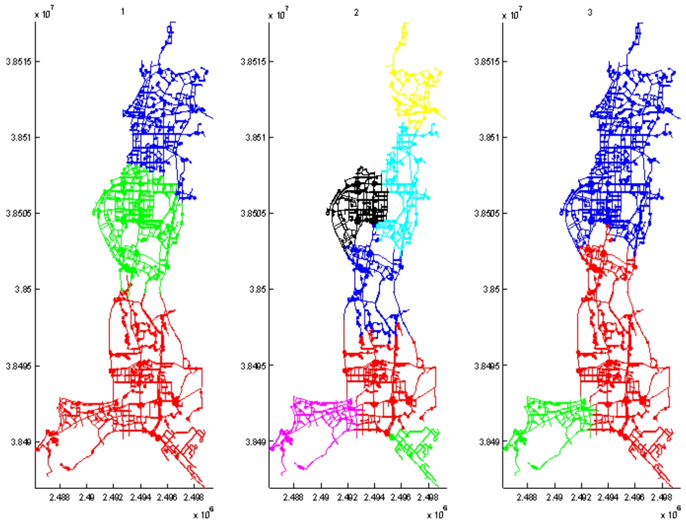

Dynamic Partitioning of Urban Transportation Networks

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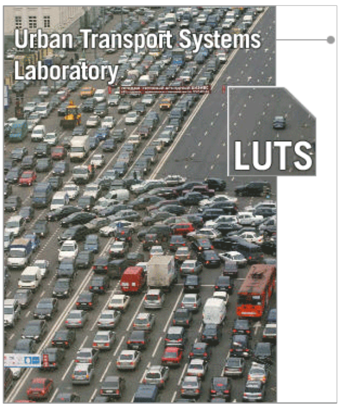

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Abstract

With increasing population and number of vehicles in large cities, traffic conditions are becoming worse nowadays with limited facility and resources in city networks, especially during the rush hours. However, the congestion formation and propagation follows the same spatial patterns every working day. This phenomenon is clearly observed in large city networks in Shenzhen China. This paper analyzes large scale GPS data in Shenzhen and proposes an effective and simple method on capturing congestion propagation in urban transportation networks based on maximum connected components. Firstly, the speed of each link is estimated by GPS data from taxi and the spatial smoothing algorithm is developed. The dynamic traffic condition of the city during the day is extracted. The congestion formation and propagation in the city can thus be visualized dynamically. Secondly, the MCC is proposed to capture the dynamics of congestion formation and propagation. The phenomenon that the congestion propagates from the city center to the outside is clearly observed in Shenzhen. Finally, algorithms are developed to identify the congestion origins in the city based on the maximum connected components. The results show that networks experience a small number of critical pockets of congestion and spatiotemporal correlations significantly influence congestion propagation.

Keywords

congestion propagation, network partitioning, maximum connected component, network structure

1 Introduction

In urban networks, the Macroscopic Fundamental Diagram (MFD) simplifies the urban traffic micro-modeling, where the collective traffic flow behaviors of subnetworks capture the main characteristics of traffic dynamics, such as the evolution of space-mean flows and densities in different regions of the network. The MFD provides a unimodal, low-scatter relationship between network vehicle density (veh/km) and network space-mean flow or outflow (veh/h) for different network regions, if congestion is roughly homogeneous in the region. Alternatively, the MFD links accumulation, defined as the number of vehicles in the region, and trip completion flow, defined as the output flow of the region. The physical model of MFD was initially proposed by Godfrey (1969) and observed with dynamic features in congested urban network in Yokohama by Geroliminis and Daganzo (2008), and investigated using empirical or simulated data by Buisson and Ladier (2009), Ji *et al.* (2010), Mazloumian *et al.* (2010), Daganzo *et al.* (2011), Zhang *et al.* (2013) and others.

Control strategies utilizing the concept of the MFD have been introduced for single-region cities in Daganzo (2007) and later a linear control approach applied for a micro-simulation environment by Keyvan-Ekbatani *et al.* (2012). These strategies provide some useful insights towards system coordination, but might not operate in an efficient manner and might be far from optimal if congestion is heterogeneously distributed or if many trips have destinations outside the area of analysis, which is the case in many congested cities. the macroscopic traffic modeling and control of a large-scale mixed transportation network consisting of a freeway and an urban network is studied recently by Geroliminis *et al.* (2012), Haddad and Geroliminis (2012).

Modeling and clustering dynamic congestion propagation based on traffic flow mechanism and vehicle behaviors has always been a difficult task, due to the high complexity of physical models and unpredictability of user behaviors. Spatial correlation and spillovers have been studied in Geroliminis and Sun (2011); Geroliminis and Skabardonis (2011). Static partitioning of networks based on traffic conditions has been proposed recently Ji and Geroliminis (2012), though the discussion on dynamic clustering and congesting propagation is limited. In this paper, we analyze GPS data from Shenzhen and propose a method for capturing congestion propagation dynamics in large urban transportation networks.

The remainder of this paper is organized as follows. Section 2 analyzes the GPS data and estimates the traffic conditions in Shenzhen. Section 3 describes the model for identifying the evolution of congestion propagation. Section 4 tracks and finds the congestion origins based on propagation results. Section 5 concludes our work.

2 Link speed estimation

In order to obtain the evolution of traffic condition during the day, we estimate the link speeds for different time intervals by using the taxi GPS data from Shenzhen China. The GPS data contains more than 20 thousands taxis. Each taxi records its location and passenger information at different time during the day, with format as: (x coordinate, y coordinate, current time, passenger exists 1 or not 0). The time interval for recording is not fixed, possibly ranging from every 1 second to hours. In total, there are around 50 million taxi records per day. In addition, we have the map information of Shenzhen which contains 10 thousand links. Based on the above information, we estimate the speed of links in Shenzhen during different time intervals. Due to the large amount of data and high noise, the data was firstly cleaned up based on hardware fault such as GPS or timer breaking down. Secondly, the speed is estimated based on each passenger trip less than 5 minutes, and longer trips segmented into smaller pieces for the purpose of more accurate estimation. Finally, all the estimated taxi speeds are integrated and projected to the corresponding link speeds. With these efforts, the traffic condition can be clearly observed in Shenzhen. Particularly we hightlight the evolution of traffic conditions in the upper side of Shenzhen during the morning rush hours between 6am and 8am. Specifically for each link , average speed during a 15-minute interval is estimated and the time step is 5 minutes. Thus we obtain 24 time slices during these two hours. The histograms of the link speed distribution are shown in Figure 1. It is observed clearly that the histogram of speed distribution moves leftwards as time passes, indicating that the average speed of the city decreases gradually during the rush hours.

3 Congestion Propagation modeling

Based on the link speed profiles obtained, we identify the congested links with speed less than 1/3 of the maximum speed and construct the connected components for the congested links. A connected component in a graph has the property that in this component (i.e., a set of vertices and edges), each vertex is reachable from any other vertex by following a path between them. In addition, no more vertices or edges can be added into this component without breaking this property. Thus the maximum connected component means the one with the maximum size among all the connected components. We find the maximum 6 connected components of the congested links during all the time slices and show them in Figure 2. We can see clearly that the maximum connected component (red) of the congested links grows and merges with other components as time passes. Thus the maximum connected component can easily and effectively help us identify the congestion propagation.

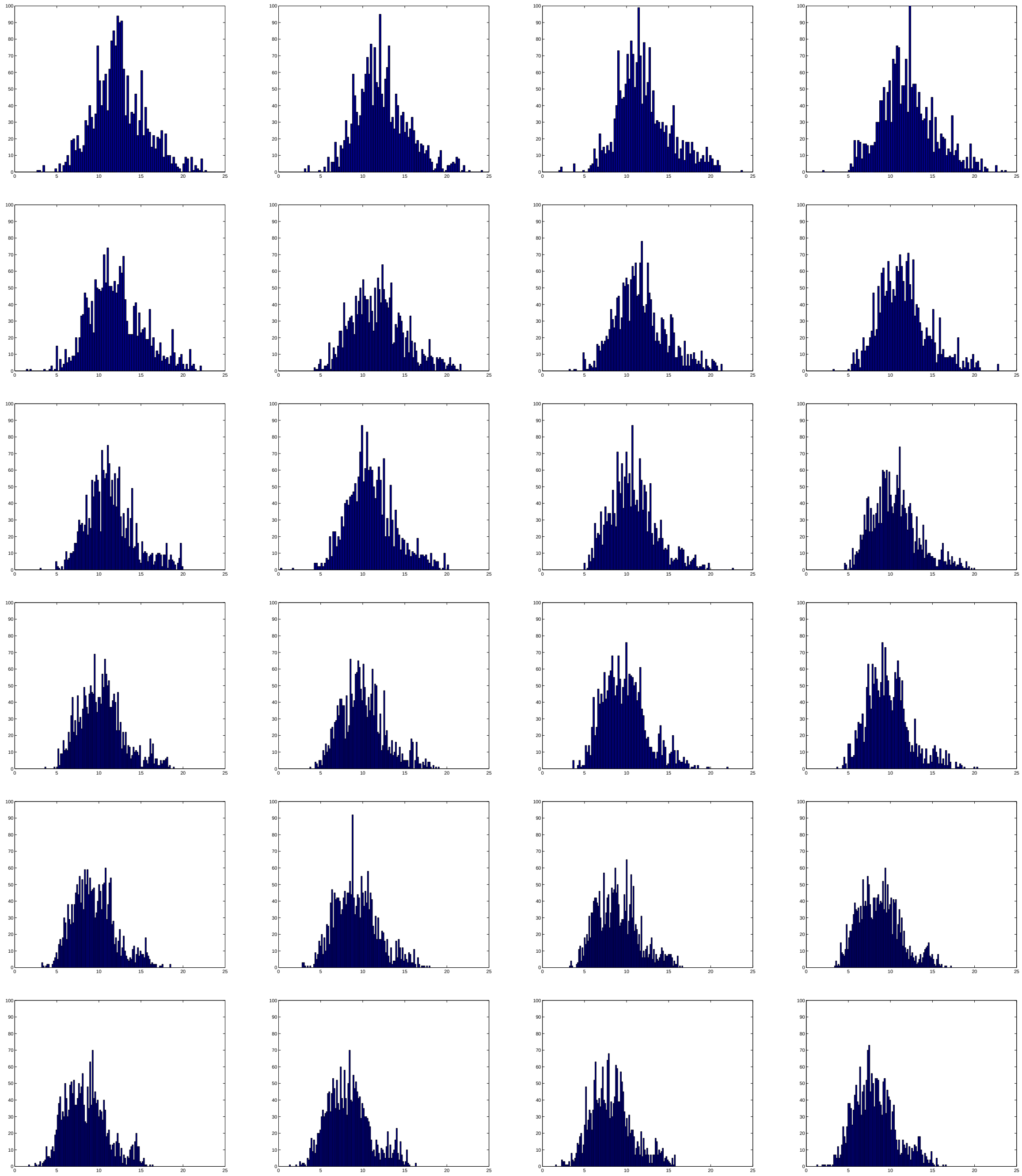

Figure 1: Link speed distribution from 6am to 8am

4 Congestion origin tracking

With the connected components, we can track and find the congestion origins in the city. We first start in the end by finding the maximum connected component at 8am and marking it as the congestion center. Then we find among all the components at the time slice before (i.e., 7:55am) the component that has the maximum overlap of congested links with the maximum connected component at 8am. This component found is marked as the new congestion center. This process is repeated recursively backwards until the beginning at 6am. Then the origin

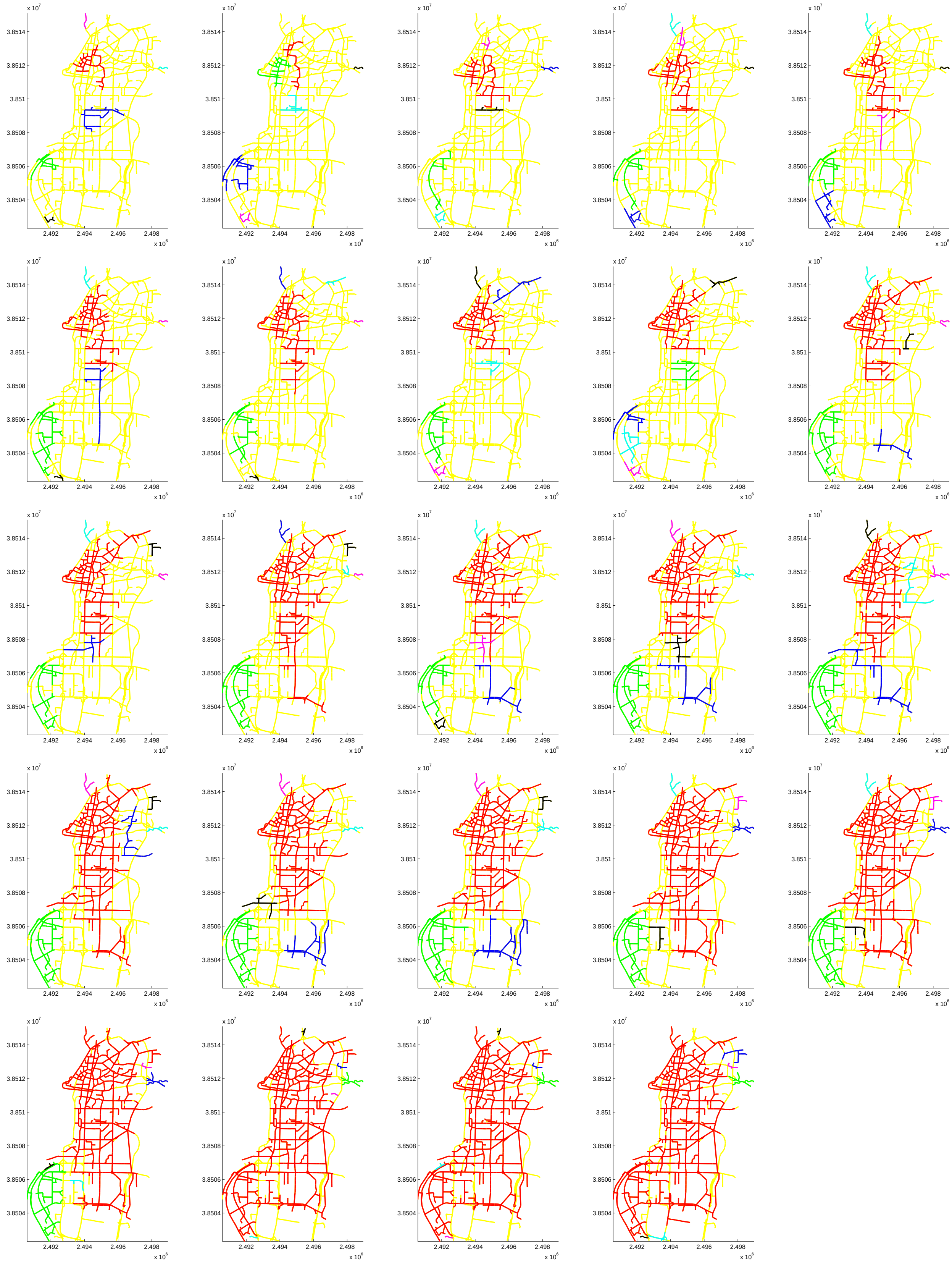

Figure 2: Evolution of maximum connected components of congested links from 6am-8am

of the congestion center can be identified. The algorithm is described as follows. Figure 3 shows the maximum two congestion origins tracked by this procedure. Note that the congestion origins obtained are not necessarily the maximum two connected components during all time slices.

1. Identify the maximum connected component in the last time period t, and mark it as congestion origin, CO_t
2. Find in the time period at $t-1$ the component that has maximum overlap with CO_t and mark it as CO_{t-1}
3. Repeat the second step for $t-2$, $t-3$, $\ldots$, 1, and find the origin at $t=1$.

5 Conclusions

Modeling traffic and congestion propagation has been a difficult task. In this paper, based on GPS data from a large Chinese city Shenzhen, we proposed an effective and simple method, the maximum connected component of congested links, for observing and identifying congestion propagation in large networks. The evolution of congestion propagation can be clearly observed. In addition, the congestion origins are easily identified. The results show that networks experience a small number of critical pockets of congestion and spatiotemporal correlations significantly influence congestion propagation. Currently, we are working on evaluating the dynamic partitioning of the network based on congestion propagation.

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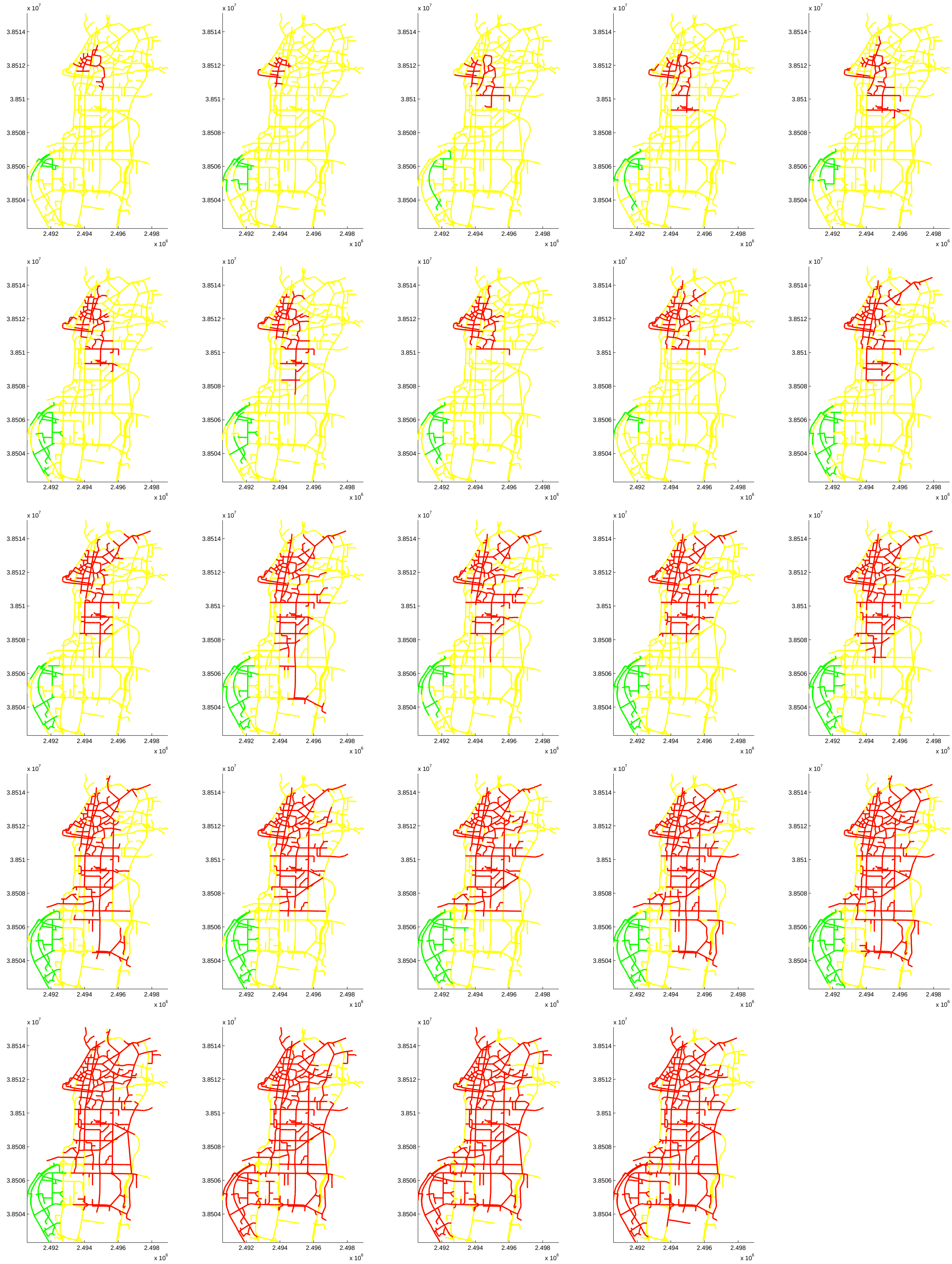

Figure 3: Congestion origins and propagation of congestion from 6am-8am

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