Spatio-temporal epidemiology of emergency medical requests in a large urban area. A scan-statistic approach

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Abstract

Pre-hospital care is provided by emergency medical services (EMS) staff, the initial health care providers at the scene of disaster. This study aimed to describe the characteristics of EMS callers and space-time distribution of emergency requests in a large urban area. Descriptive thematic maps of EMS requests were created using an empirical Bayesian smoothing approach. Spatial, temporal and spatio-temporal clustering techniques were applied to EMS data based on Kulldorff scan statistics technique. Almost 225,000 calls were registered in the EMS dispatch centre during the study period. Approximately two-thirds of these calls were associated with an altered level of patient consciousness, and the median response time for rural and urban EMS dispatches was 12.2 and 10.1 minutes, respectively. Spatio-temporal clusters of EMS requests were mostly located in central parts of the city, particularly near the downtown area. However, high-response time clustered areas had a low overlap with these general, spatial clusters. This low convergence shows that some unknown factors, other than EMS requests, influence the high-response times. The findings of this study can help policymakers to better allocate EMS resources and implement tailored interventions to enhance EMS system in urban areas.

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Key words: Geographical information systems; emergency medical service; space-time clustering; ambulance calls; Iran.

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Ethical issues: the identity of all callers was anonymous for privacy issues.

See online Appendix for additional Tables.

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Introduction

Emergency medical services (EMS), also known as ambulance services, provide medical transport and/or out-of-hospital medical care to people exposed to accidents or otherwise in need of immediate medical care (Spaite *et al*., 2001). EMS is thus the first meeting point for people who need emergency health care, and if timely service to seriously ill patients fail, a life may be lost (Leonardsen *et al*., 2021). Therefore, considering the importance of timely addressing the unique needs of at-risk people, pre-hospital emergency care is one of the priorities of the global health system (Nichol *et al*., 2008). Given the vital role of high-quality and efficient emergency care in saving patients' lives from unpredicted life-threatening injuries or critical conditions, the EMS goal is to provide timely and well-monitored care (Aringhieri *et al*., 2017). To achieve this goal, having a full perspective of the EMS system including the medical characteristics and location of the callers as well as access to available resources distribution is undeniable (Wang *et al*., 2012).

In developing countries, high death rates and/or irreversible injuries in pre-hospital care are quite common (Mawani *et al*., 2016). Based on a report by Haddadi *et al*. (2017) more than 50% of those who have lost their lives in critical situations died at the scene and about 16% died on the way to the hospital. Patient survival rate in pre-hospital care is mainly associated with response time (Ong *et al*., 2009) and it has been proven that timely emergency services will improve outcomes in sensitive situations (MacKenzie *et al*., 2006). However, other fundamental factors, such as heavy traffic, poor-quality roads are the main reasons for delay in Iran, but also scattered, inadequate and under-equipped EMS stations also play a role (Haddadi *et al*., 2017).

In Iran, the accepted EMS response time is defined as less than 8 and 15 min in urban and suburban areas, respectively (Bahadori *et al*., 2010). However, the response time varies in different cities, *e.g*., in Tehran, the capital of Iran, the average response time has been reported at 12.54 min (Bidari *et al*., 2007). Another study conducted in Urmia, north-west Iran, showed a mean response time for city locations of 5 min and 10.6 min for interurban road locations (Bigdeli *et al*., 2010). In Yazd, central Iran, 81.2% of EMS requests were responded within the 8 min standard (Bahrami *et al*., 2011).

Recently, researchers and health organisations have increasingly applied spatio-temporal analysis to represent and control health-related issues (Ahmadian *et al*., 2020), applying geographic information systems (GIS) to explore the pattern of pandemics and health events (Nykiforuk and Flaman, 2011; Mena *et al*., 2018; MohammadEbrahimi *et al*., 2021). GIS is a highly useful tool for decision-making, and it effectively visualises space-time information in different *overlays* (Adin *et al*., 2019). Indeed, the growth of data storage and analysis technologies in the 21st century and increasing attention to the efficiency of the emergency medical system has promoted GIS applications in EMS-related studies (Ong *et al*., 2009; Schuurman *et al*., 2009; Hashtarkhani *et al*., 2020; Tabari *et al*., 2020;). This approach is useful for visualising the distribution of EMS incidents showing that they do not follow random spatio-temporal patterns but rather have particular space-time patterns in different geographical areas (Warden *et al*., 2007). Already two decades ago, Peters and Hall (1999) utilised GIS to arrange and appraise ambulance stations and their response times finding that socio-spatial characteristics were good predictors for the spatial-temporal patterns of response times. Bassil *et al*. (2009) focused on mapping heat-related diseases in Toronto, Canada in relation to all EMS calls made and found that the EMS medical dispatch data followed a similar pattern between the timing of the heat events and extreme heat alerts in different areas. Similarly, Ong *et al*. (2009) explored the geospatial patterns of EMS requests in Singapore discovering a definite spatio-temporal pattern leading them to recommend that ambulance deployment be based on real-time call monitoring. Some factors such as circadian rhythms, time of day and geographical epidemiology of the population were influential with respect to the patterns of EMS calls and ambulance demands. Along these lines, Xia *et al*. (2019) concluded that accessibility to EMS in the central area of the city is temporally sensitive due to large and frequent population flow based on a large volume of data from the global positioning system (GPS) and the enhanced two-step floating catchment area (E2SFCA). Thus, EMS requests follow spatio-temporal patterns, and the incidents are dynamic, especially in big cities with high mobility levels (Azimi *et al*., 2021). At this time, there is not enough knowledge about the spatio-temporal distribution of EMS requests in Iran's large cities. The main questions regard the pattern of EMS requests in its big cities and how the most effective EMS deployment strategy can be designed in the future.

A spatio-temporal measurement based on EMS requests distribution will enable closer attention to response times in circumstances where time delays are critical. The current study aimed to study this in Mashhad, the second-most populous city of Iran, focusing on the spatial and temporal distribution of EMS calls to identify any potential pattern(s) of ambulance enquiries. Studies along these lines have been conducted in Mashhad but only with reference to specific health conditions, such as cardiovascular diseases (Azimi *et al*., 2021) and road traffic injuries (Tabari *et al*., 2020). No prior work has investigated the spatio-temporal distribution of all EMS requests in the Mashhad area and the potential clustering of incidents, and we wished to demonstrate the high utility of GIS in EMS requests analysis; identify the influential factors on EMS response rate; and inform allocation decisions of EMS resources in future. We opted to carry out a retrospective cross-sectional study employed ambulance call data to discover characteristics and patterns of ambulance enquiries.

Materials and methods

Study setting and population

This ecological study was conducted in Mashhad, the capital of Razavi Khorasan Province. It is located in the northeast of the country and the latest census estimated the population at 3,785,567 (https://www.amar.org.ir/english/Population-and-Housing-Censuses). Mashhad is known as a place of religious pilgrimage and is the most popular tourist destination in the country, with over 20 million visitors per annum (Kafashpor *et al*., 2018). Figure 1 illustrates the census tracts, population density and location of EMS stations in urban area. The downtown area includes the Holy Shrine with a high concentration of hotels, residential complexes and shopping malls.

Data collection

Two sets of data were used: i) ambulance call data from 1 June 2018 to 31 May 2019 from the database at Mashhad's EMS centre; and ii) the population's spatial distribution from the city municipality. Calls that did not lead to an ambulance mission were removed from the analysis. The EMS data also included demography information, dates and response times, the main medical condition/complaint either recorded by the nurses in the EMS dispatch centre or the ambulance staff's individual personal digital assistants (PDAs). Data for all EMS dispatches (inside and outside the city) were collected for descriptive analysis, while only requests from the city area were included for map generation and spatial analysis. Additionally, we used median and interquartile ranges to report central tendency statistics for the time mission intervals.

Thematic mapping

Smoothed cumulative incidence rates were mapped at the census tract level (n=1301). The heterogeneity of the variance and spatial autocorrelation of EMS rates were adjusted for smoothing by using empirical Bayesian smoothing (EBS) (Robertson, 1999) to show the pattern of requests. This technique is suitable when the areal population size and aggregation vary and when there is spatial autocorrelation in the data (Pringle, 1996), so it was applied given that the population size varied by census area (SD=2680) and the presence of spatial autocorrelation of the EMS rates (global Moran's I=0.13 at P<0.001). The EBS smoothed incidence rates, which computes the risk as a weighted sum of the raw rate for each unit and a prior mean (Manton *et al*., 1989), were grouped into five categories using the natural breaks classification algorithm. For analysis of diurnal variation, we adopted the four-hour interval scheme (starting at 3:00 a.m.) used by Ong *et al*. (2009). A separate map was generated for each of the six periods.

Spatial and temporal clustering

The descriptive maps show the spatial pattern of EMS requests during each time interval, but to identify the high-risk (hotspots) areas of EMS requests by time, we needed to add scan statistics introduced in health sciences by Naus (1965) with spatial and temporal extensions introduced by Kulldorff (1997). These techniques can identify spatial, temporal and space-time clustering as used by (De Carvalho *et al*., 2020; Punyapornwithaya *et al*., 2020; Silva *et al*., 2020). In Kulldorff's scan statistics, the first step is to determine a congruous probability model of the data and compute the likelihood ratio for each scan window. Then, the primary cluster candidates with the maximum likelihood ratio are identified and the Monte Carlo hypothesis procedure tests the statistical significance, *i.e*. P-value (Kulldorff, 1997). Relative risk (RR), Log likelihood ratio (LLR) and the Mont Carlo test constitute the approaches used for the interpretation of scan statistics (Kulldorff, 2018).

Purely spatial cluster analysis

Purely spatial scan statistics was used to discover spatial clusters of high EMS demand. A retrospective discrete Poisson model was used, assuming that the number of calls in each census tract is Poisson-distributed, based on a known background population (Kulldorff, 1997). Latitude and longitude coordinates for each census centroid were calculated. The maximum spatial cluster size was set to 50% of the population at risk as recommended by Kulldorff (2018).

Purely temporal cluster analysis

Purely temporal scan statistics was performed to discover the timing of the meaningfully higher rate of EMS requests. This was done by searching for purely temporal clusters analysis without addressing their spatial variations or patterns (Kulldorff, 2018). The Poisson discrete scan statistic was set as the probability model to detect high rate time clusters of the day. The length of time aggregation was set at 4 hours (six time intervals as introduced in descriptive analysis) and the window size was set to 50%.

Space-time cluster analysis

Space-time scan statistics was used to identify the geographical locations where EMS requests were significantly high at certain times of the day. A circular scanning window was selected to detect large, compact clusters. The scanning window moved across space and time simultaneously comparing the rate of EMS requests inside the scanning window to the rate of EMS requests outside of

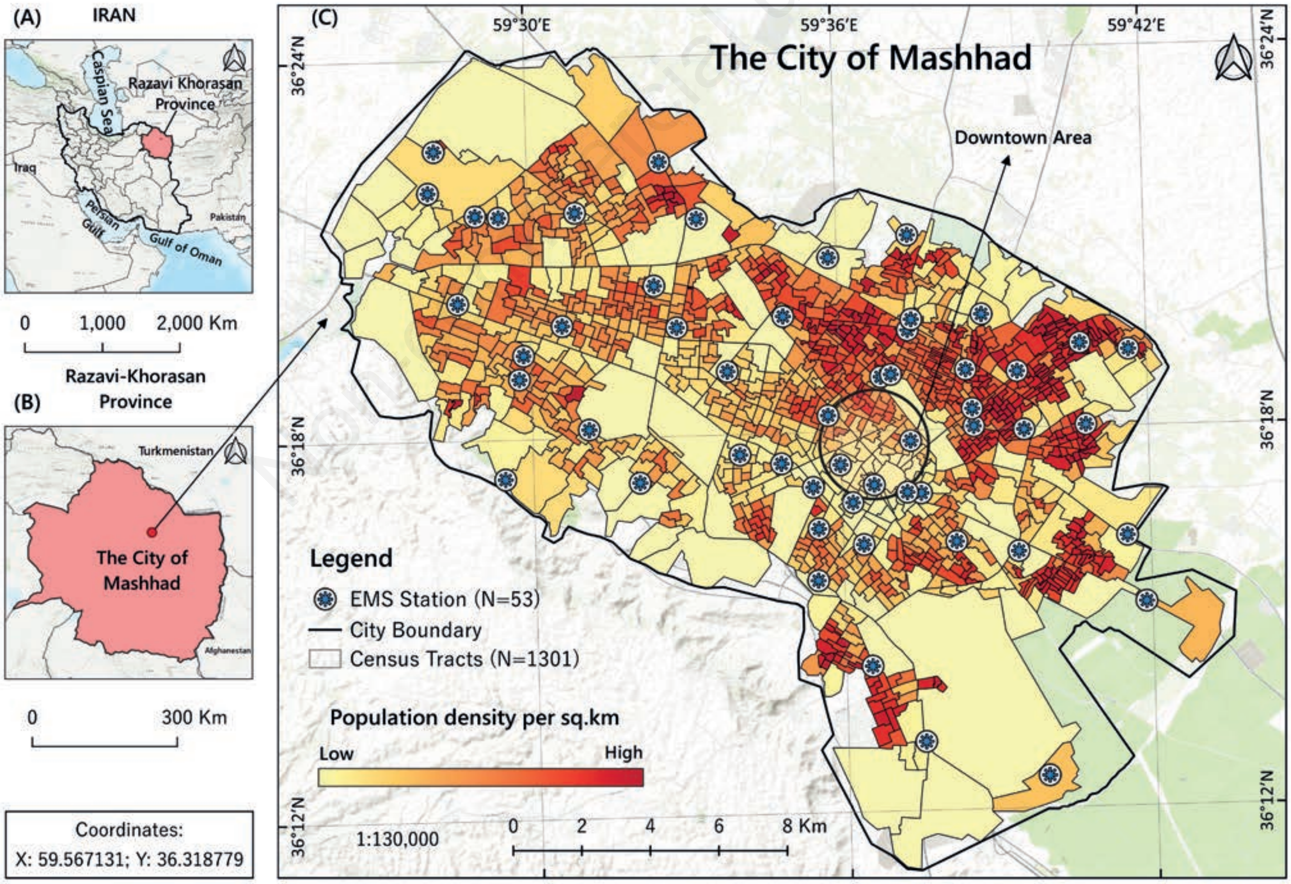

Figure 1. Map showing the population density in census tracts and the distribution of emergency medical services (EMS) ambulance stations in the city of Mashhad.

the scanning window. If the calculated rate is significantly ($P \leq 0.05$) higher inside the window, the RR is estimated, and a potential high-rate cluster identified. We set the scanning window to include up to 50% of the study population and up to 50% of the study period to detect large primary and secondary clusters.

Analysis of spatial variation in temporal trends

Spatial variation in temporal trends (SVTT) is a relatively new approach, which detects clusters with relatively higher rising or falling trend over the time (Moraga and Kulldorff, 2016). This method provides an estimate of the temporal trend throughout the study area. The null hypothesis is that the trends are the same, while the alternative assumes that they are different. A cluster can have a high trend because it has a rate that increases or decreases faster than the outside area. The maximum windows size was adjusted to 50% as well.

Convergence of emergency medical services requests and response time clusters

In this step, we studied the possible relationships between the rates of EMS requests and the resulting response time of ambulance missions. To that end, the average response time of each census tract was calculated, and the hotspots of high-response time identified using the purely spatial scan statistics. Then the clusters of EMS requests were overlaid on a single map assuming that the overlapping patterns of these two would represent the probable correlation between the response time and the number of requests.

Software

GeoDA (Centre for Spatial Data Science, University of Chicago, IL, USA) was used to estimate EBS of incidence rates. QGIS, v. 3.18.2 (https://qgis.org/downloads/) and ArcGIS, v. 10.6 (ESRI, Redlands, CA, USA) was used to create the maps. We also used SaTScan v.9.7 (https://www.satscan.org/) specialised software to perform spatial, temporal and spatio-temporal scan statistics. In order to pre-process tasks and descriptive analysis, Microsoft Excel version 2016 (https://www.microsoft.com/) was used.

Results

Descriptive analysis

The 224,355 calls received during the study period that fitted the inclusion criteria. Mean age of patients were 43.6 (SD=22). The characteristics of the callers are listed in Table 1.

Figure 2 shows time intervals for each step of missions. The average preparation time, *i.e.* the time interval from patients' call to ambulance departure from the station, was almost equal for urban and rural missions (2.2 *vs* 2.3 min). The average response time, *i.e.* the time it takes to reach the scene after an EMS call, was 12.2 min for rural missions, which is 10.1 min loner than urban missions with. The average time at the scene for both urban and rural missions were exactly equal (11.2 min). Understandably, the transport time from rural locations was considerably longer (20.3 min) compared to 11.2 min in the urban area.

Figure 3 demonstrates the temporal variations in EMS demand during the study period, with a higher value in July and August and relatively lower one in February. Although Saturday is the first day of the week and Friday considered as weekend in Iran, this did not impact on the EMS demand that was were relatively high on Saturdays, Wednesdays and Thursdays with two peaks: at 12 p.m. and 9 p.m.

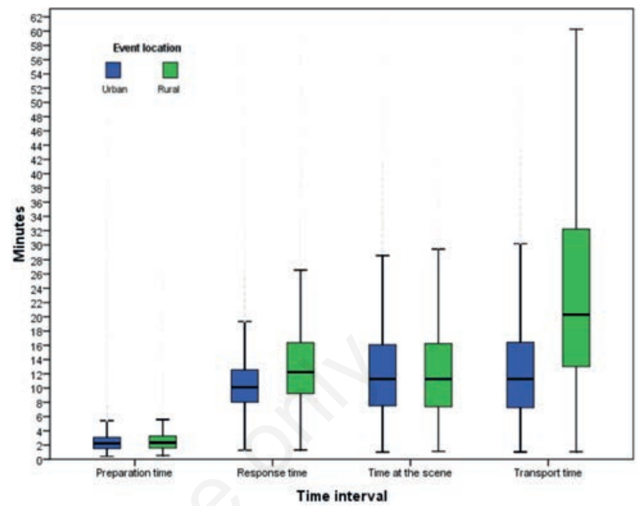

Figure 2. Box plots of time intervals of urban and rural emergency medical services missions in Mashhad, Iran from Jun 2018 to May 2019. The preparation time is the time interval from the call made to the ambulance departure from the station.

Table 1. Characteristics of emergency medical services callers in Mashhad, Iran from Jun 2018 to May 2019.

Characteristics	Number of patients	%
Location	224,355	100.0
Urban	203,072	90.5
Rural	21,283	9.5
Sex	206,253	100.0
Male	106,776	51.8
Female	99,477	48.2
Chief complaint	188,885	100.0
Altered consciousness*	64,835	34.3
Traumatic injury	60,822	32.6
Chest pain and cardiac conditions	26,016	14.0
Airway obstruction, respiratory distress	9175	5.0
Poisoning, intoxication, drug overdose	7406	4.8
Abdominal pain/problems	7291	3.9
High/low blood pressure	5880	3.8
Behavioural/psychiatric disorder	3036	1.6
Obstetric and gynaecologic emergencies	1662	0.9
Stroke/cerebrovascular accident	979	0.5
Other	1783	0.9
Mission status	221,757	100.0
Transfer to healthcare	136,989	61.8
Lack of patient cooperation	77,735	35.1
Treated and released	4258	1.9
Dead at scene	2775	1.2

*Syncope, shock, seizure and diabetic emergencies.

Thematic mapping

Figure 4 demonstrates the geographical distribution of emergency requests at the census level divided into the six time intervals of the day. The highest smoothed incidence rates of requests were concentrated in the south-eastern part of the city at all times.

Spatial and temporal clustering

Purely spatial clustering

Using SaTScan software v.9.7, seven significant (P=0.05) spatial clusters of EMS requests were detected (Figure 5). These hotspot areas were categorised as most likely clusters or secondary clusters based on the P-value and RR. The first cluster incorporated 52 census tracts containing a residential population of 31,912 and 8012 emergency cases located in the downtown area. The second cluster involved a larger area with 112 census tracts with a population of 230,570 and 13,416 cases. Although this most western cluster had an observed/expected ratio of 1.37 times it is far from the 7.81 recorded for the first cluster in the downtown area. The third cluster almost covered the second one, reinforcing the importance of the area in terms of EMS requests. Other secondary likely clusters were mainly distributed in the southern part of the city. Cluster summary information is provided in the text boxes (Figure 5), with detailed description available in the supplementary Table S1.

Purely temporal clustering

Table 2 shows the results of a purely temporal analysis of EMS requests during the different four-hour periods of the day. The results indicate that high-rate clusters of EMS requests were predominantly distributed from 11:00 a.m. to 10:59 p.m. This tempo-

Table 2. Detected clusters of purely temporal emergency medical services requests in Mashhad, Iran from June 2018 to May 2019.

Type of cluster	Time coverage	Observed number of cases	Expected number of cases	Annual number of cases/100,000	OE	LLR	RR	P-value
Most likely	11:00 a.m. - 02:59 p.m. 03:00 p.m. - 06:59 p.m. 07:00 p.m. - 10:59 p.m.	79,444	63,512.50	322,272	1.25	4039.3	1.67	0.001

A cluster is statistically significant when its test statistic is greater than the critical value, which is 8.49 for 0.0001 significance level according to Gumbel critical values. OE, observed/expected; LLR, Log likelihood ratio; RR, relative risk.

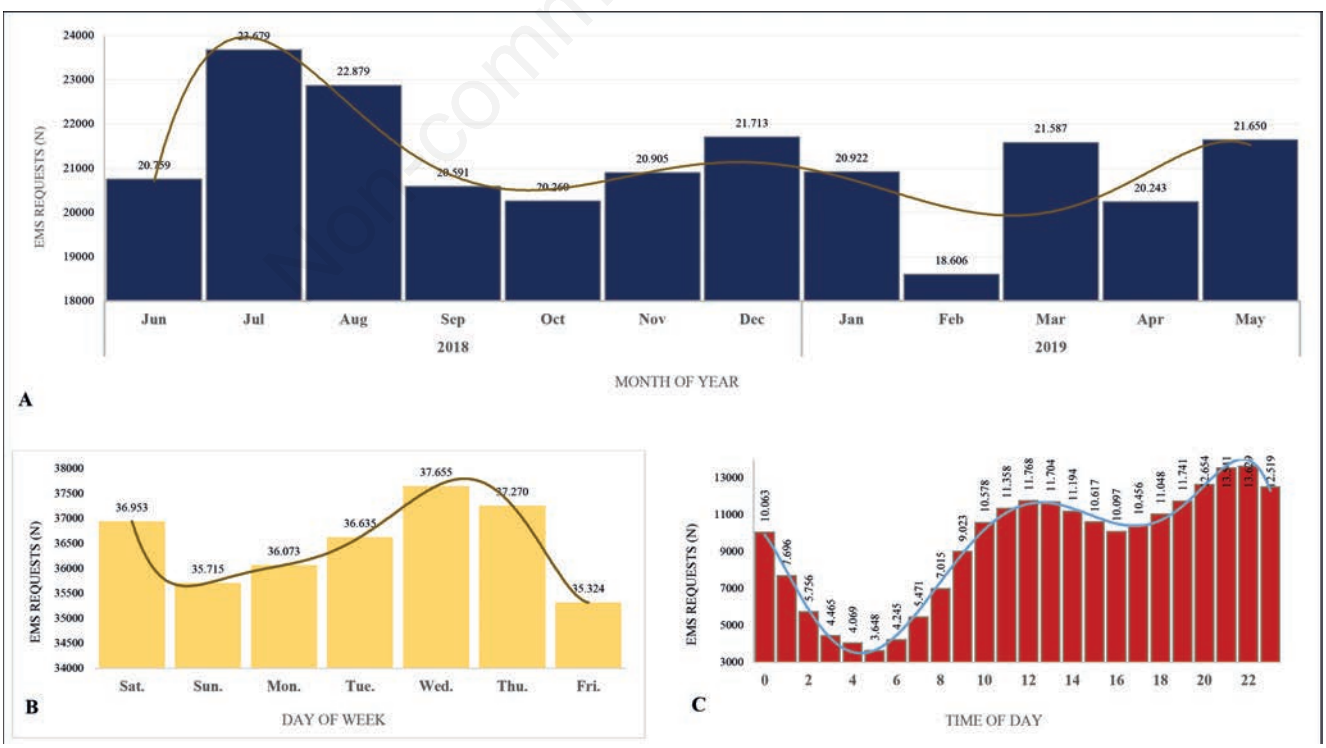

Figure 3. The temporal distribution of emergency medical services (EMS) requests in Mashhad, Iran from June 2018 to May 2019. A) Monthly variation; B) weekly variation; C) diurnal variation.

ral cluster had an observed/expected ratio of 1.37 times with a RR of 1.67.

Space-time clustering

Figure 6 displays clusters of EMS requests in both spatial and temporal dimensions. Two clusters were identified, both of them between 11:00 a.m. to 10:59 p.m., which is in accordance with the purely temporal clustering results. While cluster 1 included a relatively small area with 54 census tracts and 31,912 people in the eastern part of the city (downtown), cluster 2 covered a wider area with 168 census tracts and 375,591 people in the west of the city. Similar to the purely spatial scan statistics, the result of observed/expected cases for the first cluster was significantly higher than the second one (9.82 *vs* 1.54). Cluster summary information is provided in the text boxes (Figure 6), with detailed description available in the supplementary Table S2.

Spatial variation in temporal trends

Figure 7 demonstrates the result of SVTT for areas with higher temporal trends of EMS requests. According to this figure, two

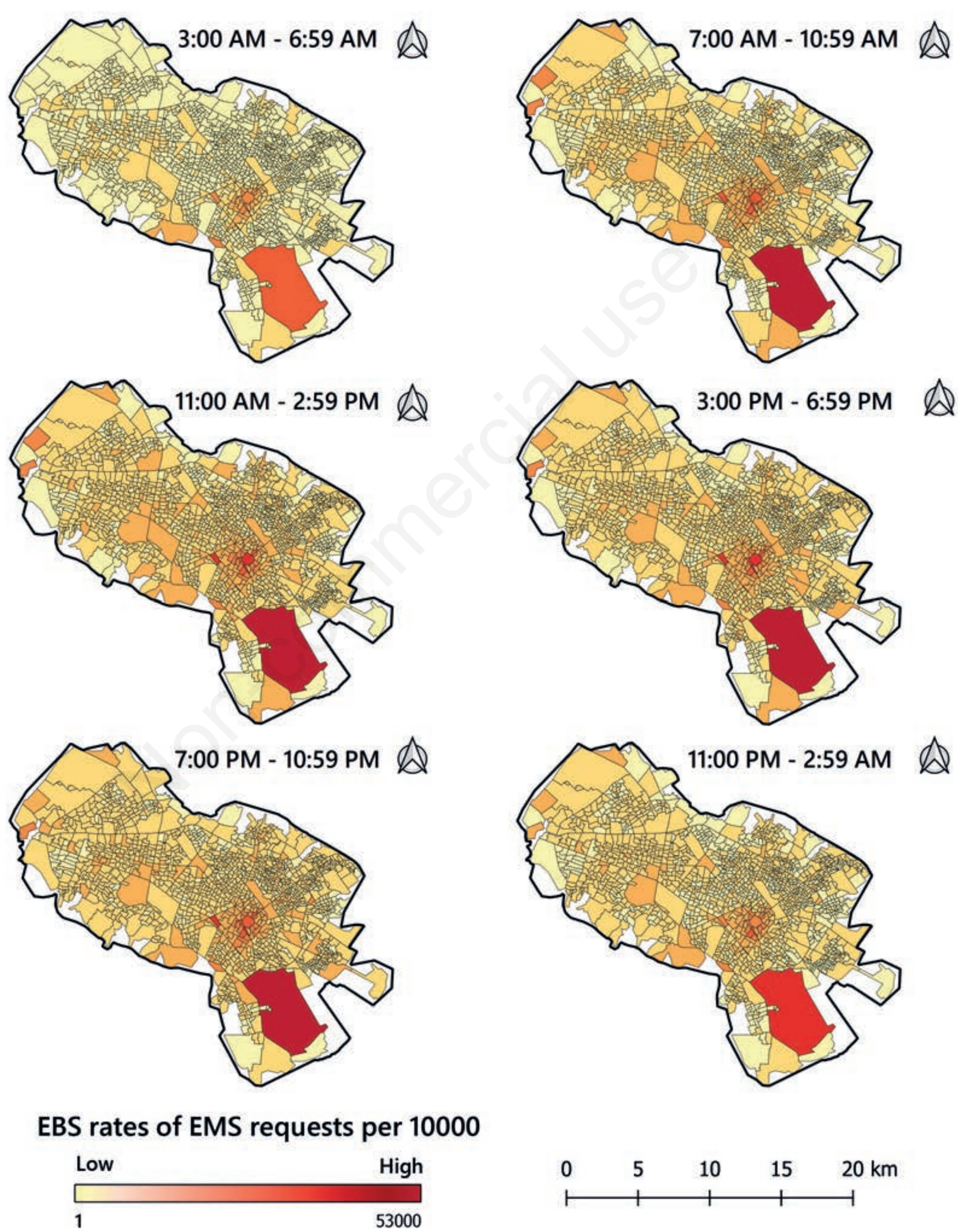

Figure 4. Empirical Bayesian Smoothed rates of emergency medical services (EMS) requests in Mashhad, Iran from June 2018 to May 2019.

high-trend clusters in EMS requests were found to be statistically significant. The first high-trend cluster was identified in the North-east of Mashhad with almost 655,000 residents and the second high-trend cluster in the South-east of the city with almost 69,000 populations. The inside time trends for these clusters were 15.2% and 21% while the outside time trends were 11.4% and 12.04%, respectively. Cluster summary information is available in the supplementary Table S3.

Convergence of emergency medical services requests and response time clusters

Figure 8 demonstrates the convergence of purely spatial clusters of EMS requests and clusters of high response time of ambulance missions. Both were categorised as primary and secondary clusters based on P-value and RR. While they were near the centre of the city, the response time clusters were found adjacent to the border parts. Accordingly, the second cluster of high response time had no convergence with the emergency requests clusters; the clusters had also a minor overlap. Cluster summary information are provided in the text boxes (Figure 8), with detailed description available in the supplementary Table S4.

Discussion

We investigated the spatial epidemiology of EMS requests in Mashhad in 2018 and 2019 using scan statistics and descriptive epidemiological methods. The results identified a significant variation of EMS requests over space and time. To the best of our knowledge, this is the first study in the city of Mashhad to assess spatiotemporal patterns of EMS requests.

The rate of EMS requests in urban area of Mashhad was 53.4 calls/1000 citizens and year, which is very close to that in Izmir, Turkey [56.4 calls/1000 citizens and year (Sariyer *et al*., 2017)] and Copenhagen, Denmark [60 calls/1000 citizens and year (Moller *et al*., 2015)] but higher than Singapore [with 20.5 calls/1000 and year (Ong *et al*., 2009)].

Traumatic injuries and altered level of consciousness (includ-

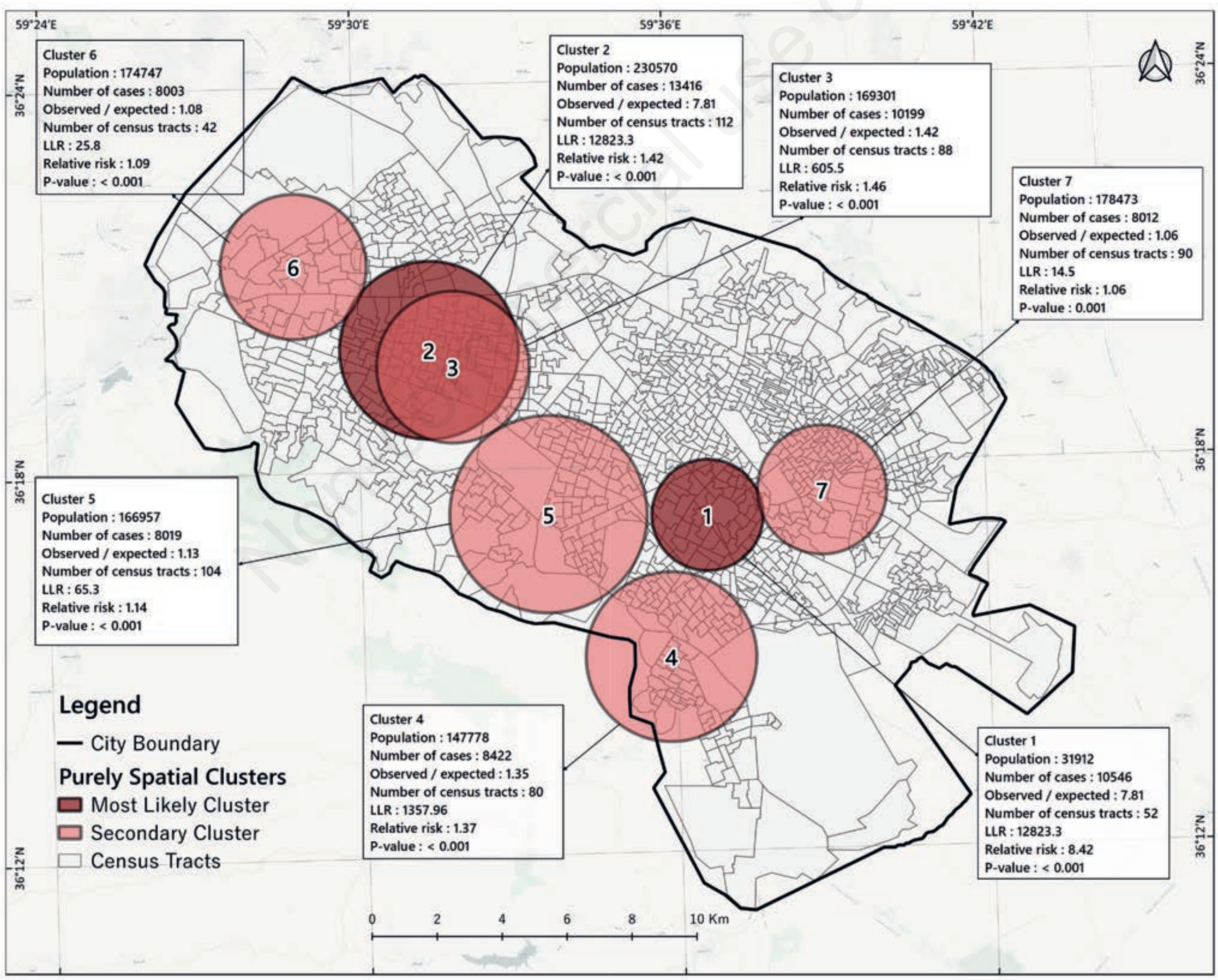

Figure 5. Purely spatial clusters of emergency medical services requests in Mashhad, Iran from June 2018 to May 2019.

ing syncope, shock, seizure and diabetic emergencies) each accounted for almost one third of the chief complaints. This result is in accordance with a study in USA that reported that these two factors were the most frequent complaints with 23.4% and 21.7% of the total requests (Mueller *et al*., 2016). Interestingly, almost 35 percent of callers refused pre-hospital care. One of the common reasons for this was the wish of many patients to be transferred to a specific hospital. In Iran, ambulance staff are not allowed to transfer patients to private hospitals except for some specific reasons. Also, sometimes callers cannot wait for ambulance arrival and try to transfer patients with their personal vehicles. There is a need for more education and information to the public about the situations when they need to call ambulance services and also the associated risks of transporting a patient in a car or van lacking trained staff.

The standard response time is defined as eight min in most settings (Berlin and Liebman, 1974) which is directly related to higher survival rate and reduced mortality (Blackwell and Kaufman, 2002). This figure was higher in Mashhad by almost two min in the city area and four min in rural areas. The time spent at the scene is another important criterion in assessing the EMS performance. The global gold standard for this criterion is 10 min (Raeissi, 2012). Patients should be managed in such a way so as to minimise delays in their transfer to clinical centres. The average time spent at the scene in our study was about one min longer than the international standard.

Our study showed some temporal variation in EMS requests by month, weekday and time of day. Exact reasons for the variations are unknown but the results may generate hypotheses and have implications for the management of EMS resources. Our study identified increases in the number of emergency requests received for different temporal periods; for example, we found an increased incidence at certain times: i) around mid-day and evening/night-time (specifically, 8:00 p.m. - 11:59 p.m.); ii) on Saturdays and Wednesdays; and iii) in the months of July and August. Other studies found similar patterns in this regard. In some studies the weekly

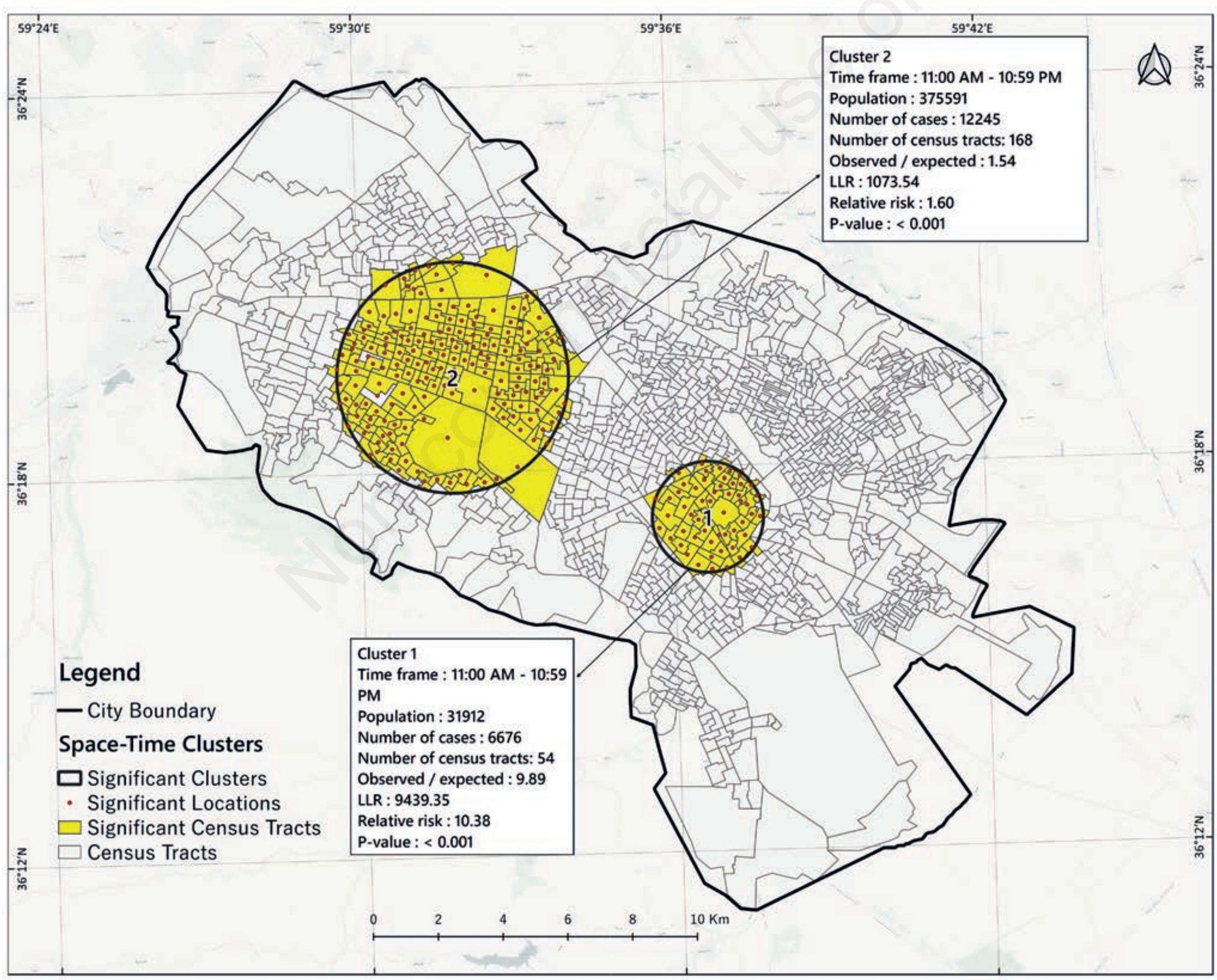

Figure 6. Detected significant spatio-temporal clusters based on space-time permutation scan statistic model for areas with high rates of emergency medical services requests rates in Mashhad, Iran from June 2018 to May 2019. Each circle specifies a significant cluster area in a specific time interval.

pattern of peak incidence rate was identified as occurring on Mondays (Ong *et al*., 2009; Sariyer *et al*., 2017). In our study Saturdays had relatively higher EMS demand as it is the first day of week in Iran but somewhat surprisingly Wednesdays had the highest demand for pre-hospital emergency care. For diurnal and monthly variations, our findings are not much different than other studies (Willich *et al*., 1994; Arntz *et al*., 2001; Gruska *et al*., 2005; Ong *et al*., 2009).

Based on the thematic maps of EMS requests, downtown and the south-eastern part of the city had higher rates in all of the periods of the day (Figure 4). The reason for the higher request rate in downtown is because this is an area near the Holy Shrine, a focal destination for tourists and pilgrimage. Downtown Mashhad has a high population density and heavy traffic congestion in this area as compared to the rest of the city. On the other hand, EMS requests were also high in the south-eastern part of the city which includes the airport and a large census tract with a lower population density. This could be due to the higher number of travellers to and from the airport who are not residents of this census tract.

Based on the purely spatial analysis, seven areas mostly in centre and southern part of the city identified as hotspots of emergency events (Figure 5). The figure confirms that downtown area has statistically higher demand of EMS services. The considerably higher values of observed/ expected cases and relative risk in the downtown area compared to other clusters demonstrate the unique characteristic of this location. The results of spatial scan statistics did not identify the south-eastern census tract (the airport) as a hotspot which was in red colour in the thematic map of EBS rates. This shows that having a high rate does not necessarily lead to being a spatial cluster.

Results of the purely temporal analysis identified three out of six time intervals of the day (11:00 a.m. to 10:59 p.m.) as temporal clusters of EMS demand. Although we did not find any study using temporal clustering analysis for diurnal variations, it was expected

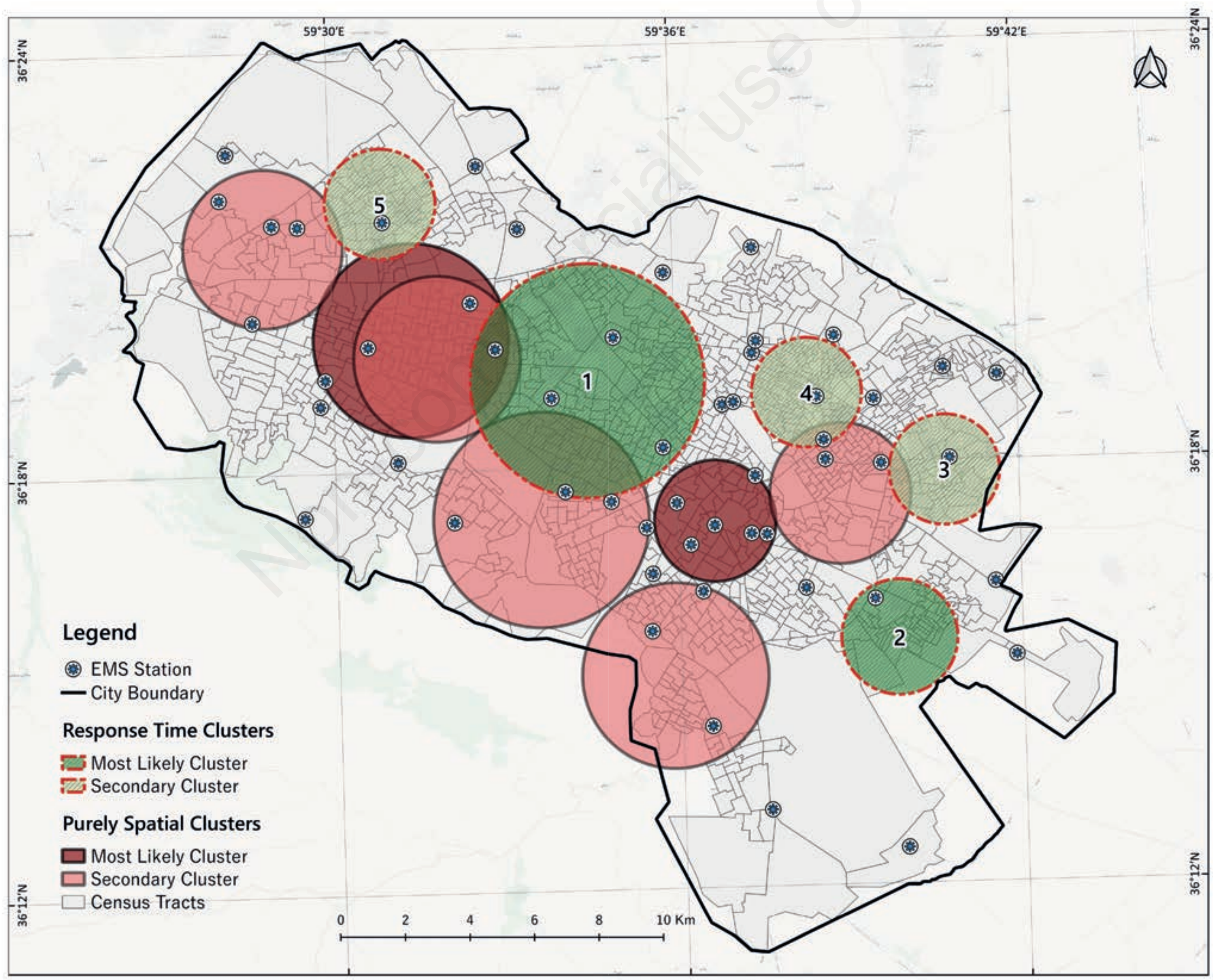

Figure 7. Detected significant clusters based on spatial variation in temporal trends of high emergency medical services (EMS) request rates in Mashhad, Iran, Jun 2018 to May 2019. Each circle specifies a significant clustered area in a specific time interval.

that temporal clusters would be during certain hours of the day. The lower number of EMS requests at night and on Fridays (weekend in Iran) showed the association of daily activities with emergency events. The EMS system should be at its maximum capacity during these times to serve potential patients.

Based on the spatio-temporal clusters presented in this study (Figure 6), two clusters were detected to both occur between 11:00 a.m. to 10:59 p.m. This analysis is the combination of two prior analyses as it considers both spatial and temporal dimensions. The two identified clusters were similar to the most likely clusters in purely spatial clustering and the time intervals are equal to the detected time intervals in purely temporal clustering. Again, the considerably higher statistics for the downtown area represents the higher demand around the Holy Shrine, which is much more crowded in daytime.

The two areas found by the SVTT technique are with higher variations during the time intervals of the day (Figure 7). Higher variations of emergency requests in these areas need different approaches to supplying the right set of service policies by the associated authorities. For example, dynamic allocation of ambulances here might cover the variation of demand for emergency services.

We can infer from Figure 8 that a high number of calls in an area does not necessarily increase the ambulance response time. Although EMS demand in the downtown area of the city was a hotspot in both spatially and spatio-temporally, the average response time of ambulances was not significantly high in this area. This fact can imply that higher response time of EMS missions is associated with several factors (*e.g.*, accessibility and road traffic) and not only due to higher number of requests and busy schedule of ambulances. Future studies can identify factors that increase the average response time of EMS missions in some areas.

The limitations experienced have mainly to do with the quality of EMS mission data, which varies as it is generated by ambulance staff in real-time, emergency and stressful situations. Secondly, the frequency of travellers/tourists in census tracts and across the study period was unknown, which will change the population at risk at some degree. There are no good data on how tourist rates

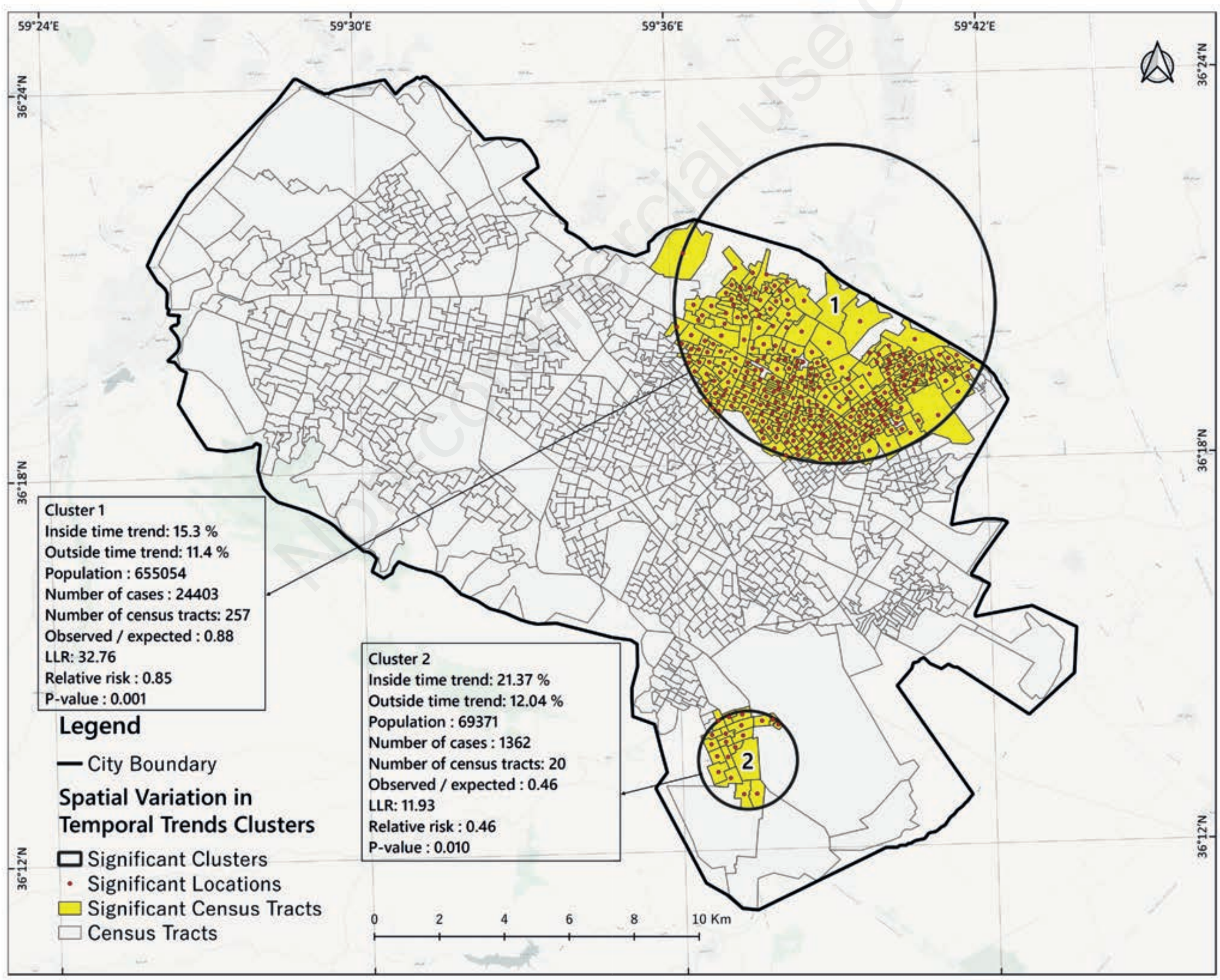

Figure 8. Comparison of detected significant spatial clusters pattern with response time clusters of emergency medical services requests in Mashhad, Iran from June 2018 to May 2019.

within Mashhad vary by month or season, and how the religious festivals that attract visitors to the city are distributed across the year. Thirdly, this study was conducted before the COVID-19 pandemic, which had a big on the EMS requests and needs to be further explored. However, as the pandemic subsides, the situation should return what it was when the study was carried out. Finally, the issue of modifiable areal unit problem (Openshaw and Taylor, 1981) remains inherent to the studies that focus on aggregated spatial data for a single predefined area.

Policy implications

Based on our findings, we have the following suggestions. The policymakers should investigate associated factors with high EMS requests in areas detected by spatial clustering analysis. Almost one-third of EMS dispatches were terminated due to lack of patient cooperation, a fact that needs a careful review. Rates can be reduced by actions such as reforming the laws or further training of the staff. Also, some interventions should be implemented, especially during the day-time in specified areas identified by spatio-temporal analysis. These interventions can include more restricted traffic control, public awareness and improved screening of potential applicants. In addition, there are some areas that have a higher response time despite low demand. If policy makers prioritise these cluster areas in allocating ambulance resources, lower mortality and morbidity could be achieved.

Conclusions

EMS requests in Mashhad demonstrate clear spatial and temporal gradient. Although the downtown area has seen significantly higher volume of EMS enquiries, especially in the daytime, the average EMS response times are relatively acceptable. On the other hand, some areas with a normal rate of ambulance calls have significantly longer response time. The use of GIS and spatial analyses in modelling and quantifying EMS requests enables policy makers to design tailored interventions to improve quality of service. This study can serve as a model for analysis of other public health services provided in urban areas.

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