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Spatio-temporal analysis of the COVID-19 pandemic in Türkiye: results of the controlled normalization

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Abstract This study investigates the spatio-temporal structure of the pandemic in Türkiye during the normalization process. An analysis has been conducted based on spatial and space–time scan statistics of the province-based numbers of confirmed COVID-19 cases during the normalization process from February 27 to May 7, 2021. The clusters affected by regional application differences has determined. The increase in cases has been observed, and the risk classes that supported the spatial relationship have been determined. Positive spatial relationships have been observed. Moran I measurements have also directly overlapped with the developments in the timeline of the COVID-19 pandemic in Türkiye. Local Moran I analysis has shown the transition of clusters from different regions to others over time. According to the results, controlled normalization has not happened as expected and the increase in the number of cases eventually led to the start of a total lockdown. Spatial and spatio-temporal analysis may show how to respond to a potential new pandemic. Regulations that vary from region to region can be meaningless depending on the spatial interaction. Decision makers may benefit in the future from these analyses, which reveal the results of experience to control current worsening scenarios.

Keywords Spatio-temporal analysis · COVID-19 · Türkiye · Space–time scan statistics · Geographic information system

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1 Introduction

Coronavirus disease (COVID-19) outbreak in December 2019 and has been up-to-date since the day it emerged. After that, the World Health Organization (WHO) announced that it is a global pandemic [1, 2]. Since that date, studies have been addressing different aspects in relation to the COVID-19 pandemic and its effect. Time and space are two fundamental dimensions for the study of the pandemic and its effects. A contagious disease spreads over time and is transmitted by interaction. At this point, analysis in the context of time and space is necessary to understand a disease declared as a pandemic. Indeed, the pandemic has been discussed in studies from different perspectives. For details see [3–5]. The possible factors affecting COVID-19 spread, severity, and mortality and the effect of social distancing on these factors are investigated by [3]. Economic, social, regional, and statistical impacts are discussed in the report of the Committee for the Coordination of Statistical Activities [4]. A methodology is presented by [5] that uses COVID-19 pandemic data in order to measure the risk of disease spreading outside of China in terms of globalization and international aviation connectivity.

There are fewer studies dealing with the COVID-19 outbreak in terms of spatio-temporal patterns relative to other patterns. However, in the case of a pandemic, determining the spatio-temporal pattern is one of the critical points. In this context, some studies have been carried out for the top 3 most populous countries—China, India, and the United States. For instance, studies [6–11] have addressed the COVID-19 pandemic with the spatio-temporal pattern for the most populated countries. Spatio-temporal distribution characteristics of COVID-19 for city-level modeling and spatio-temporal characteristics and control strategies in the early period of COVID-19 spread are investigated respectively by [6, 7]. Spatio-temporal analysis of COVID-19 and multiple change point estimations of trends in COVID-19 infections and deaths are addressed by [8, 9] for India, respectively. Spatio-temporal characteristics of the COVID-19 pandemic and spatio-temporal effects on COVID-19 incidences are investigated by [10, 11] for the United States. Moreover, spatio-temporal analysis has been performed for Brazil [12], Italy [13], England [14], and South Korea [15, 16]. In addition, prospective space–time scan statistics and spatio-temporal event sequence has been compared for COVID-19 surveillance by [17] and the prospective space–time scan statistics have been investigated for COVID-19 surveillance by [18].

Many countries have taken various measures to prevent the spread of the virus. To give a few examples of the measures taken in Türkiye: obligatory mask usage in public and indoors, social distancing, and hygiene applications are at the forefront. In addition, the identification of personal codes and the monitoring of the risk situation were carried out with the *Life Fits Home* app in Türkiye, as in the *Immuni* app in Italy. Extra precautions have been taken in closed areas such as public transportation vehicles, schools, markets, etc. (for further details see Study of Scientific Advisory Board [19]). Moreover, as in other European countries, Türkiye has adopted partial curfews such as weekend curfews and midnight curfews in certain periods.

A controlled normalization process was carried out in Türkiye as of March 1, 2021, due to the relatively low rate of weekly province-based cases. In addition, during the normalization process, different risk schemes were determined for all provinces of Türkiye according to the number of weekly cases. According to the aforementioned risk scheme, different measures were planned for each province in a different risk class. These risk classes were composed of 4 groups very high risk, high risk, medium risk, and low risk class. Each risk class, which is shown with a colour and thematic risk map, has been announced weekly on the official website of the Republic of Türkiye Ministry of Health regarding COVID-19 [20]. Moreover, the R shiny application for reporting and comparison of the risk classes and the number of cases in Türkiye spatio-temporally with interactive graphs and automated reports has been designed [20].

In this study, the spatial and spatio-temporal patterns of the COVID-19 pandemic in Türkiye are investigated. Most of the studies related to exploring spatial and spatio-temporal clusters of COVID-19 cases include a larger study period in literature [12, 15, 21]. These studies were also conducted during the time of adopting rigid emergency measures. Our study only focuses on a controlled normalization process in which a loosening of the strict measures was adopted and a transition policy of application of these measures from a national perspective to a regional perspective was made. Another issue is in most of the studies, it was tried to determine the factors along with spatial and spatio- temporal characteristics of COVID-19 cases in countries conducted. However, detecting the quick progress and changes in the pandemic, the clusters (spatial associations locally) either spatially or spatio-temporal wise must be explored periodically in shorter time periods first to take emergency measures regionally just in time. In this way, these analyses could bring solutions and contribute to decision-makers in national health sectors. Our study differs from the literature in two aspects which are the inclusion of a relatively short time domain and examination of a controlled normalization process.

The rest of the paper is organized as follows. Section 2 includes the modelling techniques and statistical properties of spatial and spatio-temporal analysis methods for data of province-based counts of COVID-19 cases confirmed in Türkiye. In Sect. 4, all results and a discussion along with some recommendations are shared and in Sect. 5, a detailed conclusion of the study are given to reveal how the spatio-temporal statistical indicators clarify COVID-19 cases.

2 Methodology

2.1 Data source

The first known coronavirus case in Türkiye was announced by the Republic of Türkiye Ministry of Health on 11 March 2020. At the end of March 2021, Türkiye was exposed to a severe outbreak of COVID-19. The increase of the cases in March 2021 can be evaluated as the main reason for applying the total lockdown in April 2021 in Türkiye. Türkiye did not issue a legal total lockdown order until April 2021, when it enforced the first nationwide restrictions. This situation can be evaluated as a late period compared to Europe. Therefore, county-based counts of COVID-19 cases confirmed in Türkiye from 27 February to 7 May 2021 are used in this study. In this way, the data included the controlled normalization period, which started on March 1, 2021, and caused a serious increase in the number of cases, and the lockdown period, which started on April 2021, is taken into account in the study.

The 10-week basis data county-based counts of COVID-19 cases confirmed in Türkiye from 27 February to 7 May 2021 are used in the analyses. Data are taken from the official site of the Republic of Türkiye Ministry of Health website (https://covid19.saglik.gov.tr/). In this way, the effect of the controlled normalization process on the spread of the virus and the progression of the pandemic are examined spatially and spatio-temporally in this study. The spatial association of the COVID-19 pandemic in Türkiye between 8 February and 28 May 2021 is investigated by [22]. The exploratory and confirmatory spatial data analysis is employed in [22], however, in addition to Spatial Statistics Methods, Prospective Space–Time Scan Statistics Methods analysis is used in this study. Therefore, the geographical relationship of the number of COVID-19 cases has been revealed.

2.2 Analytical strategies: spatial and spatio-temporal methods

The well-known measure is Moran's I to explore the spatial autocorrelation, Moran's I identify global spatial clustering. Moran's I statistic can be written as follows:

$$I = \frac{n}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{1}$$

$$I_i = n \times \frac{x_i \sum_{j=1}^{n} w_{ij}(x_j - \overline{x})}{\sum_{j=1}^{n}(x_j - \overline{x})^2} \tag{2}$$

where I and I_i are global and local spatial autocorrelation measures. x_i and x_j are the values of the variable of at regions i and j, n represents the number of regions. w_{ij} is a measure of connectivity between region i and region j. In this study we have used rook matrix.

The interpretation of the Moran's I value can be summarized as follows [23]:

$$\begin{aligned} &I < 0 \quad \textit{negative spatial autocorrelation} \\ &I = 0 \quad \textit{No spatial autocorrelation} \\ &I > 0 \quad \textit{positive spatial autocorrelation} \end{aligned} \tag{3}$$

In addition [24], has stated that large positive I_i values represent the local clustering of data around the i-th location. On the other hand, large negative I_i values represent that the sign of data value at the i-th location is the opposite to those of its neighbours. It has been stated by [25–27] that the local Moran's I is used to the identification of local indicators of spatial association (LISA). Local measures of spatial association are studied by [28]. The local measure of spatial autocorrelation has identified the presence of deviations from global patterns of spatial association and regions such as local clusters or local outliers [29, 30].

Geographically-based COVID-19 case counts have been examined in this study to determine the characteristics of regions with high COVID-19 burden and spread, in terms of clustering. Spatial and Space–Time Scan Statistics introduced by [31, 32] are utilized to present the characteristics of counties with a high burden of COVID-19 in this study. Moreover, the Poisson prospective space–time scan statistics are utilized in this study. Space–time scan statistics have been implemented in SaTScan [33–35].

The spatio-temporal clustering of confirmed COVID-19 cases in Türkiye from 27 February to 7 May 2021 is analysed. Spatial and Space–Time Scan Statistics identify the most probable clusters of the event of interest using a space–time permutation statistical model. It uses a predefined circular window with various dimensions and time periods to scan the workspace. For statistical inference, the Monte Carlo simulation approach of generating 999 random datasets is used to calculate statistics. In this study, we defined the parameters of the scan window as follows: 400 km maximum geographic radius and weekly period as minimum temporal scan unit. The population at risk is set to 50% of the population and the maximum temporal cluster size is set to 50% of the whole domain as we have got a short time period whereas the minimum temporal cluster size is set to two specific time units. The time units are weeks in our case. We chose the Poisson model because the population is the key element in the spread of the disease which is person to person within mostly considered as 1–15 day infectious time. To define the dynamics of geographic hotspots of newly confirmed COVID-19 cases, Geographic clustering has been specified in each of 10 time periods. The most likely high-risk clusters/ hotspots were captured based on the Monte Carlo rank with $p < 0.05$ [11]. As stated before, considering the population and the duration of infection, the Poisson model was used in this study. The likelihood function and test statistics are as follows:

$$L(Z) = \begin{cases} \frac{e^{-n_G}}{n_G!}\left(\frac{n_Z}{\mu(Z)}\right)^{n_Z}\left(\frac{n_G-n_Z}{\mu(G)-\mu(Z)}\right)^{n_G-n_Z}\prod_{x_i}\mu(x_i) & \textit{if}\ \frac{n_Z}{\mu(Z)} > \frac{n_G-n_Z}{\mu(G)-\mu(Z)} \\ \frac{e^{-n_G}}{n_G!}\left(\frac{n_G}{\mu(G)}\right)^{n_G}\prod_{x_i}\mu(x_i) & \textit{otherwise} \end{cases} \tag{4}$$

where n_G represents number of points. N and $N(A)$ denote a spatial point process and the random number of points in the set $A \subset G$, respectively. A collection $\mathcal{Z}$ of zones $Z \subset G$. It should be emphasized that Z denote both a subset of G and a set of parameters defining the zone [36]. The test statistics λ of the likelihood ratio test can be shown as:

$$\lambda = \frac{sup_{\mathcal{Z}\in Z}L(Z)}{\frac{e^{-n_G}}{n_G!}\left(\frac{n_G}{\mu(G)}\right)^{n_G}\prod_{x_i}\mu(x_i)} = \begin{cases} sup_{\mathcal{Z}\in Z}\frac{\left(\frac{n_Z}{\mu(Z)}\right)^{n_Z}\left(\frac{n_G-n_Z}{\mu(G)-\mu(Z)}\right)^{n_G-n_Z}}{\left(\frac{n_G}{\mu(G)}\right)^{n_G}} I\left(\frac{n_Z}{\mu(Z)} > \frac{n_G-n_Z}{\mu(G)-\mu(Z)}\right) & \textit{if}\ \frac{n_Z}{\mu(Z)} > \frac{n_G-n_Z}{\mu(G)-\mu(Z)} \\ 1 & \textit{otherwise} \end{cases} \tag{5}$$

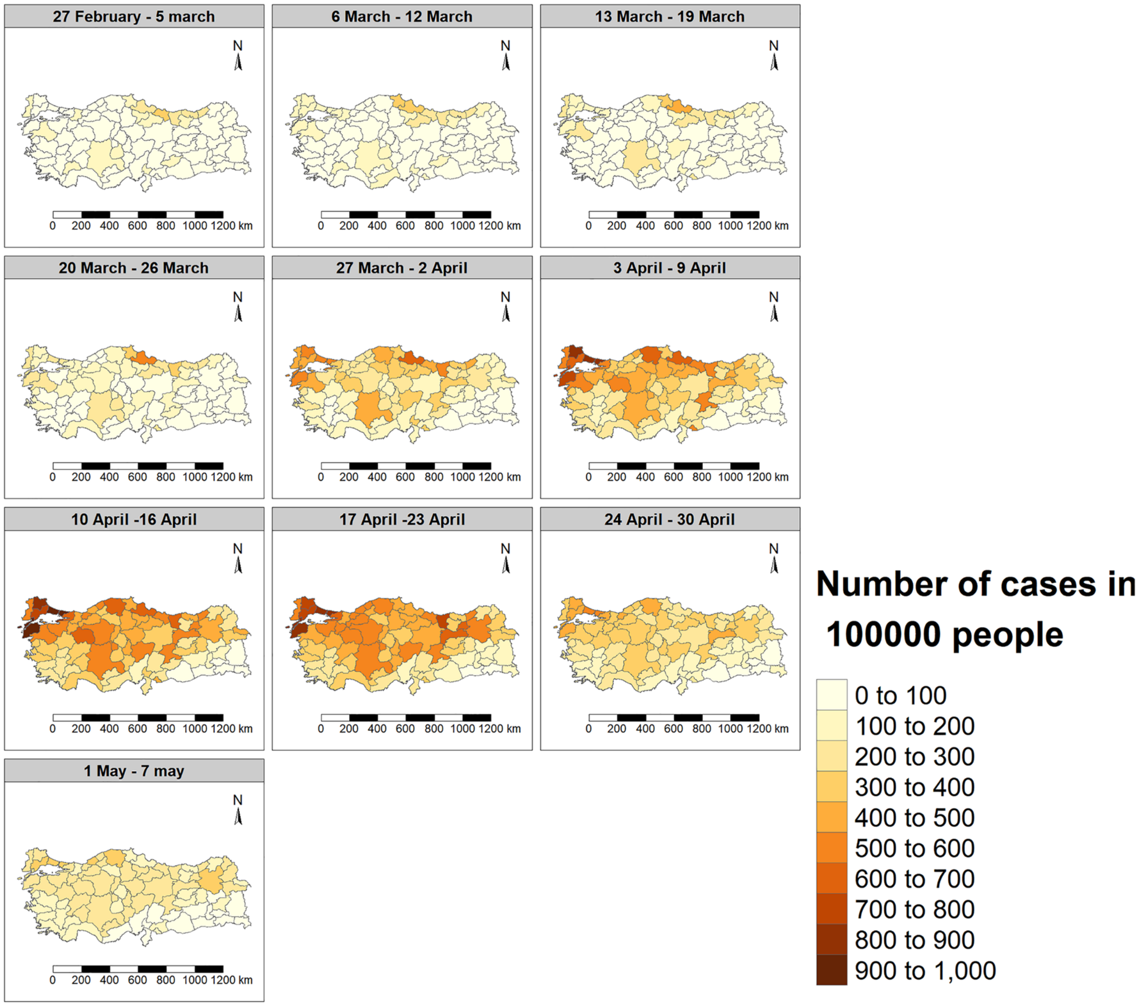

Fig. 1 Equal interval map of Türkiye through using weekly confirmed cases

$I(.)$ represents the indicator function [36].

3 Results

3.1 Exploratory spatial analysis and analyses of spatial autocorrelation

Cases and risk classes are shared in Figs. 1 and 2, respectively. The COVID-19 pandemic in Türkiye statistics through using weekly confirmed cases has been taken into account. The thematic maps were created by using *tmap* package in R. *tmap* is an open-source R-library for drawing thematic maps [37]. A remarkable rise in the number of cases was observed in Fig. 1 especially starting from the 5th week of the study period corresponds to 27 March–2 April. Furthermore, most provinces turned into a high-risk status that is coloured red in the risk classes map in Fig. 2. A distinctive property is that from starting time of the study period the black sea region was high in a number of cases and most of the provinces in this region were classified into high-risk classes when compared to other cities.

As another spatial analysis, Moran's I measurements and maps are presented in Fig. 3 and Fig. 4. Spatial analysis is performed in GeoDA software [38]. Global Moran I values in all weeks showed a high positive spatial autocorrelation that 0.649. This is a sign of spatial clustering throughout the study period. The degree of the spatial autocorrelation might be considered as a medium because of the ranging global Moran I values between 0.405 and 0.659.

Generally, Local Moran I maps indicated that most of the cities showed high–high or low–low clustering types. There are a few outliers showing the low–high and high–low local spatial autocorrelation during the whole time domain of the study. In the first week of the study period, 6 cities are in the high–high cluster class indicating higher values. These cities

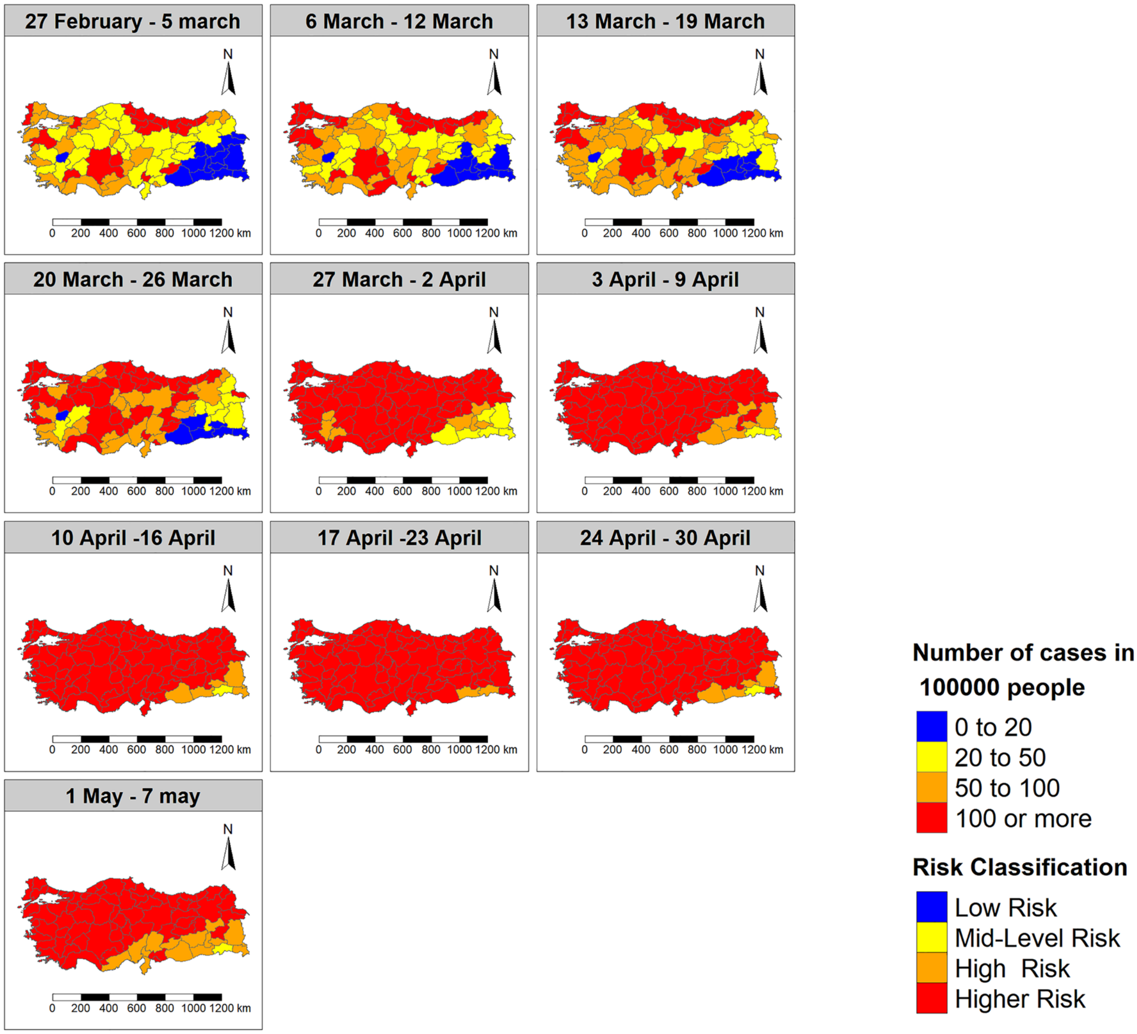

Fig. 2 Risk classes of Türkiye through using weekly confirmed cases

are Giresun, Gümüşhane, Tokat, Trabzon, Samsun and Ordu. In the low-low cluster, there are 13 cities including mostly east Anatolian and south-east Anatolian region cities like Ağrı, Batman, Diyarbakır, Mardin, Van and etc. The diverging city in this cluster is Kırıkkale which is a city located in the central Anatolia region. Adıyaman and Bayburt, Sivas are identified as outliers respectively since they are placed in the high–low and low–high cluster classes.

In the last week of the study period, there are 14 cities in the high–high cluster class, 14 cities in the low–low cluster class, and only a city is included in the low high cluster class. Artvin is a city that is in the low–high cluster class. On the other hand, high–high and low–low clusters consist of divergent cities of different two or more geographical regions. For instance, Bartın, Eskişehir, and İstanbul are classified in high-high local cluster classes which are respectively located in the Black Sea, Central Anatolia, and in Marmara Region. Adıyaman, Batman, Bitlis Adana, Diyarbakır, Gaziantep, Hakkari, Hatay, Mardin, Şanlıurfa, Siirt, Van, Osmaniye and Şırnak are the 14 cities which are cluster in the low–low cluster in the last week of the study period.

In Fig. 5, the evolution of global Moran I values over the study period is given as a time series graphic. At first, a horizontal trend has been observed and followed by an increasing trend with a peak in the 8th week. Afterward, a decrease in the global spatial autocorrelation trend has been started.

In Fig. 6, a partial autocorrelation function graph of the global Moran I value is given. Only the first lag is statistically significant and the meaning of spatial autocorrelation is valid. Thus, the first-degree neighbours are statistically significant.

3.2 Spatio-temporal Scan Statistic Results

Through the space–time Poisson scan statistic, significant clusters have been detected. The cluster table and map of

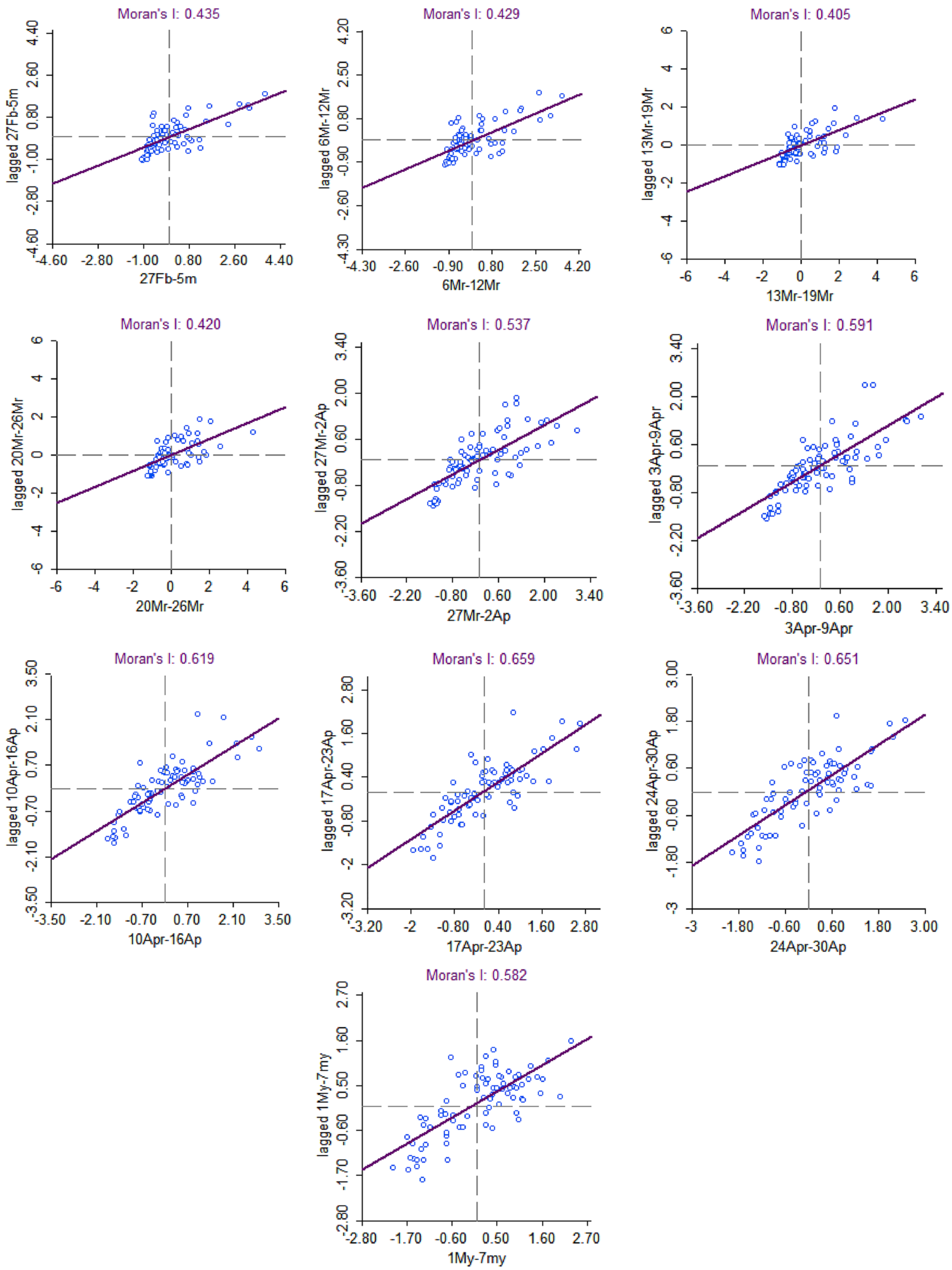

Fig. 3 Global Moran's I measurements for Türkiye using weekly confirmed cases

the obtained results are presented in Table 1 and Fig. 7, respectively. Figure 7 is created in an open GIS platform [39]. There are 9 clusters that were identified as statistically significant after using the Poisson model perspective type space–time scan statistics analysis. Whole clusters overlapped in time which was between the 6th and 10th week. On the other hand, there were no overlapped clusters in space. There are cluster areas that were created by more

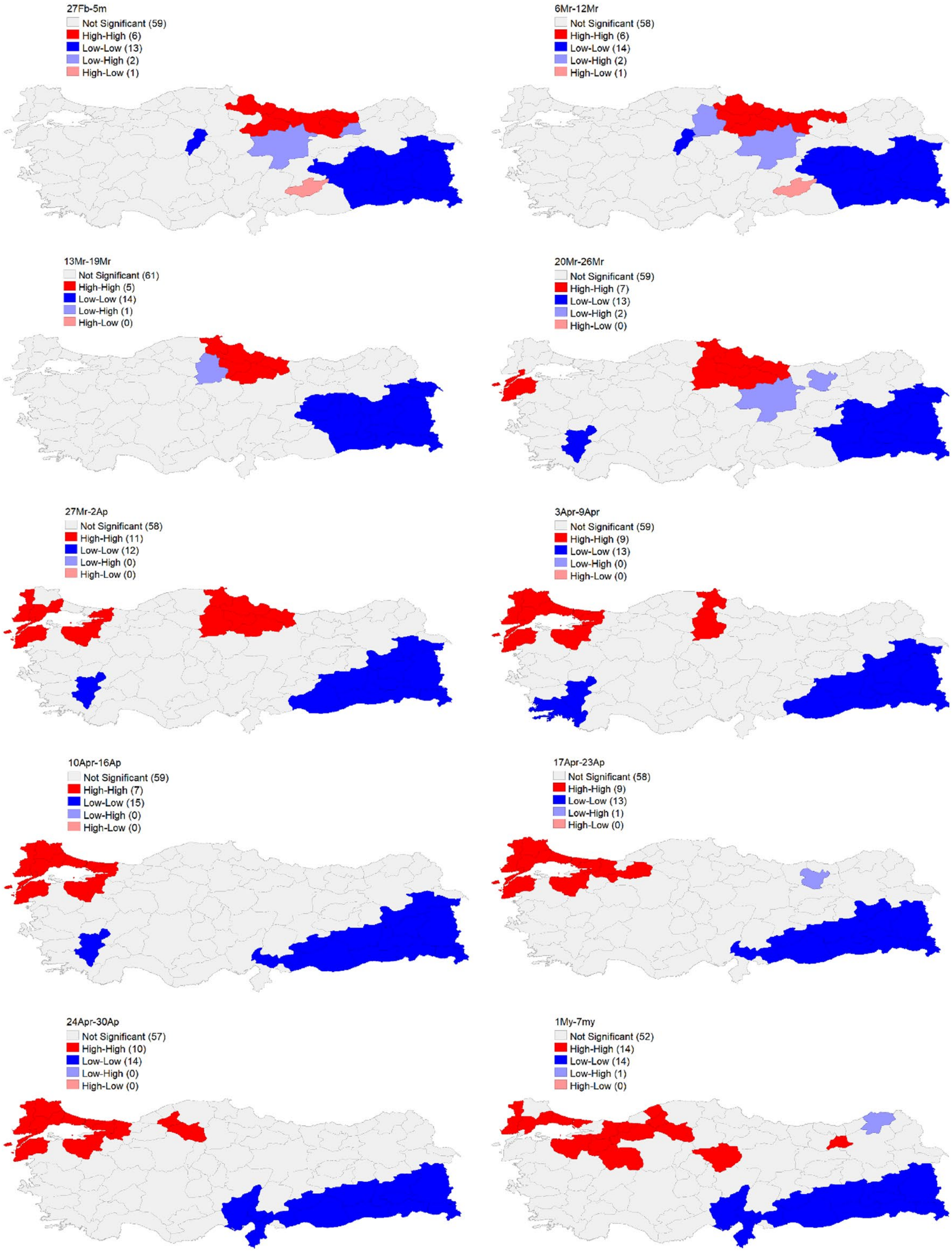

Fig. 4 LISA cluster maps for Türkiye using weekly confirmed cases

than two cities together. Hence, they are represented as circular cluster areas in Fig. 7. Indeed, there are 3 clusters that were formed only by a city itself which is represented by only a dot on the map. All the relative risk values are higher than one. In addition, clusters that consist of only themselves as a city have got the highest relative risk while the cluster areas formed by cities together except for the space–time cluster which was formed by Hakkari city. No

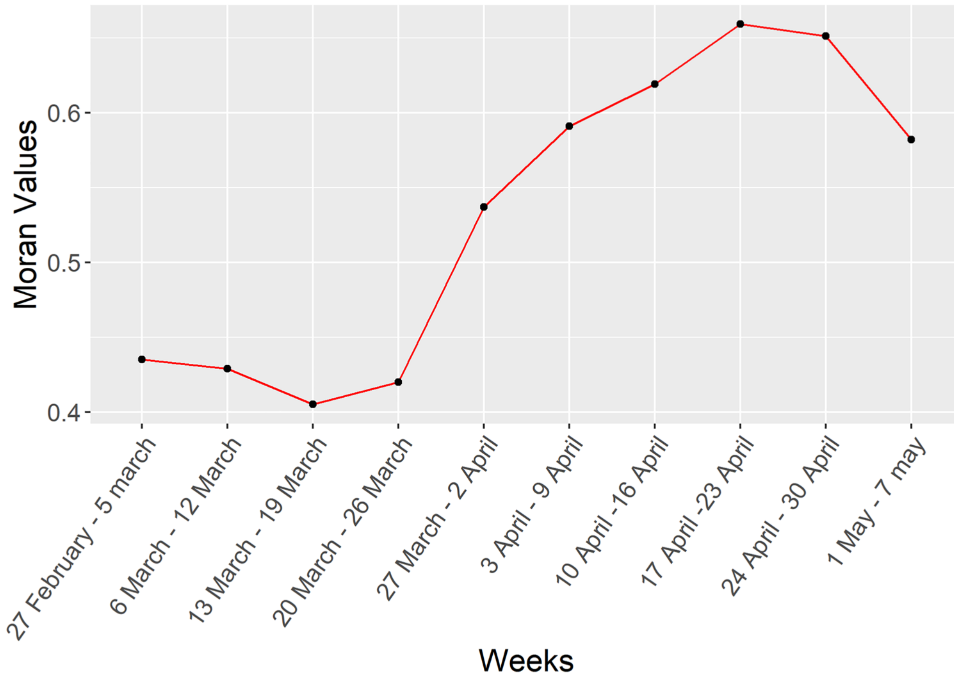

Fig. 5 Global Moran's I measurements over study period

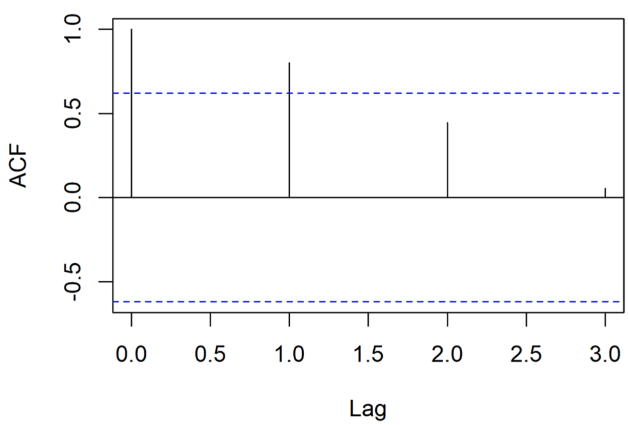

Fig. 6 PACF Graph of Local Moran's I measurements

adjacent clusters were observed. The highest observed cases were in cluster 8 which includes 15 cities from different regions like the Black Sea Region and East-Anatolian Region. In addition, cluster 8 has got the biggest area and highest number of cities. Then, cluster 8 was followed by cluster 4 and cluster 3 both in the area wise and in the number of cities they have respectively.

4 Discussion

This study aims to reveal the spatial and spatio-temporal patterns of the COVID-19 cases at the city level in Türkiye. Our fundamental goal is to identify the clusters spatially and

Table 1 Spatio-temporal clustering results

Clusters	Cities	Observed cases	Expected cases	Relative risk
Cluster 1 (C1)	Edirne, Tekirdağ, Kırklareli, Çanakkale	2473	968.35	2.58
Cluster 2 (C2)	Yalova	543	117.58	4.63
Cluster 3 (C3)	Afyon, Isparta, Uşak, Eskişehir, Kütahya, Burdur, Denizli, Bilecik	3745	1933.31	1.96
Cluster 4 (C4)	Kastamonu, Çankırı, Karabük, Bartın, Sinop, Çorum, Zonguldak, Kırıkkale, Amasya, Bolu	5916	1610.34	3.77
Cluster 5 (C5)	Aksaray, Nevşehir, Niğde, Kırşehir	1885	525.12	3.62
Cluster 6 (C6)	Karaman	474	108.58	4.37
Cluster 7 (C7)	Kilis	590	118.71	4.98
Cluster 8 (C8)	Artvin, Ardahan, Rize, Erzurum, Kars, Bayburt, Trabzon, Ağrı, Gümüşhane, Iğdır, Muş, Bingöl, Erzincan, Giresun, Bitlis, Tunceli	7462	2230.22	3.45
Cluster 9 (C9)	Hakkari	212	119.48	1.77

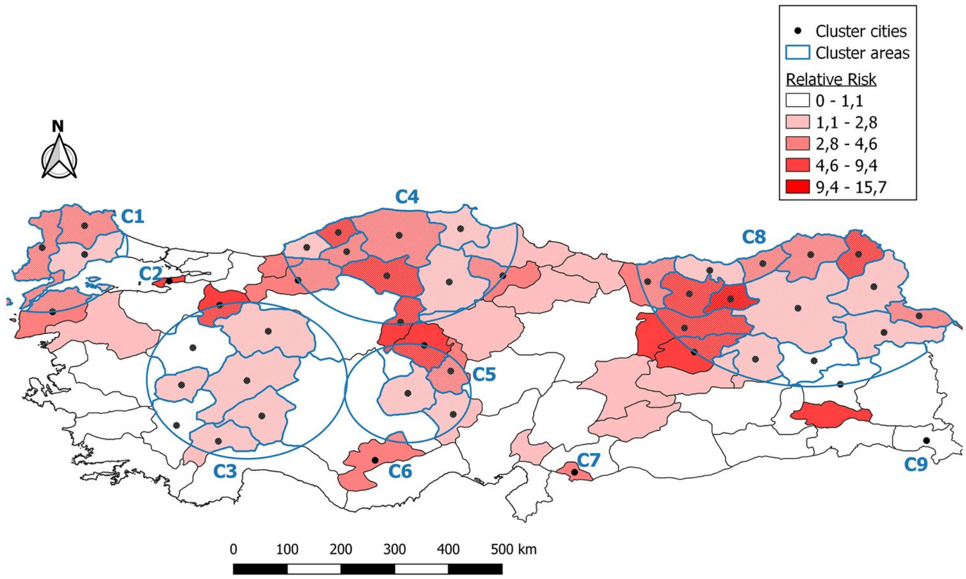

Fig. 7 Clusters* on the Türkiye map. *C1: Edirne, Kırklareli, Çanakkale, Tekirdağ, C2: Yalova, C3: Bilecik, Eskişehir, Afyonkarahisar, Uşak, Isparta, Burdur, Kütahya, Denizli C4: Kırıkkale, Çankırı, Bartın, Karabük, Bolu, Kastamonu, Amasya, Sinop, Çorum, Zonguldak, C5: Kırşehir, Nevşehir, Niğde, Aksaray, C6: Karaman, C7: Kilis, C8: Tunceli, Erzincan, Gümüşhane, Bayburt, Ardahan, Iğdır, Giresun, Rize, Artvin, Trabzon, Bingöl, Erzurum, Ağrı, Kars, Muş, Bitlis, C9: Hakkari

spatio- temporally and determine the effect of the controlled normalization process on the progress of the pandemic. To the best of our knowledge, this is the first-ever study that examined spatio-temporal patterns by using scan statistics in Türkiye. Furthermore, the focus of the study is its time domain which includes a controlled normalization process. In addition, the time period which involves a short interval was selected in order to find out the efficacy of the controlled normalization process. The space–time scan statistics analysis and Moran I measurements have been shared. The space–time scan statistics analysis has determined clusters affected by regional application differences. The increase in cases caused by the controlled normalization process has been observed, and the risk classes that supported the spatial relationship have been determined. Positive spatial relationships have been observed. Moran I measurements have also directly overlapped with the developments in the timeline of the COVID-19 pandemic in Türkiye. Local Moran I analysis has shown the transition of clusters from different regions to others over time. Consequently, controlled normalization has not happened as expected and the increase in the number of cases eventually led to the start of a total lockdown.

However, there are several limitations of the study. The situation beforehand concerning provincial-based cases is not known because datasets were started to be announced at the beginning of our study domain. The time domain is special and a relatively short one but includes the controlled normalization process. We used common simple spatial statistics to explain the situation in Türkiye. We only wanted to explain the COVID-19 situation related to the spatiotemporal effect at the time of the controlled normalization process and therefore we do not have any implication of the factors that were effective in the forming of the regional clusters and spatial association. It should be noted that the high number of undetected or asymptomatic COVID-19 cases limits the dynamics of the approach used and the modelling performed.

The normalization process that is less common in COVID-19 literature is examined in this study. The findings representing and revealing the effort of the study are as follows: According to the global Moran I values, we can infer that there is a spatial pattern across the whole country. The values remained stable at the beginning, however, the cases increased in the following periods and decreased again with the lockdown. Local spatial autocorrelation analysis enables the finding of outliers and local correlations across the country. Low-low and high-high clusters were dominant in whole weeks with a few outliers however local correlation characteristics changed over time spatially which had been stable over a few weeks at the start of the time period. Low-low clusters and high-high clusters both moved through the West and inner parts of the country. High-high clusters have been moved from the Black Sea Region to Marmara and Central Anatolia regions. This situation can be easily seen in Fig. 4. A prospective space–time scan statistics analysis was performed and then 9 space–time clusters were formed. Some of the clusters were consistent with local spatial autocorrelation maps. For instance, cluster 1 and cluster 4 are some of them. Population plays a key role here and causes forming of different clusters from local spatial autocorrelation analysis which only takes cases into account. The biggest cluster was Cluster 8 in the area wise and the property of having the highest number of cities. Clusters mostly consisted of the cities of one geographical region of Türkiye except clusters 3,4 and 8. A dramatic increase across the country during the study period was observed due to the activation of intercity mobility and the relaxation of quarantine measures. No strict fines were applied in this period and people mostly exploited the market shopping times which was defined as an exception. As far as we consider the controlled normalization process did not maintain as expected and resulted in a total lockdown from 29th April 2021 to the 17th of May 2021 nation-wise. This can be seen as an example representing the transition from a city-based policy to a national policy in the event of a pandemic. We had to use the weekly data because the COVID-19 cases were announced weekly by the Republic of Türkiye Ministry of Health. Therefore, this study may differ from other studies as dealing of the time perspective related to different countries' COVID-19 studies which data have consisted of the daily number of cases spatially. Strict measures were taken in South Korea to prevent the spread of coronavirus with the utilization of contact tracings (real-time) such as CCTV footage and credit card transaction history [15]. In fact, this situation reveals the importance of the applicability and traceability of the measures rather than their strictness. In addition, although the measures are adapted to different countries and the general personal characteristics of the people of the country, the measures should not detract from their main purpose and most importantly, the measures should be traceable.

The relationship between socioeconomic variables and COVID-19 cases at the city level with a spatial regression model was examined [22]. This study gave more importance to spatio-temporal clustering of the COVID-19 cases using a space–time scan statistic together with the examination of the effects normalization process mentioned. The weekly data is aggregated into monthly data in [22]. Therefore, our study also showed more detail as we stuck to the original weekly announced data. We can emphasize that the progression of the local and global Moran I measurements carries more information.

With the controlled normalization process, the increase in the number of cases has been observed spatially, risk classes have been determined. It has been observed that the results were consistent. Moran I measurements also directly overlap with the developments in the timeline of the COVID-19 pandemic in Türkiye and provide important information for the *spatial* analysis of the pandemic. Moreover, the first-degree neighbours is statistically significant. Clusters were determined with the *space–time scan statistics* analysis. It has been observed that regional application differences are effective in clusters. The dates of the developments in the timeline of the COVID-19 pandemic in Türkiye and spatio-temporal analysis overlap. Controlled normalization did not occur as expected, and the increase in the number of cases led to the onset of total lockdown. It has been observed that national measures instead of regional measures significantly reduce the rate of spread in certain periods. As a result, city-level policies may not produce the expected results, and at this point, policy changes that are binding at the national level may be carried out despite the economic consequences.

The COVID-19 pandemic, whose spatio-temporally effects were discussed for Türkiye in this study, affected humanity at different points. The Sustainable Development Goals (SDGs) accepted as the *roadmap for humanity* has been affected by the COVID-19 pandemic. We can say that 3 of the 17 SDGs, GOAL 3: Good Health and Well-being, GOAL 8: Decent Work and Economic Growth, and, GOAL 11: Sustainable Cities and Communities, are directly affected by the COVID-19 pandemic. The United Nations Development Programme (UNDP) draws attention to the *2030 Agenda* and the SDGs in the shadow of the COVID-19 pandemic. UNDP offers that the COVID-19 pandemic has much more to do with the SDGs.[1] It has been discussed how the coronavirus pandemic may influence the SDGs and their implementations [40]. The spatial view of the COVID-19 pandemic in Türkiye, especially in the controlled normalization process, has caused significant problems in terms of sustainability, as in many countries. Spatial consideration of the pandemic, which affects the SDGs and hinders sustainability, especially health and economy in countries, may affect decision makers. Thus, the problem can be converted to an easily solvable local problem, instead of a hardly solvable national-based problem.

5 Conclusion

The spatio-temporal analysis is an approach that raises the question of how countries will respond to a possible new pandemic. In other words, the spatio-temporal analysis offers the opportunity to analysis the current situation and take precautions for a new possible pandemic.

In this study, spatio-temporal analyses have been done for Türkiye. During the controlled normalization process, an increase in cases has been observed, and also risk classes have been changed. Thus, the effects of the controlled normalization process were directly observed. The relationship between the timeline of the COVID-19 pandemic in Türkiye and the spatial analysis of the pandemic is remarkable and the spatial effects of the decisions to be made in this context are clearly visible. Moreover, the space–time scan statistics analysis shows that regional application differences are effective in clusters. Controlled normalization and regional obligations can accelerate the increase in the number of cases. As a result, although national measures are seen as stricter obligations, they can have better results for public health.

In this context, decision-makers could benefit from the results of our study. Some recommendations based on our findings to slow down the spread of the pandemics can be

1 https://feature.undp.org/covid-19-and-the-sdgs/.

proposed. We believe that the examination of a controlled normalization process contributes to the literature itself even though uses mostly employed spatial and spatio-temporal methods. Finding and detecting clusters spatially and spatio-temporally beforehand would make a great difference in dealing with pandemics along with the detection of the events that might trigger local increases in cases. Also, we think that following the transmission of the disease personally with filiation and good quarantine measures and policies would play a key role in managing the pandemics. The city-level policies may not produce the expected results, and at this point, policy changes that are binding at the national level may be carried out despite the economic consequences. The intercity travel limitations can be applied according to our local Moran I results that limitations could be adopted between high-high, low–high, and high-low cities. In addition, the common factors that contribute to the increase may be investigated after the obtaining of the spatial and spatio-temporal clusters and different measures may be put forward according to the region's common properties. A periodical spatial and spatio-temporal analysis method in our study could be conducted on a regular basis to find out the progress of the pandemic. A web-based application could be designed for these purposes.

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Declarations

Conflict of 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.

Consent for publication All the authors of the paper give their consent to publish the material presented in the paper.

Ethical approval Ethical approval was not required for this work. Data gathered from the official website of the Republic of Türkiye Ministry of Health regarding COVID-19 is public use data.

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