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Spatiotemporal Analysis of Cardiovascular Disease Mortality with Geographical Information Systems

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Abstract

In the world, cardiovascular diseases (CVD) are known as the type of disease with the highest mortality. The mortality rate for this disease is very high in Turkey. Therefore, studies on this disease may direct the activities to be carried out by public health workers/policy makers and effective surveillance studies. In this context, GIS-based spatial analysis offers critical tools to reveal the spatial epidemiology of the disease by modeling the spatial distribution of cardiovascular disease over time and to investigate the risk factors.

In this study, it was aimed to analyze CVD mortality spatiotemporally with GIS-based methodologies and to reveal preliminary information on whether deaths from CVD are related to geographic location and environmental risk factors. Accordingly, CVD mortality that occurred in Turkey at province level between 2009 and 2018 was analyzed through spatial statistical tests (Global Moran's I, Getis-Ord General G, Anselin Local Morans I and Getis-Ord Gi*) and Geographical Information Systems (GIS). The results of spatiotemporal analysis were evaluated. Mortality caused by CVD was examined spatiotemporally with the help of the developed user interface program and spatially significant clusters of CVD were determined. Based on our findings, this study can contribute to understand the spatial nature of the disease and to provide the decision makers with required information on surveillance studies.

Keywords Cardiovascular disease · GIS · Cluster analysis · Spatial statistics · Spatiotemporal analysis

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Introduction

Various statistical data from different sources is published at certain time intervals in developed countries. According to the data from the World Health Organization (WHO), cardiovascular diseases (CVD) constitute approximately one third of total deaths in the world (WHO, 2018). CVD, which is one of the leading causes of death in Turkey, make up two-fifths of the total deaths in recent years (TurkStat, 2018). Knowing/measuring the spatial domains and spatial distribution of these diseases, which have a high prevalence in the world, is extremely important in combating this disease (Lim et al., 2014; Mena et al., 2018; Zhang et al., 2011).

Spatial epidemiology has focused on the use of spatial analysis and statistical methodologies underlying diseases (Elliott et al., 2001; Kirby et al., 2017). In the models examined in spatial epidemiology, Geographical Information Systems (GIS) offers critical tools in reaching important patterns in terms of the relationship between the place of the disease and its occurrence and in measuring the potential risk factor and the degree of the disease. GIS contribute as a decision support mechanism for public health workers in epidemiological studies that reveal the geographical distribution of diseases, environmental risk factors, spatiotemporal spread rate and frequency of occurrence (Waller & Gotway, 2004; Cromley & McLafferty, 2011; Türk, 2013; Caprarelli & Fletcher, 2014; Ince & Turk, 2019).

Calculation and standardization of mortality in diseases play an important role in obtaining reliable spatial and statistical results. With this information, the effect of the disease on the public health can be determined, the spatial pattern of the disease can be mapped and the spatiotemporal clusters of the disease can be investigated (James et al., 2004; McLaughlin & Boscoe, 2007; Ruiz et al., 2004). Thus, spatial dependence analysis can be performed in regions where cluster distribution is observed in order to determine the correct resource allocation, early diagnosis and risk factors for public health with geographical epidemiological studies (Waller & Gotway, 2004). Although the mortality of the diseases depend on the hereditary characteristics, it is not the only determinant to be considered. Disease mortality may differ between countries, and this difference may be inherited or acquired (later) in noncommunicable diseases (Ruzicka & Lopez, 1990). In spatial epidemiology, revealing of spatial dependence with risk factors in the investigation of acquisition effects constitutes one of the key factors in combating the disease. At this point, studies that examine the relationship of disease events with environmental risk factors through spatial clustering tests and regression analyzes and reveal the relationship with a possible risk factor such as air pollution can be given as examples (Leiva et al., 2013; Mortimer et al., 2012).

Studies that investigate disease data with spatial and temporal statistical tools are available in the literature. In the study conducted to evaluate the spatial models of cardiorespiratory diseases with statistical approaches such as spatial autocorrelation, cluster degree, semivariogram and k-function in all age groups in Brazil, it was determined that disease distribution was different between age groups and various solutions were proposed (Requia & Roig, 2015). Ischemic heart disease (IHD) was analyzed using Global Moran's I, Local Moran I (LISA) cluster analysis and Bivariate Moran's I spatial autocorrelation methods in Brazil, and it was observed that IHD clusters were positively correlated with aging, unconsciousness and urban development (De Andrade et al., 2013). Mortality due to respiratory system diseases were analyzed with spatial statistical methods in the GIS environment in Turkey (Yalçın & Kaya, 2019). As a result of this study, clusters with high significance level in the Western and Central Black Sea regions of the country and low significance levels in Eastern and Southeastern Anatolia regions were determined.

Spatial clusters of CVD have been revealed by similar studies from different parts of the world. Spatial clusters related to heart disease, cerebrovascular diseases and hypertension mortality were tested with spatial scan statistics in Tehran (Iran) (Gohari et al., 2015). Gender differences have been observed in spatial clusters defined by the Moran Index (Moran I) and Local Spatial Autocorrelation Index (LISA) in Madrid (Spain) (Gomez-Barroso et al., 2015). A study to determine the relationship between social deprivation and CVD mortality was performed using the Global Moran's I and the Geographically Weighted Regression (GWR) methods in USA (Ford & Highfield, 2016). The correlation between PM10 concentrations and cardiovascular mortality in Seoul (South Korea) was investigated by Geographic Weighted Regression (GWR) and a statistically significant relationship was found (Lim et al., 2014). On the other hand, spatial clusters of CVD cases in Iran overlapping with the industrial zone were examined by Hotspot analysis (Namayande et al., 2016). In Beijing (China), positive clusters were detected as a result of spatiotemporal analysis between 2013 and 2017 using Global Moran I and LISA cluster tests in CVD cases (Amsalu et al., 2019). In studies that use GIS-based analysis in the healthcare field, it is emphasized that it is beneficial to understand the impact of environmental factors on CVD, and CVD has a direct relationship with the socioeconomic level, population, urban structure, and education (Mena et al., 2018).

In this study, cluster analysis of areas with high CVD mortality was performed in the provinces (provincial borders) in Turkey between 2009 and 2018. GIS-based user interface, which includes Global Moran's I, Getis-Ord General G, Anselin Local Morans I and Getis-Ord Gi* spatial statistical analysis, has been developed in ArcGIS 10.4 software environment in order to automatically and easily detect the areas where mortality caused by CVD is clustered. The statistical findings obtained were discussed and the areas where mortality caused by CVD clustered were interpreted.

Study area

This study was performed in Turkey (Fig. 1). Turkey is composed of 81 provinces. It is a country with a population of 83,154,097 (as of January 1, 2020) and a surface area of 783,562 km^2 (TurkStat, 2018). The country is divided into seven geographical regions: Mediterranean, Eastern Anatolia, Aegean, Southeastern Anatolia, Central Anatolia, Black Sea and Marmara regions. It is located between the temperate zone and the subtropical climate zone with its climatic characteristics varying according to the regions (David, 2017; Çağlar, 2019).

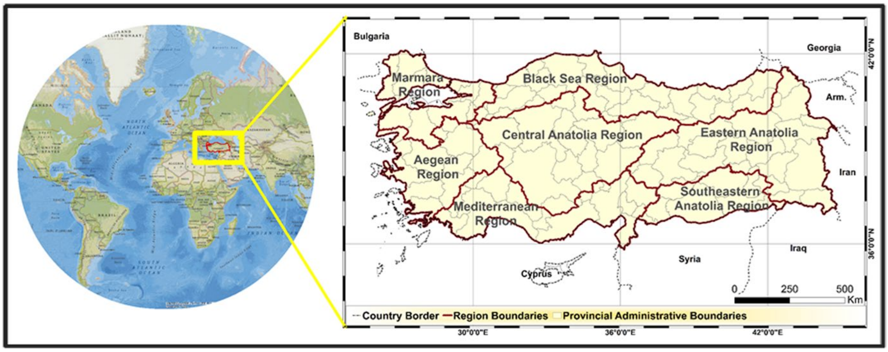

Fig. 1 Study area

Material and Methods

In this study, province-based CVD mortality data, population data and geographical data showing province borders were used. CVD mortality data consists of the number of deaths caused by the annual CVD published by the Turkish Statistical Institute (TurkStat) in 81 provinces between 2009 and 2018. Population data (entire population within the provincial borders) includes 10-year provincial population numbers belonging to 81 provinces obtained from TurkStat from 2009 to 2018. Geographical data (provincial administrative boundaries of Turkey) consist of polygon geometry type that include 81 provincial borders (Fig. 1). They were associated with the CVD mortality data obtained by provinces between 2009 and 2018 in the geographical database. In TurkStat data, the diseases included in this group (CVD) consist of ischemic heart disease (IHD), cerebro vascular disease, other heart disease, hypertensive diseases, and other diseases.

Geographical data including 81 provinces associated with CVD mortality data were taken into account for use in spatial analysis. For the selection of "distance band or threshold distance" with the Feature class obtained, "Ripleys K function" analysis has been applied to the attributes of each year. By evaluating the common clustering distance range, the "threshold value" was decided and spatial analyzes were performed (Fig. 2).

The crude death rate indicates the number of deaths in the total population and, for the sake of manageability, is usually calculated per 1,000. It is calculated as follows (Open, 2016):

$$\begin{array}{c}\text{The annucal } \textit{crude} \\ \textit{deathrate}\text{per} \\ 1{,}000\text{population}\end{array} = \frac{\text{Total number of deaths in a calendar year}}{\text{Estimated mid} - \text{year population that year}} x1{,}100$$

CVD mortality table data has been obtained according to provinces and years, considering the above equation. In this study, the workflow specified in Fig. 2 was followed.

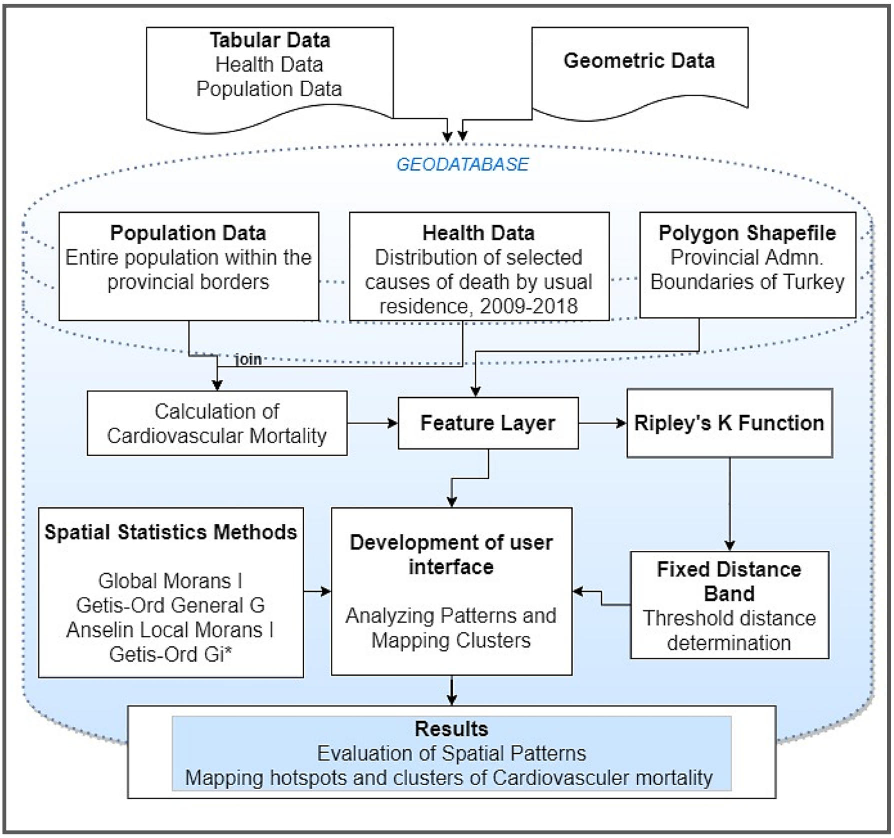

Fig. 2 Workflow followed in the study

It is extremely important to use the spatial pattern concept as a base for evaluating spatial relationships between variables (Kurland & Gorr, 2007). Analysis and evaluation of clustered areas is a guide for monitoring the spatial pattern of CVD mortality and its change over time. For this reason, GIS-based spatial cluster analysis was performed in the study. While Global Moran's I and Getis-Ord General G global statistics were used for clusters, scatter and randomness analysis of the general spatial distribution of the disease, Anselin Local Moran's I local statistical test was used to determine in which geographical location the clusters were distributed. On the other hand, Getis-Ord G* local statistic test was used to determine the confidence level of the clusters.

Global Moran I: Global Moran I was used as the first measure of spatial autocorrelation. Moran's I ranges from -1 to + 1, representing positive / negative spatial autocorrelation. If the Z score (Fig. 4) is less than -1.96 or more than 1.96 in the analysis of spatial autocorrelation, then the pattern is dispersed or clustered ($p < 0.05$). If the Z score is between -1.96 and 1.96, then the pattern is randomized (Fu et al., 2014; Mitchell, 2005). The spatial autocorrelation method provides information about the pattern of the spatial distribution of CVD mortality (clustering, random and scattered). The Global Morans I equation used in the test is given below (Eqs. 1 and 2).

In the first equation; where; n is the number of features representing 81 provinces; Z_i, is the deviation of the number of deaths for polygons that represent each of the 81 provinces; in the second equation S_o, is the aggregate of all the spatial weights. $W_{i,j}$ is the spatial weight between i and j, n equals the number of features.

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \tag{1}$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j} \tag{2}$$

Getis-Ord General G (GOGG): The null hypothesis at GOGG states that no spatial clustering is on the feature values. It is rejected depending on whether the cluster is high or low. If the Z score (Fig. 4) is more than 1.96 and the index value observed with this method is higher than expected, it indicates that the higher values are clustered in the study area. If the Z score (Fig. 4) is less than -1.96 and the observed value of GOGG is lower than expected, low values are clustered in the study area ($p < 0.05$) (Affan et al., 2016; Getis & Ord, 1992; Mitchell, 2005). This method overall is calculated by the Eq. 3.

$$G(d) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j}(d) X_i X_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j}, \quad \forall j \neq i \tag{3}$$

where; X_i and X_j are attribute values for features i and j; and $W_{i,j}$ *(d)* is the spatial weight between feature i and j (Eq. 4); n represents 81 provinces belonging to the polygon feature class. Equation 5 expresses the expected value of G (d).

$$W = \sum_{i=1} \sum_{j=1} W_{i,j}(d), \ \forall j \neq i \tag{4}$$

$$\mathrm{E}[G(d)] = W/[n(n-1)] \tag{5}$$

While global tests give results for clustering in the study area, they do not provide information about where the clusters are located. Therefore, in the study, Spatial statistics tests of Anselin Local Morans I, which test heterogeneity, and Getis-Ord Gi *, which analyze hot and cold spots, were used (Anselin, 1995; Getis & Ord, 1992).

Anselin Local Morans I: This method aims to measure the strength of the pattern for each feature. By testing heterogeneity in the work area, it determines local clusters and outliers (Eq. 6). Statistically significant outliers can be surrounded by a high or low value P values should be small enough for the cluster or outlier to be considered statistically significant ($p < 0.05$) (Affan et al., 2016; Anselin, 1995).

$$\mathrm{I}_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j=1, j \neq 1}^{n} \left[w_{ij} \left(z_j - \bar{z} \right) \right] \tag{6}$$

Here; Z_i, the value of the variable in location i; $\bar{z}$; the average mortality rate in 81 provinces; Z_j the value of variable z in all other positions $(j \neq i)$; σ^2; variance of variable z; w_{ij} is the spatial weight between feature i and j.

The positive value in this method shows that a feature has neighboring features with the same attribute values either high or low (Affan et al., 2016; Anselin, 1995). Clusters of value involve the high value (High-High) and lower value (Low-Low). In addition, wi,j can be determined using a distance band or threshold distance. While the same weight is given to the field within a distance band, those outside the distance band are given 0 weight value (Zhang et al., 2008).

Getis-Ord Gi *: This method is a local test form of the Getis-Ord General G method (Eq. 7). It measures the value of high or low clusters with a degree of confidence (Ord & Getis, 1995; Mitchell, 2005; Affan vd., 2016).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{x} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \tag{7}$$

Here; $w_{i,j}$ is spatial weight matrix between polygons i and j; x_j is mortality value in location j; n specifies the number of features representing 81 provinces.

Multi-Distance Spatial Cluster Analysis (Ripley's K-function): In many feature pattern analysis studies, the selection of an appropriate scale of analysis is required. For example, a **distance band** or **threshold distance** is often needed for the analysis (Mitchell, 2005). How the CVD mortality cluster changes at different distances (analysis scale) was examined in this study. In this method, for statistically significant spatial clustering to occur, the observed K must be greater than the expected K and again the observed K must be greater than the high confidence envelope (Bendib, 2020). The K-function is given in Eq. 8.

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1, j \neq 1}^{n} k_{i,j}}{\pi n(n-1)}} \tag{8}$$

where d is the distance of threshold, n is equal to the total number of feature, A represents the total area of the features and ki,j is a weight. If there is no edge correction then the weight will be equal the one when the distance between i and j is less than d, and will equate to zero otherwise. Using a given edge correction method will modify k(i,j) slightly.

User interface program developed: ESRI ArcGIS 10.4 software was used in this study. From 2009 until 2018 in 81 provinces in Turkey, CVD mortality was analyzed spatiotemporally with the interface program developed in ArcGIS 10.4 environment (Analyzing Patterns and Mapping Clusters). This interface, which automatically performs a total of 40 analyzes with the click of a single button, includes Global Moran's I, Getis-Ord General G, Anselin Local Morans I and Getis-Ord Gi* spatial statistics methodologies (Fig. 3). "Fixed distance band" method was used in

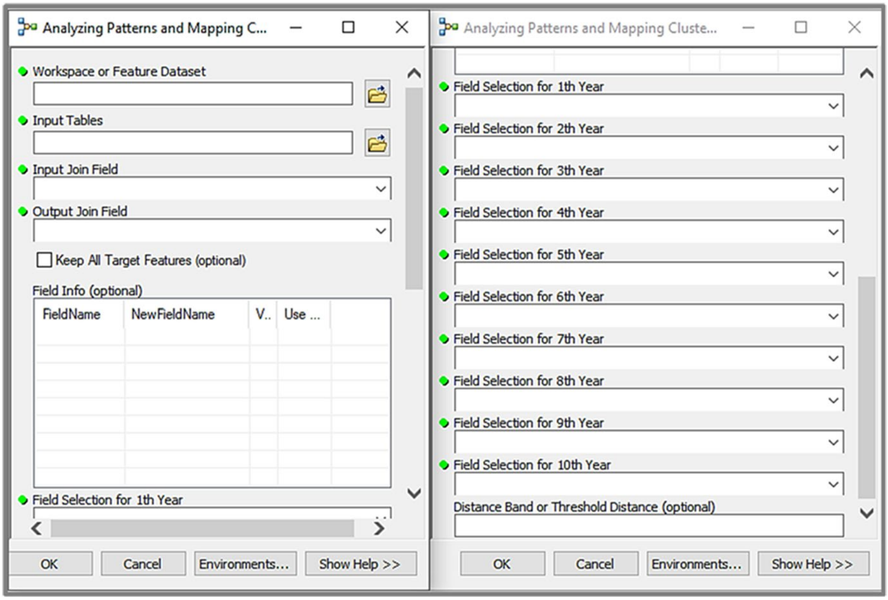

Fig. 3 The user interface developed

the conceptualization of spatial relationships. The selection of "Distance band or threshold distance" value has been investigated with Multi-Distance Spatial Cluster Analysis (Ripley's K Function) analysis methodology. While the area of some provinces with high population values in the study area is smaller, the surface area of some low-population provinces is much larger in Turkey. Threshold distance was used as approximately 205 km because it is compatible with the polygon feature type and to obtain stable clusters.

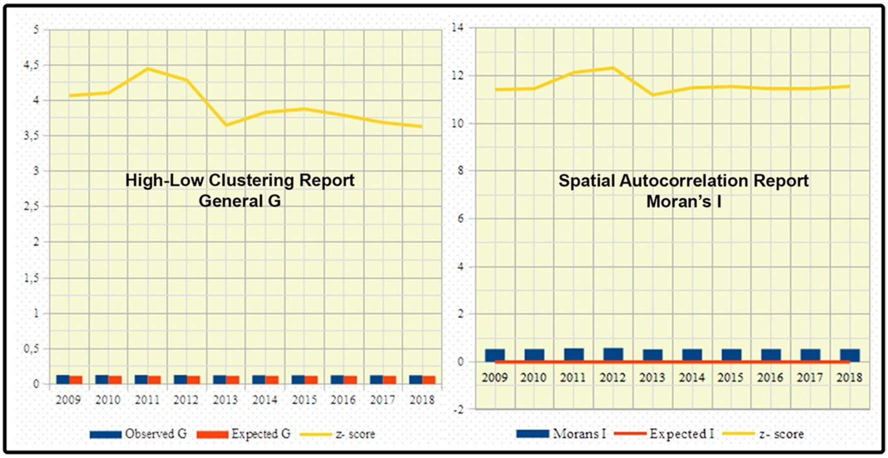

Fig. 4 Global cluster test reports between 2009 and 2018

Results

10 distance bands have been chosen for Ripley's K functions analysis. In the distribution by years, the observed K value (min distance ≈ 142 km and max distance ≈ 205 km) is larger than the expected K value (min distance ≈ 140 km and max distance ≈ 200 km). Namely, the distribution is clustered in this distance range. Additionally, the mean distance of the observed K value (≈205 km) is greater than the mean distance of the high confidence envelope (≈ 199 km). This means that the multi-distance spatial clustering over the years is statistically significant for this distance range. Consequently, the observed K value, which is statistically significant in the common distance bands from 2009 to 2018, was selected as the **threshold distance** (205 km).

Spatial patterns of CVD mortality was analyzed in this study. According to the General G and Morans I statistics, significant clusters were determined for every decade (Fig. 4). For General G, the lowest cluster was achieved in 2018, while the highest was found in 2011. In the General G test for all years (Expected General G = 0.1172; z-score > 2.58; p-value > 0.01) Spatial clusters are significant according to the 99% confidence interval.

Morans I value takes the value between -1 and + 1. The "Morans Index" value being close to zero indicates that the cluster test has random distribution. A negative value of the Moran index indicates that it contains outlier, while a positive value indicates that similar values are spatially clustered. In the Morans I test for the study area between 2009 and 2018 (Expected I = -0.0125; z-score > 2.58; p-value > 0.01), a high spatial cluster was detected in the 99% confidence interval. As a result of clustering and outlier analysis, the highest cluster was obtained in 2012, while the lowest cluster was observed in 2013 (Fig. 4).

Clusters of CVD mortality between 2009 and 2018 were mapped using LISA and Getis-Ord Gi* methods (Fig. 5). When the results are evaluated for all years, it is concluded that the high spatial clusters cover the West and Central Black Sea, and in the following years, a cluster was formed from the Thrace Region to the Southern Marmara. Low spatial cluster is observed to be frequent in Eastern Anatolia and Southeastern Anatolia regions. High clusters that repeat every year have been identified in the Western and Central Black Sea regions such as; Bartın, Kastamonu, Sinop, Çankırı and Çorum provinces. Low clusters that repeat every year are observed in Eastern Anatolia and Southeastern Anatolia Regions (Ağrı, Iğdır, Batman, Bingöl, Bitlis, Diyarbakır, Muş, Mardin, Siirt, Şırnak, Şanlıurfa, Hakkâri and Van provinces).

In the Getis Ord Gi * statistics, the fact that the positive z values are heavily clustered indicates that the available data are statistically significant. This statistic measures the areas clustered in high and low values together with the confidence interval. In this context, clustered provinces up to 90% confidence interval were observed within the study area (Fig. 6). In the Gi * test, in which high and low cluster degrees are measured, positive high spatial clusters are observed in the same areas repeatedly in the Western and Central Black Sea, Thrace and Southern Marmara Regions. The cities of Kastamonu, Karabük, Bartın, Çankırı, Sinop, Çorum have a similar distribution and hotspot clusters with a 99% confidence level have been determined. In

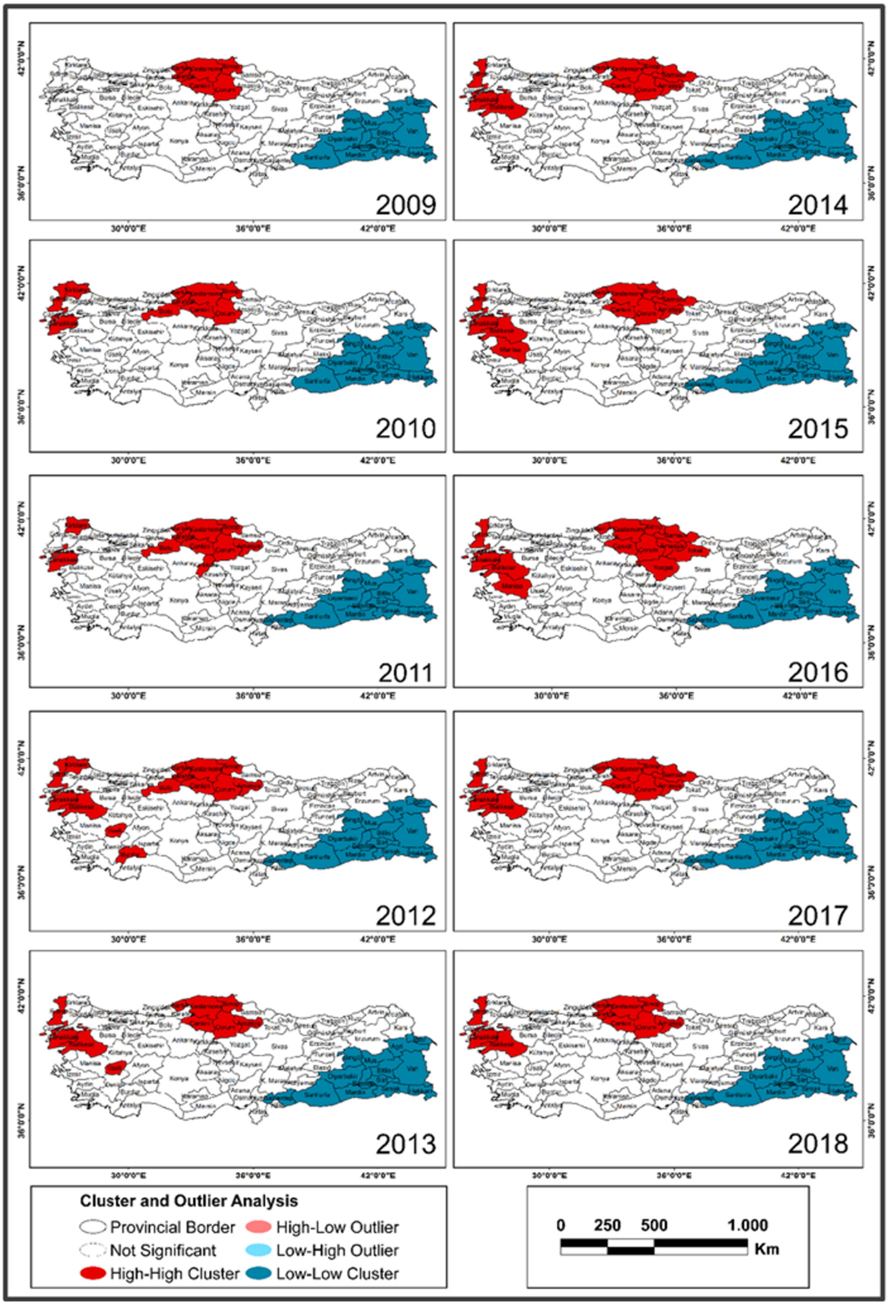

Fig. 5 Spatial clustering and outlier map of CVD mortality between 2009 and 2018

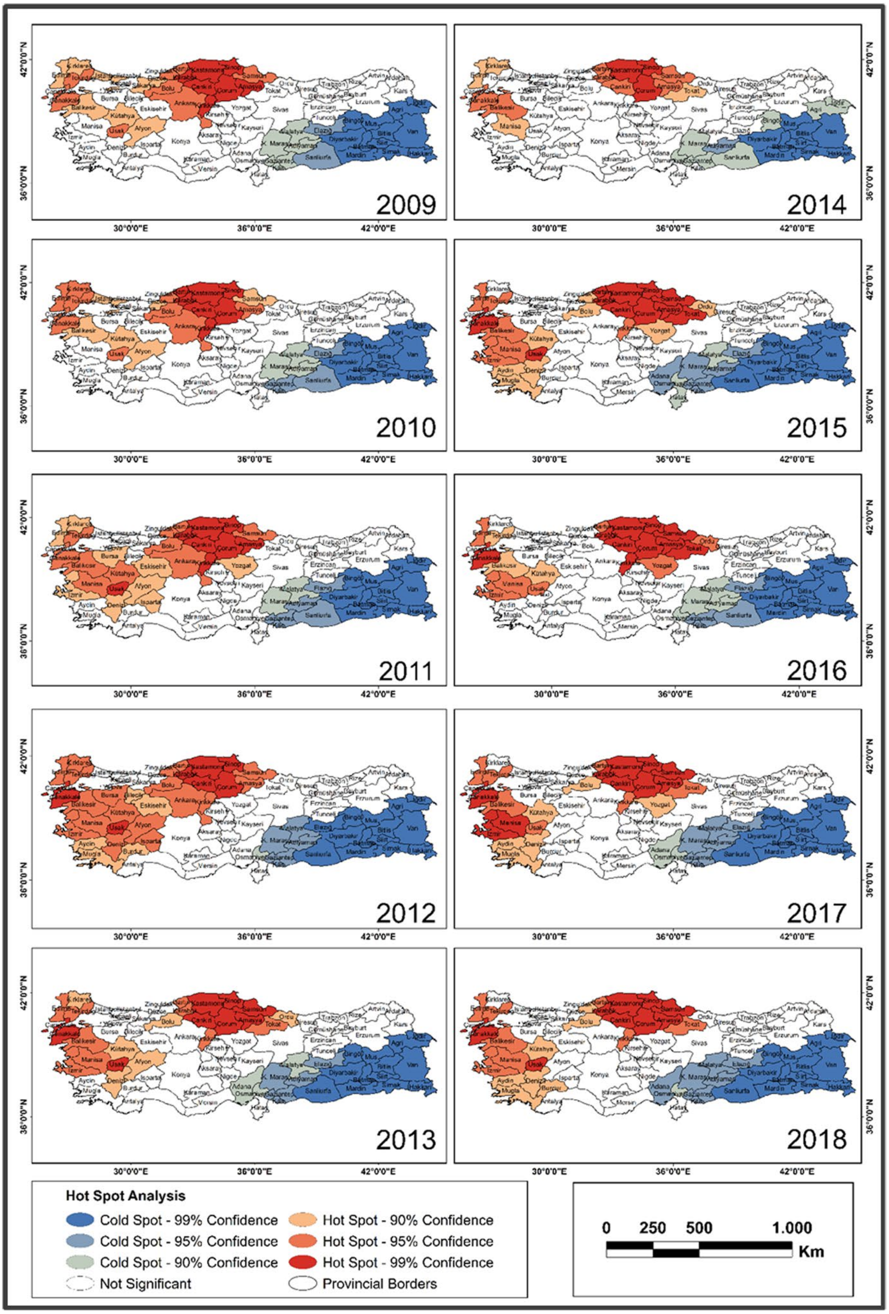

Fig. 6 The clusters obtained as a result of hotspot analysis between 2009 and 2018

the low clustered regions of Eastern Anatolia and Southeastern Anatolia, low spatial clusters were detected every year in Ağrı, Iğdır, Batman, Bingöl, Bitlis, Diyarbakır, Muş, Mardin, Siirt, Şırnak, Şanlıurfa, Hakkâri and Van provinces (Fig. 6).

Discussions

According to the findings obtained from the study, both spatial local test results of CVD mortality from 2009 to 2018 showed clustering in similar regions. Clusters within the fixed distance band with a threshold distance of 205 km were investigated over all years and changes over time were observed in different cluster sizes. However, it has clustered each year as local hot or cold spots in some provinces. On the other hand, there are some limitations due to the lack of sufficient data in the study. Firstly, statistical methods are used to analyze neighborhood relations of irregular geographical regions formed by surface area depending on distance. LISA can detect any cluster shape, but can cause outlier, especially if it has a variable size in poorly sampled areas (Gelman & Price, 1999; Amsalu, 2019). Secondly, risk factors such as exposure to air pollution in the environment causing CVD, age, gender, smoking, socio-economic level, educational status, medical conditions could not be taken into consideration and spatial dependency tests could not be performed. In addition, since the study only included CVD mortality data at the provincial level, the hotspots and cold spots, which were found significant in the data, could not be evaluated at the smaller administrative unit level such as district, village and neighborhood. Therefore, it could not be measured whether the existing clusters are predominantly occurring in urban or rural areas. In the future, if data are available, studies on CVD can also be conducted in small administrative units, and the results can be further detailed by performing spatial regression analysis with different risk factors. In this sense, this study has undertaken the function of determining the locations of clusters in terms of CVD in general. Necessary measures can be taken by doing more detailed studies in these areas. In general, researching and examining the location-based relationships of factors affecting CVD may be effective for disease surveillance.

In the literature, the following results have been obtained in various studies on CVD. It is determined that lower risk clusters occur in urban areas in Portugal (Almendra and Santana 2020). In Sweden, hotspots are generally detected in low-density rural areas that have elderly and high-wealth population (Rajabi et al., 2018), in rural and suburban Beijing (Li et al., 2012; Zhang et al., 2011) high prevalence and cluster were found. In this study, the urban or rural relationship of the provincial borders clustered with neighborhood relations is not known. The reason is that the data is published at the provincial level by TurkStat. In the future, in case more detailed data are obtained, it can be possible to reveal the relationship of the clusters according to different scale factors.

There are studies in the literature on the relationship between air pollution and its health effects. These studies are carried out using various spatial analyzes and an important spatial correlation between health and air pollution is determined. For example, a statistically significant relationship was found between PM 10 and cardiovascular mortality in Seoul (Lim et al., 2014). Akçın and Şekertekin (2016) examined the location-based change of environmental pollution in the Western Black Sea Basin and Zonguldak Hard Coal Sub-Basin (Zonguldak, Turkey). As a result of this study, they regarded the increase in coal production and the use of this coal in the industry as a threat that causes pollution in forests and water resources, especially after 2013, with the acceleration of thermal power plant activities. Ibret and Aydınözü (2010) evaluated the effects of false urbanization on urban development in Kastamonu (Turkey). They emphasized that the pollutant particles spreading from the industrial facilities established in the direction of the wind in the province, which continues to urban growth throughout the valley, are falling on the city. Besides, they stated that the polluted air remained in the city for a long time due to the inversion effect, while the vertical rising buildings prevented the winds blowing through the valley and caused an intense air pollution. It is observed that the air quality decreases in Çorum, Tokat, Düzce, Zonguldak and Kastamonu, which are among the cities in the Black Sea Region where air quality deteriorates, due to factors such as environmental pollution, low temperature and adverse topographic conditions (Garipağaoğlu, 2003). Impairment of air quality due to pollution may threaten urban and public health. This can turn into a global problem from just a local threat in the long run. According to the results obtained from our study, significant clusters in terms of CVD occurred in almost all of these mentioned provinces and there is also an air pollution problem in determined provinces. Obtaining detailed information on the pollution can reveal relationships between Turkey CVD mortality and environmental pollution.

Kocaman et al. (2011) emphasized that the Ergene River was heavily polluted due to the industrial facilities, urban and domestic wastes, and artificial fertilizers and pesticides, and this situation has many adverse effects especially the living life. In addition, they revealed that the agricultural lands irrigated from this river were also adversely affected. Dokmeci (2017) stated that the lead concentration, which is a common metal in the entire environment, is above the maximum limit value and there is an increase in all types of cancer between 2006 and 2011, as a result of the study that integrated the cancer data with the factors causing heavy metal pollution in the Ergene basin. This pollution problem, which threatens part of the South Marmara region along with the Thrace region, coincides with the clusters formed by CVD (Fig. 5 and Fig. 6). It is extremely important to conduct necessary researches to determine whether the environmental risk factors in these regions have a relationship with the clusters identified as a result of this study.

The spatial patterns of the data related to environmental risk factors along with the incidence, mortality and hospitalization associated with clustering of CVD can be investigated, and the spatial dependence of clusters in mortality with risk parameters. The findings in this context will facilitate the management of health resources and / or assist in the implementation of policies to be established for the prevention of these diseases (Horst & Coco, 2010; Lim vd., 2014; Ford & Highfield, 2016). For example; In areas with high cluster in terms of CVD, activities to promote sports can be done, and if spatial dependency is detected between air pollution and CVD, necessary measures can be taken. Nutritional habits in high local clusters can also be evaluated in this context and its relationship with obesity can be investigated. It can be examined whether tobacco crops or alcohol use in clusters that show high or low clustering in CVD. In low local clusters, it can be investigated why CVD mortality is less and its relation with spatial dependence in order to know the effect parameters. For example; In our study, the relationship to the subject can be evaluated by looking at the number of applications to the relevant hospital related to CVD in the Southeast and Eastern Anatolia Regions.

Conclusions

Pollutants in the form of dust, smoke, gas and water vapor in the atmosphere adversely affect human health. It has been demonstrated by many scientific studies that air pollution causes many different diseases such as respiratory tract, cardiovascular, skin, eye, lung cancer and nervous system. However, CO exposure in the environment is known to increase cardiovascular mortality. Today, factors such as rapid and unplanned urbanization, heavy traffic and poor quality fuel use pollute the air and leave adverse effects on human health. For people living in regions where air pollution is intense and continuous; the risk of developing various chronic diseases such as lung cancer and CVD, especially respiratory diseases, is also increasing. When evaluated in this respect, this study provides preliminary information on whether there is a relationship between CVD and environmental risk factors. Thus, GIS-based spatiotemporal and cluster analysis make a great contribution to public health decision-makers and policy makers.

CVD is a disease with a high incidence and mortality in the world. In this study, spatiotemporal analysis of the mortality due to CVD in Turkey at province level was performed. As a result, significant clusters were detected and the spatial pattern of CVD was revealed. When local cluster formations and changes by years are examined, it has been demonstrated with both Gi * and Morans I spatial statistical tests that the high spatial cluster repeats every year with a high confidence interval for the Western Black Sea region. Although cluster analyzes were carried out in different years using different methods, clusters occurring each year in the same provinces were observed. On the other hand, mortality caused by CVD was tried to be revealed easily and effectively with the user interface program developed in the GIS environment. However, the findings obtained were discussed in comparison with previous studies and provide a comprehensive perspective on future studies on different diseases.

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