shown through Bivariate Moran's I, while the meaningful clusters were determined via Multivariate Local Geary. The results regarding the spatial distribution charactersitics of

Covid-19 show a clear pattern of clustering across provinces. Clusters of provinces with similar high infection levels and vice versa clusters of provinces with low density have been determined. The relevant results show that the Covid-19 values present similarities in terms of location.

On the other hand, despite ongoing various active prevention strategies, Covid-19 continues to spread. Therefore, more studies on the factors influencing the transmission of the pandemic are needed. Spatial analyses of the Covid-19 pandemic reveal the relationship between Covid-19 cases and the factors affecting them at the spatial level. There are some limitations of this study, which is carried out with this motivation and examines the factors affecting Covid-19 in Turkey by considering the spatial dimension. One of these limitations is related to the number of explanatory variables; while many variables could be used, only 5 variables were employed. Since only the number of cases by province is accessible, the evaluation of mortality rates, vaccination rates, etc. has not been completed. However, Covid-19 mortality rates after vaccination and vaccinated population comparisons can be made. At this point, the results to be obtained will be useful both in demonstrating the importance of vaccination and in deciding on the regional restriction policies. In addition, although the measures taken against the pandemic and its results have influenced people's happiness, observations related to this were not evaluated in this study. Finally, it is important to take into account the psychological factors of the Covid-19 process. These factors can be taken into account in future studies.

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