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Analyzing Dynamics of Urban Traffic Congestion using Google Traffic Data and Map Overlay Techniques

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Abstract

In recent years, traffic congestion has changed into a common challenge for traffic engineers in urban areas particularly where population density is high, and there is a significant reliance on private vehicles.

Therefore, knowledge of how traffic congestion develops spatially and temporally, and exploring the propagating patterns, can be effective in providing appropriate solutions to reduce its negative consequences. The rapid development of information technologies and portable devices enables the collection of a large amount of traffic data, and therefore, enables the evaluation and analysis of traffic congestion in more detail.

By applying Google traffic congestion images collected during one month of study (21st January-19th February 2018), change detection analysis for morning-peak was applied to investigate and monitor the expansion of traffic congestion.

In the next step, the areas which experience congestion in 90% of times during morning peak hours have been explored using map overlay analyses.

The results of this research can help urban planners and traffic engineers for improving infrastructure, suggesting better public transportation options, strategies for congestion pricing, smart traffic management systems, and policies that encourage sustainable transportation choices.

1- Introduction

The rapid expansion of road construction and urban development led to significantly increase the number of vehicles. Although it has considerably contributed to more welfare benefits, wider communications and high-speed transition, its negative impacts upon traffic congestion in urban areas has turned into a challenging concern of urban managers.

Traffic congestion is the result of complex interactions between demand (the number of passengers making trip at a given time and place) and supply (capacity or maximum volume at a specific time or place).Such problem arises due to the lack of technologies that can attain well-organized network utilization. Most of developed countries attempted to address the problem of traffic congestion trough developing new technologies for collecting traffic data and sophisticated traffic management systems based on Intelligent Transport Systems (ITS). In return, in developing countries, no or little improvement of required transportation infrastructure along with non-conforming investments has led to inconsistencies. Such incompatibilities as well as economic losses due to the irregular fuel consumption and its relating adverse effects upon the movement of freight and passengers as along with the increased environmental pollution, traffic incidents and accidents has changed into a permanent concern of traffic engineers. Another point to note is that in case of free-flow conditions, the analyses relating to traffic congestion is relatively less complex so that by increasing the traffic flow, congestion either becomes a function of traffic characteristics such as density, volume and speed. However; when saturated or oversaturated conditions persist, the traffic situation becomes more complicated with spatial-temporal variations (e.g. during peak and non-peak hours in the area of interest). Given that, the traffic conditions are affected by several factors, which influence both demand and capacity, introducing a method to explore the dynamic pattern of congestion for further change detection analyses is essential. Such analyses can be considerably fundamental for both road users and transportation planners since travel time and its resulting indices such as traffic congestion play a critical role in the Advanced Traveler Information System (ATIS), and Advanced Traffic Management Systems (ATMS).In case the road users are provided with appropriate information in priori or en-route, their decision relating to trip making or departure time choice, travel mode and especially in some emergency cases might heavily be influenced. Such information may involve locations, traffic congestion data, alternative roads, and so on.

Review of past studies indicates the importance of congestion analyses due to its undesirable impacts on urban areas. Accordingly, traffic congestion has been analyzed from different perspectives. Some researchers attempt to explore the urban traffic congestion through developing the single indicator such as speed and travel time.(He et al., 2016; Jia et al., 2011),or multiple indicators (Bertini & Tantiyanugulchai, 2004; Bertini et al., 2002; Turochy & Smith, 2002).Several papers are concerned with prediction and estimation of traffic congestion for different time horizons (Hashemi &

different times has attracted considerable attention(Singh, 1989). Accordingly, any repeatable dataset which can provide timely, accurate and consistent information for cost- and time-efficient monitoring of changes can be considered as an appropriate alternative for change detection purposes including traffic congestion. In the meantime, multi-temporal images obtained from satellites or other sensors played a crucial role in numerous fields of applications such as urbanization (Yousif, 2015), deforestation (Achard et al., 2014), desertification (Dawelbait & Morari, 2012; Yang et al., 2005), and disaster monitoring (Bovolo & Bruzzone, 2007). The broad application in change detection can be attributed to their broad geographic coverage and availability in a wide range of spatial and temporal resolutions.

A number of change detection methods and algorithms have been developed and examined over the past decades which have focused on various aspects of the change detection processes, such as algebra methods, transformation, classification, GIS-based methods, visual analyses and time series techniques (Lu et al., 2004). Among these, GIS approach has attracted the attention of analysts due to the ability of combining multiple spatial datasets to produce new maps that incorporate information from a diversity of sources including past and current maps. The maps and image overlaying and binary masking techniques can be named as common methods employing in revealing quantitatively change dynamics in each category. Although, map overlay was first formalized in landscape planning, the idea is as old as the hills and in retrospect, it has been used in many analyses. Abdelghany, 2016; Ito & Kaneyasu, 2017; Kong et al., 2016; Sunderrajan et al., 2016). Considering the fact that traffic congestion varies over space and time and needs to be studied in the spatiotemporal dimension, dynamic clustering and congestion heterogeneity (Rempe et al., 2016; Saeedmanesh & Geroliminis, 2017; Yang et al., 2017) as long as exploring the patterns (D'Andrea & Marcelloni, 2017; Reilly et al., 2016; Wen et al., 2014; Xu et al., 2013) have been the issue of many previous research. On the other hand, when analyzing data located in proximity of each other (space or time), some common features are explored so that values of a variable in a spatial position (or time) are correlated with values of the same variable in adjacent positions (Getis, 2008). Such effects are known as spatial and temporal autocorrelation, and might violate the results obtained from conventional analyses. Additionally, the degree of variation of these effects in space (spatial heterogeneity) and time (temporal non-stationarity) is also the matter of issue. When dealing with congestion, it is evident that as a segment gets congested, the neighboring segments likely experience much congestion compared with farther ones (i.e. congestion propagates to neighboring segments). This spatial correlation of urban traffic congestion allows describing heterogeneous network as multiple relatively homogeneous and spatially connected regions (Ji et al., 2014). It must be emphasized that congestion is also strongly a time-dependent process and its spatiotemporal aspects needs to be taken into account.

Change detection which is known as the process of identifying differences in the state of objects or phenomena by observing it at from GPS-equipped devices (e.g. traffic Google Maps), also include geographic and spatial locations relating to the area of interest. Google Maps is capable of displaying both current traffic conditions and historical traffic conditions and enable spatial-temporal analyses. Traffic congestion detection is a proactive process in which, some strategies are implemented in order to tell earlier the possible advent of congestion. Congestion analyses over time contribute to understand and reveal the latent information during the process of congestion formation and dissolution. It can provide more concise and meaningful information or pattern, e.g. the start/end time, spatial related road segment and detail description of the congestion progress.

An overview of previous studies shows that specialist turned to the issue of traffic congestion from different perspectives. In the meantime, the effects of spatial heterogeneity and temporal non-stationarity and the importance of incorporating them into the process of modeling and extracting patterns have also been the matter of concern in many studies. In most studies, data relating to a limited number of segments were collected and the focus was on analyzing congestion over a limited area. Among the methods

suggested for traffic data collection, Google Maps can be considered as an appropriate technique due to the ability of displaying both current and historical traffic conditions and consequently enabling spatial-temporal analyses. The initial motivation of this research is to study the spatiotemporal changes of congested areas using

Moreover, many types of map and image overlay are possible, and it can be argued that overlay in one form or another is involved in most of the GIS operations. More description on common map overlay techniques can be seen in section 4.

The leading edge of transportation data has for long been streaming traffic data coming for a variety of sensors (loop detectors, video cameras, weather stations etc.). Traffic analyses particularly those relating to real time are generally data intensive and, therefore, directly depend on the systems and technologies available for data collection. During the recent years, the cost of new monitoring systems, the data granularity (very detailed real time information) and the availability of new sources of data, such as log sand social media data have changed. It allows the collection of large volume of spatial-temporal data, which facilitates pattern extraction and trend analyses. Advances in electronics, communications, and in particular database, as well as improving the capabilities of entering, storing, analyzing and displaying information, has led to the development of a new branch of capturing and recording data known as panel data, including time and space information. Currently a variety of sources to collect traffic data based on modern technologies and intelligent transportation systems such as personal GPS, WI-FI, tablets, and other sensors embedded in smart phones such as accelerometers, gyroscopes can be named. Video-based technologies, wireless communication infrastructures and navigation technologies have revolutionized the manner by which the analysts are convinced with data collection and data coverage. Digital images, especially images certain zones for private cars in particular hours of the day. Accordingly, two traffic zones have been introduced, namely the Odd-Even traffic zones and the restricted traffic zone (RTZ) for which, entering is monitored electronic cameras. The movement of all vehicles (except military and police vehicles, emergency vehicles and public transport and licensed vehicles) to RTZ is prohibited on Saturdays to Wednesdays from 6:30 to 17:00 and on Thursdays from 6:30 to 13:00. Entering Odd-Even traffic zones is restricted for even-numbered and odd- numbered license-plates on odd and even days.

3- Data Collection/Preparation

Traffic history data from Google Maps are available for every day of the week and provide traffic conditions at resolutions of 15 minutes. Such maps are coded with different colors which are only indicator of the amount or severity of traffic. It can be claimed that five colors appear in the historical traffic maps on Google include green, orange, red, dark red and gray. In the meantime, dark red and red are of great level of importance because they represent very poor traffic conditions in arterials and low speeds on freeways. In the next step, invalid pixel data were removed by applying screening inspection and visual procedures. Such pixels include the legend, browser extension icons logo, and other pixels relating to letters of labels on roads and places. Then, the overlay and combination analysis during 15-minute intervals were conducted.

In order to identify the road segments which frequently experience

common GIS-based change detection techniques, monitoring congestion propagation from a macroscopic perspective in Tehran the capital of Iran, and at last recognizing critical congestion segments using traffic Google Maps images captured in 15-min intervals from our study area. This can help politicians, decision makers and traffic planners strive to estimate the sustainability and efficiency of the mitigation policies applied at a wide area with high congestion levels.

2- Tehran Transportation Network

Tehran is the capital of Iran, and a metropolis with more than 8 million inhabitants which covers a wide area of 740 square kilometers surface and 10750/km^{2}population density. Tehran is known as the 25th most populous and the 27th largest city in the world. It can be named as the most important political and economic city in Iran, and due to locating countless commercial and industrial centers; many commuters are traveling to Tehran and vice versa. As a result, the daily population of Tehran exceeds more than 12 million, which along with more than 2.5 million vehicles traveling through Tehran's network will cause serious traffic congestion. On the other hand, major changes in the population, variety of land use and new urban and infrastructure development, as well as rising car usage, traffic volume and negative environment consequences, made the traffic congestion as gradually a major challenge of urban management over the past 10 years. As a result, in addition to encouraging public transportation, urban administrators prohibit or restrict access to

A. 4-1- GIS-based Change Detection and Overlay Analyses

Change detection techniques aim is to compare spatial representation of two similar locations in time by governing all variances resulting from differences in variables which are not of interest and to determine changes resulting from differences in the variables of interest (Green et al., 1994).The basic premise in using image data for change detection is that changes in the values of objects of interest will result in changes in RGB values or local textures that are separable from changes caused by other factors (e.g. the RGB combination which results the dark red in traffic Google Maps).Since digital change detection is highly influenced by many factors , and it is possible to apply almost all change detection techniques, the selection of a suitable algorithm for a given project is crucial. As mentioned earlier change detection can be conducted through several methods for which the advantages, disadvantages and the level of complexity can be provided. The advantage of using GIS is the ability to incorporate different source data into change detection applications.

Amongst the methods suggested for the application of change detection using GIS, overlay analyses has attracted the attention of analysts. Overlay analysis allows applying weights to several input layers, combining them into a single output, and subject to specifications of distribution and shape, identifying preferred locations within that result. There are several approaches for performing overlay analysis, which one to select depends on the problem needs to be addressed. Another point it needs to be congestion, chronological maps from all days in the week and at all-time intervals for one month of year (from 21st January-19th February 2018) are required. However, it seems that the congestion is not significant at times before 6:00 a.m. and after 12:00 a.m. Therefore, capturing images are limited to the 18-hour time frame between 6 a.m. and 12 a.m. each day. The geographical scale of a map changes with the resolution of the monitor and the zoom level selected to display the map and the zoom magnification will affect the type of traffic data displayed on a map. In the present study, images were captured at a zoom level of 15, a strategic choice that ensures all freeways and arterial roads within the metropolis are clearly detectable. This level of detail is crucial as it allows for the distinction between two-way roads, providing a granular view that is essential for accurate analysis and subsequent traffic management solutions. The chosen zoom level strikes a balance between a wide-enough view to encompass significant traffic pathways and the necessary detail to differentiate between road types, facilitating a comprehensive understanding of the city's traffic dynamics.

4- Methodology

In this section, the GIS-based change detection methods and overlay analyses with the concentration on the method applied in this research are investigated.

assessment of a simple mathematical function at every location on the input maps, which can be written as:

$$F(s) = \prod_{M=1}^{m} X_M(s) \tag{1}$$

In which, F(s) is the favorability assessed as a 0-1 binary value at any location (such as s) in the study area, and X_M(s) is the value at s relating to input map M, coded 1 where the cell is favorable on the factor recorded in map M, and 0 otherwise. The capital letter $\prod(n)$indicates that all input values should be multiplied together. In fact, the yes-no favorability results from a multiplication of all the 0-1 values at the same location on the input criterion maps.

Another alternative is to reduce each map layer supposed to be important to a single metric and then add up the scores to result an overall index, which is known as indexed overlay(O'Sullivan & Unwin, 2010).Accordingly, a favorability score for each location is obtained through the following equation:

$$F(s) = \sum_{M} X_M(s) \tag{2}$$

The functional form changes from multiplication to addition, but X_M remains as binary maps. The overall effect of this change is to make F an ordinal scaled variable, with M + 1 degrees of favorability from 0 (favorable/unfavorable) to M (congested/very favorable). An advantage of this approach is that it is possible to attach a weight W_M to each of the input criteria, so that the favorability changes to:

emphasized is that, the layers in analysis may not be equally important and the information relating to different layers might appear with different values. Even within a single layer, the values need to be prioritized since some values in a particular layer may be ideal for the purpose of study (for example, red and dark red pixels in traffic Google Maps which convey the highly congested areas), while others may be good, others bad, and still others unacceptable. Different methods can be named to weight multiple input layers in overlay analysis e.g. Weighted Overlay, Weighted Sum, and Fuzzy Overlay(O'Sullivan & Unwin, 2010).

B. 4-2- Boolean Overlay

In overlay analysis, it is desirable to establish the relationship of all the input factors together to identify the desirable locations that meet the goals of the model. The input layers, once weighted appropriately, can be added together in an additive weighted overlay model using the concept of a favorability function. In this combination approach, it is assumed that the more favorable the factors, the more desirable the location will be. Thus, the higher the value on the resulting output raster, the more desirable the location will be. From this point of view, the favorability of the study area for the process required is assessed using a Boolean overlay. A Boolean overlay is also, a simple logical test including yes-no nature defined such that areas are deemed either suitable or unsuitable, with no degrees of suitability in between(O'Sullivan & Unwin, 2010).It can also be regarded as the

5- RESULTS AND DISCUSSION

As mentioned in Section 4, Google traffic maps were downloaded for all weekdays for 15-min intervals during one month of year (from 21st of January-19th February) from 6:00 a.m. to 12:00 a.m. through an organized automated system. In order to reduce the amount of data, a portion of raster dataset including the freeways and arterials are extracted. Accordingly, any pixels that intersect the input template are determined. Each raster cell is then converted into point features positioning at the centers of cells that they represent. Since the input Google Maps are multiband raster, the RGB values corresponding to any cell are derived. Using RGB color model, the appropriate unique combinations which best matches the purpose of study (cells appearing in red and dark red) are determined. These items retain the parentage that was used to produce the values for the output. The weights assigned to the input images can be any value and do not need to add to a specific sum. Accordingly, the cells coding as green, orange, red and dark red are assigned the weights equal to 1, 2, 3 and 4 respectively. When adding the input images, the output values become a direct result of the addition of the multiplication of each value by the weights and the resolution of the values entered in the model is maintained.In order to assign.

5-1- Results of analyses the congestion based on multi-day averages

Traffic congestion analyses based on multi-day averages are

$$F(s) = \sum_{M} X_M w_M\,(s) \tag{3}$$

This classic approach is known as weighted linear combination(Malczewski, 2000)and the weights are also determined using numerous methods. In multi-criteria evaluation, the weights are often derived from expert opinions by a formal procedure. The flowchart of our research has been indicated in Figure 1.

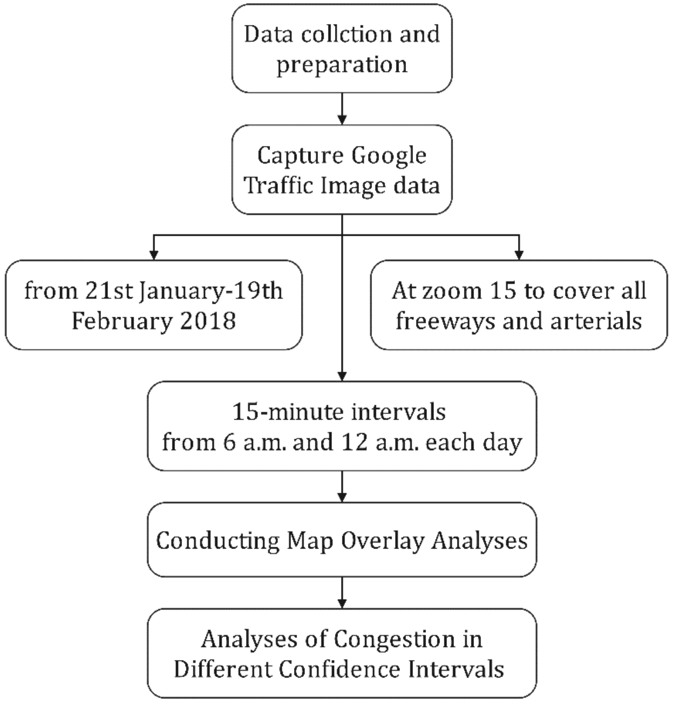
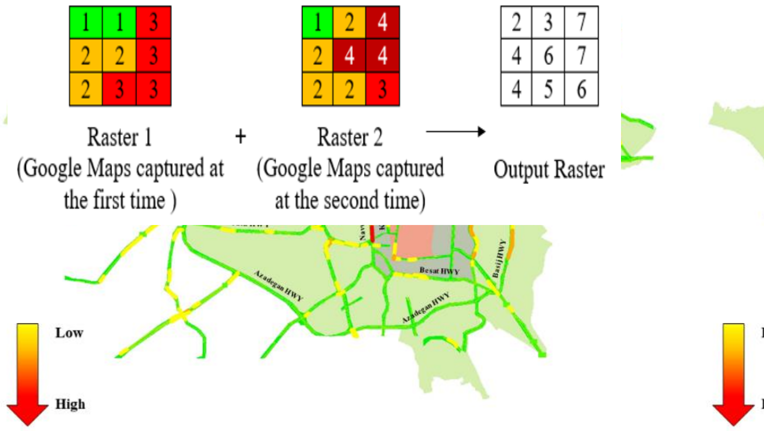


Figure 1 Flowchart of the research

conducted using weighted sum overlay which works by multiplying the designated values for each input raster by the specified weight (as defined earlier). As explained earlier, each input raster is weighted, or assigned a percentage influence, based on its importance. Then, all input raster values are summed together to create an output raster which is classified based on the level of importance such as low, medium or high .The present research, we are enthusiastic to recognize the segments appearing with higher values in output raster. A schematic overview of how the method works has been illustrated in Figure 2 for a subset of two image data corresponding to different time snapshots. As can be seen, the output raster results based on the defined procedure and consequently, the final image can be reclassified based on the relative importance of the cell values.

The results of analyses the congestion based on the level of congestion at certain time of workdays averages have been indicated in

(a)



(b)

(d)

(e)

Figure *3* and Figure 4. As explained earlier since the traffic level is updated in 15-min intervals, the results are presented for a 3-hour morning peak. As mentioned earlier, the formation and diffusion of traffic bottlenecks has been of great importance. Failure to properly identify the point formation of traffic congestion will cause it to be moved to other locations. To determine the initial location of forming traffic congestion and providing suitable solutions to the problem can prevent producing longer queues and bottlenecks in upstream of sections of interest.

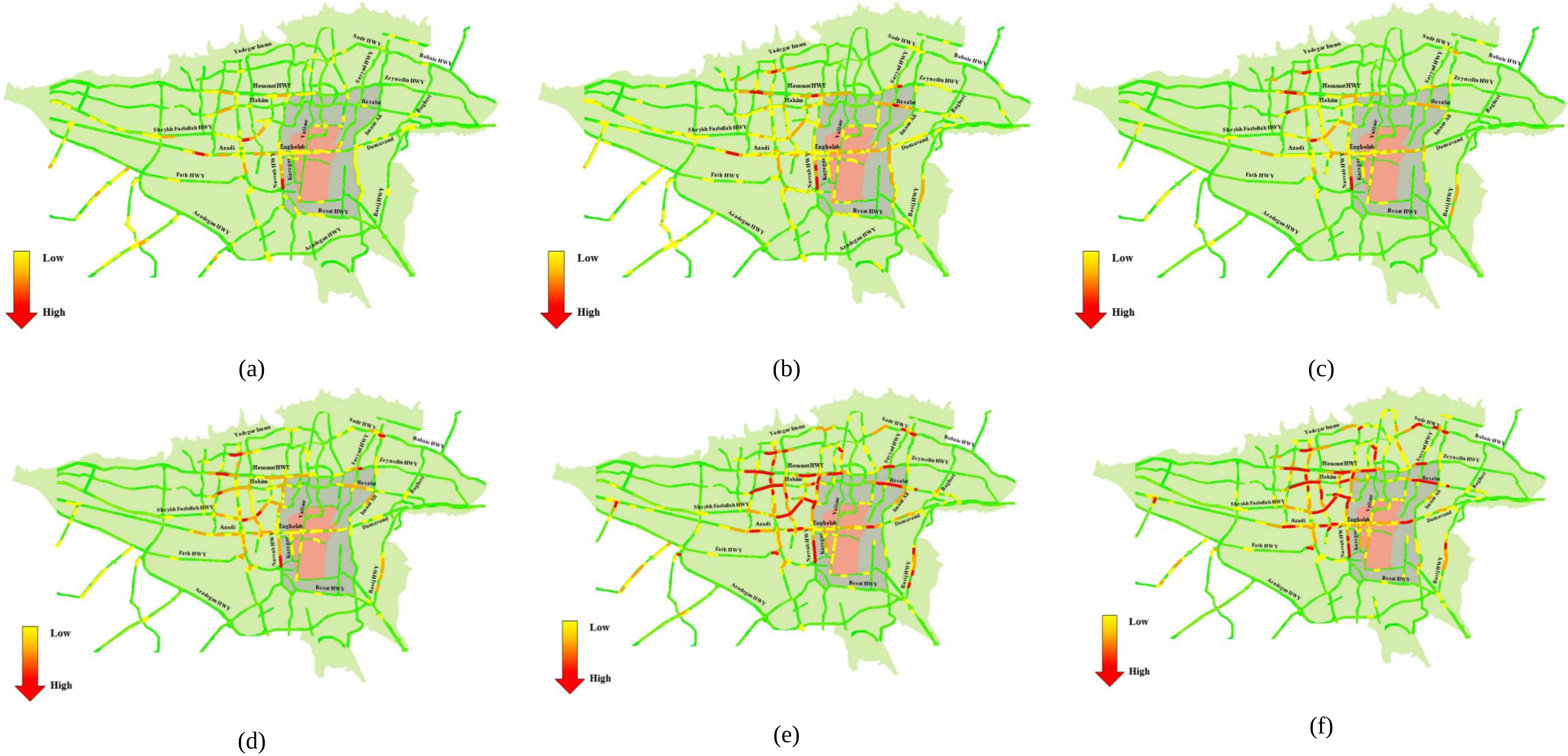
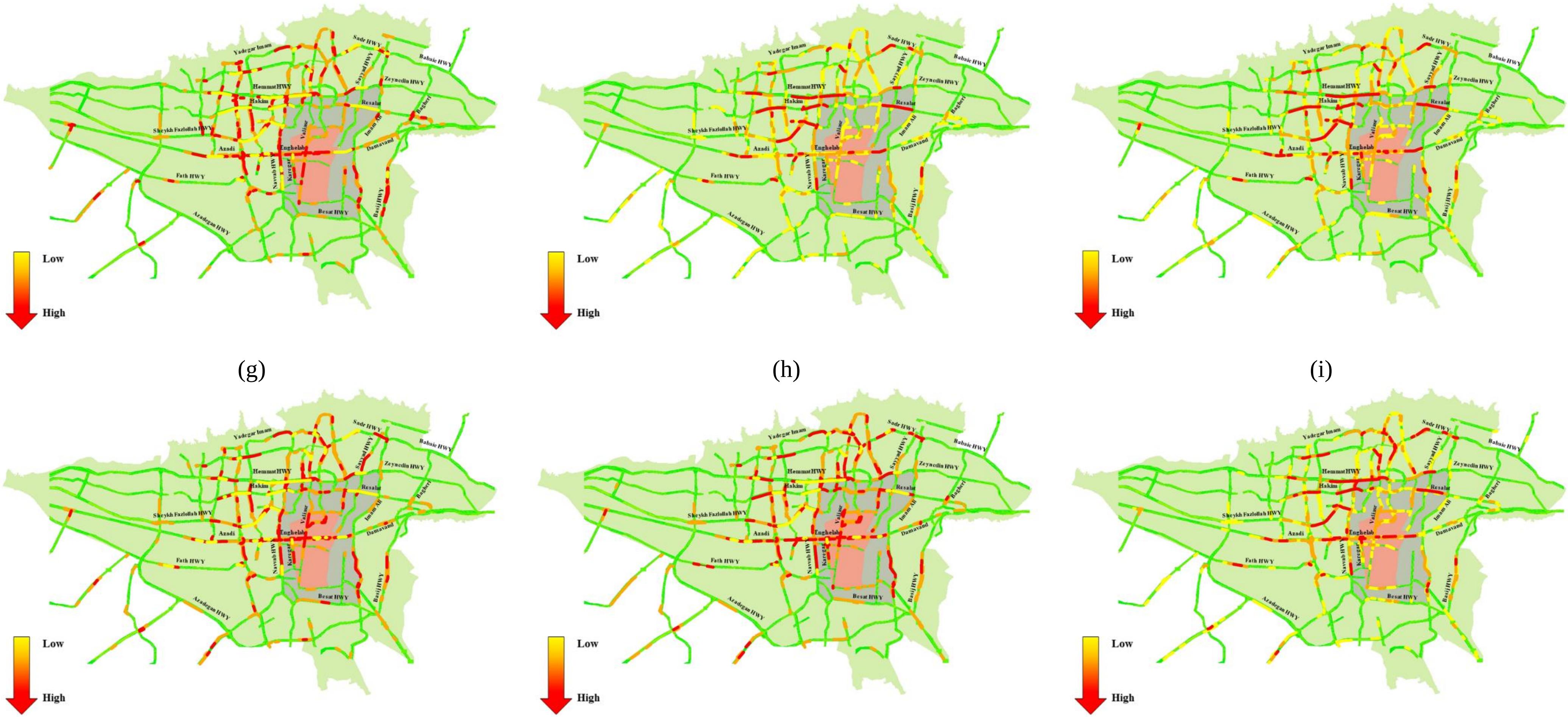


Figure 3 Results of map overlay to indicate the growing trend of congestion for the study period a) at 6:00 a.m b) at 6:15 a.m c) at 6:30 a.m d) at 6:45 a.m e) at 7:00 a.m f) at 7:15 a.m



(g) (h) (i)

(j) (k) (l)

Figure 4 Results of map overlay to indicate the growing trend of congestion for the study period g) at 7:30 a.m h) at 7:45 a.m i) at 8:00 a.m j) at 8:15 a.m k) at 8:30 a.m l) at 8:45 a.m.

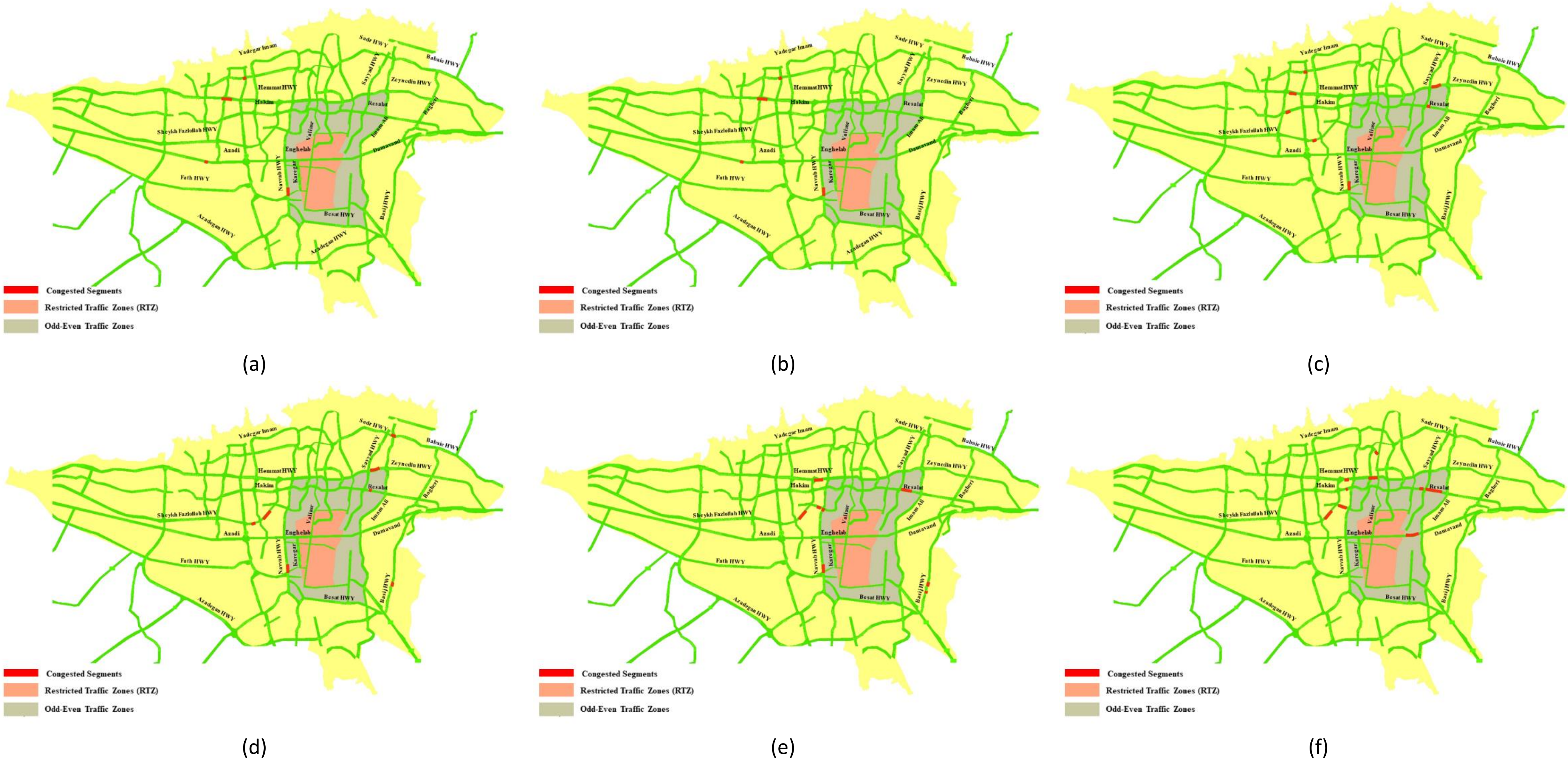
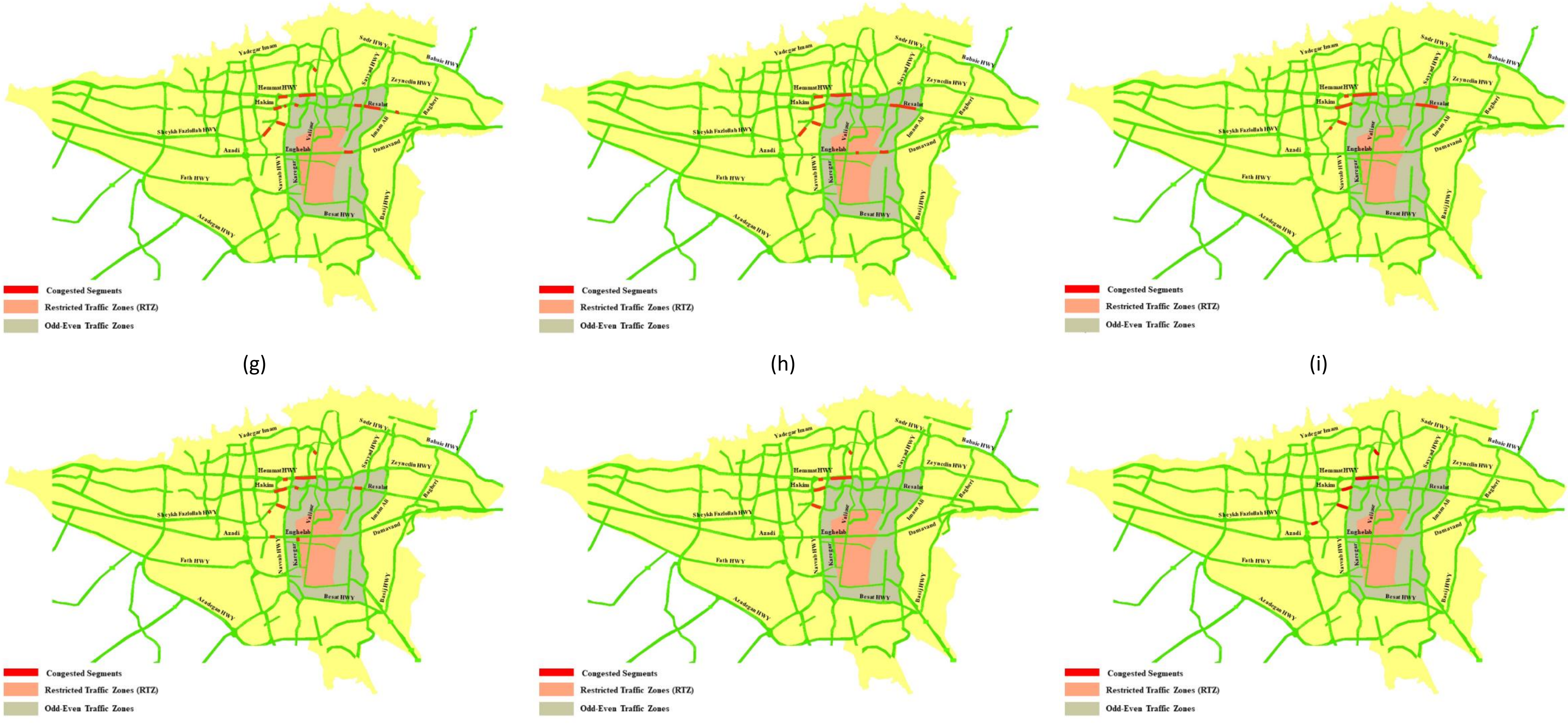


Figure 5 Areas experiencing congestion in 90% of times of workdays during the study period a) at 6:00 a.m b) at 6:15 a.m c) at 6:30 a.m d) at 6:45 a.m e) at 7:00 a.m f) at 7:15 a.m



(g) (h) (i)

(j) (k) (l)

Figure 6Areas experiencing congestion in 90% of times during the study period g) at 7:30 a.m h) at 7:45 a.m i) at 8:00 a.m j) at 8:15 a.m k) at 8:30 a.m l) at 8:45 a.m

5-2-Results of analyses the congestion in different confidence intervals

In the next step, the combine analyses were conducted in order to identify the congested and bottleneck areas for different confidence intervals. To this end, multiple input Google Maps images prepared from the previous steps were taken and a new value for each unique combination of input values in the output raster was assigned. The original cell values from each of the inputs were then recorded in the attribute table of the output raster. The names of the input Google Maps images (the time in which the map represents the congestion for a particular time in successive workdays) are respectively assigned to the field names (the maps are captured every 15 minutes). Each of these fields carries the unique input combination of values from the input Google Maps images that produces the output value. The output resulting from combination analyses relating to the example in previous section have been demonstrated in (Table 1). It is evident that considering the number of input layers, multiple combinations can be created. Given that, the number of fields and records of produced table corresponds to the number of images captured for a particular time (e.g. 6:00 a.m. of workdays) and the number of combinations generated by integrating the cell values. Since, the aim of study is to highlight the areas representing congestion during the morning peak hour; it is possible to define a query to determine the segments experiencing congestion in x% of times. The maps resulting from overlay analyses contribute to understand whether the potential ideal locations sensibly meet the criteria or not (congestion in our study). It may be beneficial not only to explore the locations identified by the model but to also investigate the second and third most preferable sites.

The congestion maps including the areas which experience congestion in 90% of times during morning peak hours have been shown using red color in Figure 5 and Figure 6. This map gives a perspective of congestion in the study area as a function of frequency of congestion occurrence during the time of study. From the map it is clear that parts of segments in Resalat, Hakim and Hemmat highways can be categorized as areas where experienced congestion in 90% of workdays. This map gives a perspective of 15-min. congestion in the city and also provides information on congestion duration. The figure shows congestion over roads near or inside restricted traffic zones (RTZ) and Odd-Even Traffic Zones.

Table 1 Illustrative example for map combination

Value	Count	In Google image 1	In Google image 2
1	1	1	1
1	1	1	2
2	0	1	3
3	0	1	4
4	0	2	1
5	2	2	2
6	0	2	3
7	1	2	4

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Depending on the study purpose, the analyses can be conducted for other confidence intervals and the areas can be evaluated and prioritized for the traffic management strategies.

Some policies which can encourage demand management, including carpooling(Nurul Habib et al., 2011), telecommuting(Mokhtarian et al., 2004), more balanced land uses (Cervero & Duncan, 2006), and flex-time (Lucas & Heady, 2002) can play a critical role in congestion situations. Demand management policies can even place driving restrictions to reduce congestion, however in the studies conducted by (Wang et al., 2014)such measures have indicated to be unsuccessful because people do not like to follow rules about where and when they can go.

Another policy with noticeable promise to alleviate congestion is shifting the price of road use. Under congested circumstances, users currently "pay" for congestion in terms of travel time and delay, but increasing the financial price of road use gives users choices about when and whether to pay to avoid congestion - either paying financially for road use during peak periods or paying in terms of adjusting the trip timing and mode of travel to avoid financial payment. But pricing designed to vary by demand and time of day, has shown to be politically unpalatable in the studies of previous researchers with some exceptions (Hensher & Bliemer, 2014; King et al., 2007; Vonk Noordegraaf et al., 2014).

6- Conclusion

Traffic congestion in urban areas is an increasingly severe problem particularly for major developing countries. To evaluate the historic and recurrent traffic congestion, it is vital to become aware of the formation and diffusion of congestion during the time of study. The quick spread of information technologies and portable devices allows gathering large scale network-wide traffic data and consequently, allows to asses and analyze congestion on a wider scale and with more details.

Map overlay analysis was applied to the city of Tehran, where the traffic situation can be investigated and monitored using a huge number of Google traffic map images. Then, the analyses of the congestion behavior of the resulting congested areas allows to recognize the times of workdays which do not behave regularly and, therefore, can be classified as congested areas. It also allows to estimate the times and duration of the congestion. It is worth noting that we conducted the analysis during morning peak hours to reveal the potential of application of the method. Needless to say, the flow direction towards a city center in the morning peak is the matter of issue, where the same roads are highly congested in the one direction and uncongested in the other. The dynamic change detection framework is capable of replicating how congestion expands or shrinks. Accordingly, it is possible to chase where congestion originates and how traffic management systems influence its formation and the time it finishes. By analyzing traffic patterns over time and space, traffic managers can optimize signal timings and provide real-time route guidance to drivers to alleviate congestion. Policymakers can use the insights gained from spatial-temporal analyses to adjust traffic policies, such as congestion pricing or vehicle restrictions during peak hours. Urban planners can also leverage the data to plan and develop transportation networks that better accommodate current and future traffic demands. On the other hand, such analyses can help identify high-risk areas for accidents, enabling targeted safety campaigns and informing the public about potential delays and alternative routes. For travelers, integrating this data into navigation apps can help in planning trips more efficiently, avoiding congested routes, and reducing travel time. By incorporating spatial-temporal traffic data into these aspects of traffic management and urban planning, cities can enhance traffic efficiency, ensure public safety, and improve overall urban mobility. Furthermore, the outputs can be used as the Advanced Information Traveler Systems to inform road users such that they can become informed of congested segments, so that they can react and take other routes change their departure drive time or even take other transportation modes. It is worth no note that Google Maps traffic data may not always have up-to-the-minute information on unusual conditions such as roads damaged by weather, blocked by street fairs, or altered by recent construction work. Therefore, although for analyses relating to current traffic management can be acceptable, for non-current traffic congestion might be applied with more caution.

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