



Change of Scene: The Geographic Dynamics of Resilience to Vehicular Accidents

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Abstract

Most have experienced the impact of vehicular accidents, whether it was in terms of increased commute time, delays in receiving goods, higher insurance premiums, elevated costs of services, or simply absorbing the daily tragedies on the evening news. While accidents are common, the complexity and dynamics of transportation systems can make it challenging to infer where and when incidents may occur, a critical component in planning for where to position resources for emergency response. The use of response resources is critical given that more efficient emergency responses to accidents can decrease the vulnerability of socio-economic systems to perturbations in the transportation system and contribute to greater resilience. To explore the resilience of transportation systems to disruptions due to vehicular accidents, a location modeling approach is described for identifying the origins of optimal responses (and associated response time) over time based upon the location of known accidents and response protocols. The characteristics of the modeled response can then be compared with those of the observed response to gain insights as to how resilience may change over time for different portions of the transportation system. The change in the location of the optimal sites over time or drift, can also be assessed to better understand how changes in the spatial distribution of accidents can affect the nature of the response and system resiliency. The developed approach is applied to investigate the dynamics of accident response and network resiliency over a three year period using vehicular crash information from a comprehensive statewide database.

Keywords Network modeling · Emergency response · Vulnerability · Infrastructure planning

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1 Introduction

Modern society is hugely dependent on the availability of networked infrastructures, such as those facilitating the movement of people, freight, energy and data, with the performance of these systems directly associated with an array of social, economic, and environmental costs. As such, the vulnerability of networks to events that can potentially degrade performance and increase costs is of particular planning concern. In this respect, greater resiliency to disruptive events is a desirable characteristic of a system. Resilience has been conceptualized in a variety of ways, but in general refers to the ability of a system to maintain an acceptable level of performance in light of disruptive activities, whether by resisting change and/or by returning to a suitable state (either prior or new) (Modica and Reggiani 2015; Reggiani et al. 2002). While higher system resiliency is advantageous, providing the mechanisms whereby which resiliency can be enhanced is a resource intensive task, as is examined in this article with respect to transportation systems.

Like other complex networks, transportation systems have an array of vulnerabilities related to factors such as their topology, use, interdependency, physical and operational condition, and potential threats that can vary greatly over space and time (Grubescic and Matisziw 2013; Matisziw et al. 2012a; Matisziw et al. 2007). Vehicular crashes are common sources of disruption to transportation systems, whose impacts often transcend many vulnerabilities, contributing to a range of social and economic costs. As most vehicular crashes involve damage to personal, private or public property, assistance with navigating legal, medical, safety, traffic, repair, and other issues that can emerge is often needed. Timely emergency response to such events is therefore essential to mitigate their impacts, assist with system recovery, foster a greater sense of social security, and to increase the overall resiliency of the transportation system and all of the other socio-economic systems to which it is tied (Klimek et al. 2019). Resilience in this sense depends in part on the way in which resources for responses are utilized as well as the adaptability of individual responders to changing conditions (Comes 2016).

Given that provision of emergency response services involves a tremendous investment in resources, ensuring that resources are used as effectively and efficiently as possible are priorities of the agencies/entities charged with maintaining those services as well as the individuals whom they support (Engel and Eck 2015). Though there have been a variety of metrics proposed for assessing effectiveness and efficiency of response services, the response time required for emergency personnel to arrive at the scene for a call for assistance has long been used as a measure of service performance in this respect (Pate et al. 1976; Stevens et al. 1980). The time involved in responding to emergencies depends on numerous factors. Given the geographic difference between the location of an incident and that of the responder, response time can be directly influenced by the availability of a responder, dispatch time, as well as travel speed and distance (Pate et al. 1976). Other factors such as such as time of day, location of the crash with respect to the lanes of traffic, and number of vehicles involved are also thought to have a notable effect on response times (Lee and Fazio 2005). However, the actual resources available for emergency response and the policies underlying their use (e.g., policies for response prioritization) are also known to exert a considerable influence on response times (Levine and McEwen 1985). For instance,

responses to crashes involving injuries may be prioritized over non-injury crashes (Lee and Fazio 2005).

As vehicular accidents are relatively commonplace, spatial and temporal patterns of crash activity often become discernable to those familiar with a region. Therefore, emergency responders are increasingly able to leverage their experiences with their regions of responsibility to better position themselves for more effective response to potential events (e.g., hot spot policing (Braga et al. 2019)). However, the spatial and temporal distribution of crashes is known to vary considerably as likely do the factors underlying the events. These instabilities in the spatial and temporal dimensions of crash incidence can lead to problems in the application of many statistical approaches to accident prediction (Mannering 2018). Those tasked with planning for and implementing emergency response are likely affected by these instabilities as well in their efforts to enhance system resilience. To this end, this research examines the extent to which resilience of a transportation system changes with respect to geographic distribution of accidents over time through an analysis of accident responses recorded by law enforcement. First, background literature related to the spatiotemporal dimensions of vehicular crashes is examined as are analysis techniques that have been applied to evaluate the dimensions of emergency response. Next, a methodology for assessing spatiotemporal variations in resilience to accidents in transportation systems is outlined. Based upon an extensive set of crash records, the analysis methodology is then applied to evaluate the geospatial dynamics of system resilience to accidents over time.

2 Background

Implementation and maintenance of emergency response services is extremely costly, especially in applications where demand (emergencies) is distributed over a large geographic area. Should the need for emergency response arise, the general societal expectation is that it be provided in a timely fashion to maximize effectiveness. As such, a common approach for providing emergency services is to partition regions into beats or zones to which emergency responders are assigned (Levine and McEwen 1985). Responses to calls for service may involve dispatching personnel from their current location, be it from a central facility (i.e., headquarters) or from another location in the transportation system. In the case of emergency fire and medical services, responses typically originate from fixed facilities, with a primary focus on incidents within a defined service area. Some types of emergency responders, such as law enforcement personnel, are tasked with a range of responsibilities, often patrolling a service zone and launching responses from their location at the time a call is received. Therefore, along with the uncertainties associated with the locations at which a response will be needed, there is also uncertainty as to where a responder will be located at any point in time.

The geographical characteristics of emergency response zones can differ considerably over a region and understanding where, when and to what extent the characteristics of these zones may influence response to accidents is important. To this end, there have been efforts to explore changes in the geographic distribution of crashes over time visually (Moellerling 1976) as well as analytically (Li et al. 2007) in order to better understand when and where certain types of crashes may occur. The extent to which

spatial associations among crashes may exist has also been examined through assessments of spatial autocorrelation (Black and Thomas 2002; Eckley and Curtin 2013; Flahaut et al. 2003; Kingham et al. 2011) and other measures of spatial dependency and clustering (Warden et al. 2011; Yamada and Thill 2004, 2007).

There have been some attempts to model how changes in resources could facilitate responses to vehicular incidents when considering dedicated response services such as freeway service patrols (Li and Walton 2013; Lou et al. 2011; Sun and Wang 2018; Wu and Lou 2014). However, regular law enforcement activities, such as local and state-level policing efforts, involve a range of daily duties beyond responding to crashes, such as monitoring for adherence to laws and regulations, addressing crimes, traffic management, promoting transportation safety, responding to requests for assistance, as well as providing many other public services. Responding to vehicular crashes while an important goal, is therefore not the only consideration in decisions underlying the positioning of resources within a transportation system at any given point in time (Lee et al. 1979; Levine and McEwen 1985). Further, unlike other emergency responders, law enforcement personnel typically respond to crashes of any type, injury or not. Therefore, the need to prioritize the response to one incident over another may arise, leading to response times that may not reflect the realities of resource utilization. In light of all of these issues, inferring the resiliency of the transportation system to accidents simply based on reported response times is extremely difficult.

Evaluation of the spatiotemporal dynamics of transportation system resiliency to vehicular crashes has received much less attention in the literature though. One reason for this is that it is more challenging to interpret the efficiency of law enforcement response to a crash given the range of duties with which they are charged. Further, it is difficult to document what proactive measures may have been utilized in planning for the need to respond to a crash (Lum et al. 2020). However, as mentioned earlier, resilience relates in part to the effectiveness of resource utilization. One way of reasoning about the dynamics of a system is to compare its observed form with that modeled to address specific planning criterion (Matisziw et al. 2012b). For instance, one could compare the performance of actual emergency responses relative to that of those modeled from optimally sited locations to assess system resilience. In this respect, a variety of models have been proposed to assist planners with decisions regarding where to best locate resources for emergency response provided knowledge about where the need for service might exist in the future. Three general types of models that have been used to identify optimal sites for emergency services are the location set covering problem (LSCP), the maximal covering location problem (MCLP) and the p -Median Problem. The LSCP minimizes the cost of siting service facilities given that all demand locations must be within the service area of a sited facility. For example, Erdemir et al. (2010) describe a LSCP approach for determining the minimum cost required to site several different types of ambulance response units to ensure crashes are within the effective service range of each type of response unit. The MCLP seeks to maximize the amount of demand that is within the service area of a specific number of sited facilities. For example, Curtin et al. (2010) formulate a MCLP model to site a specified number dispatch stations from which a known set of incidents are within an effective response distance. Murray and Tong (2009) describe how both LSCP and MCLP approaches could be utilized in identifying the number of fire stations that would be required given other considerations such as thresholds on response times and

cooperation (or lack thereof) between planning regions. p -median problems seek to minimize the total cost of serving demand locations from a set of p facilities (ReVelle and Swain 1970). In the context of emergency response, Zhu et al. (2014) formulate a p -median type problem to site response units such that expected response time is minimized. Unlike coverage models, p -median problems allow for demand to be served from a facility regardless of the cost. This is important in the context of responding to incidents such as vehicular accidents given that a set service time/distance threshold may not reflect the realities of the response area. Thus, if responders had perfect knowledge of where crashes will occur in a particular timeframe, the median(s) would represent the location(s) from which response times to those incidents would be minimized, the most efficient location(s) from which responses could be launched.

Response time is one of the more commonly used indicators of performance for emergency responders (Levine and McEwen 1985). As such, observed response times are likely reflective of the need to minimize response time. Determining locations from which response times to incidents are optimal would require knowledge of when and where incidents will occur, the service zones within which responders will be dispatched, as well as the characteristics of the transportation system within the service zones. Provided the locations from which response times to incidents occurring in a time frame could be minimized, the total (or average) response time from an optimal location(s) could be compared with the total (or average) observed response time. Thus, in cases where observed response times are found to be very close to those modeled from an optimal location, the spatiotemporal dynamics of system resilience could be viewed as exhibiting greater stability. In cases where the observed and modeled response times are very different, the spatiotemporal distribution of crashes could be viewed as more dynamic, less predictable, contributing to lower resilience. Based upon these considerations, a methodology for comparing characteristics of optimal responses with those of actual responses to better characterize the resilience of a transportation system to vehicular accidents is now described. The methodology is then applied to evaluate the dynamics of law enforcement response to vehicular crashes over a three year period.

3 Methods

As mentioned earlier, one way to approximate the extent to which law enforcement personnel might adjust to changes in the regional distribution of activities to which they are tasked, is to compare their actual response times to incidents to response times modeled from an optimal central location to the same set of incidents. For any service zone, given knowledge of the response times to incidents occurring in a particular timeframe, the total observed response time can be easily summarized. For any service zone, given knowledge of the location of incidents occurring in a particular timeframe, the network 1-median (referred to as the network median from here on) can be used to represent an optimal location from which responses to those incidents could have been launched as is now formalized.

Consider a network G_t with N_t nodes and A_t arcs ($G_t(N_t, A_t)$) in time period $t \in T$ in which the set of incidents i occurring in time t are incorporated as nodes $i \in N_t$. Each node has a weight ($a_i \geq 0$) representing its relative demand for service. For example, node weights may be based upon characteristics of incidents at that node such as

number of incidents, number of vehicles involved, seriousness of the incident, etc. Likewise, nodes at which no incident is observed could be assigned a weight of 0.0. Arcs $k \in A_t$ are attributed with travel time (c_k) based on presumed network conditions and responder travel behavior. The network is partitioned into service zones $z \in Z$, within which each a single response site should be selected. Provided node-based demand in a network, it is known that the median location will correspond with that of a network node (Hakimi 1964). Thus, for any service zone z , the network nodes in that zone $i, j \in V_{zt} \in N_t$ can be considered as locations in need of a response as well as candidate sites from which a response could be launched. The minimum response time involved in serving demand i from any response node j (δ_{ij}) can then be calculated based on the modeled network conditions. The network median problem can then be expressed as follows to illustrate the decision making process for any service zone z in time period t .

$$\text{Minimize } \Omega_{zt} = \sum_{i \in V_{zt}, j \in V_{zt}} a_i \delta_{ij} x_{ij} \quad (1)$$

$$\sum_{j \in V_{zt}} x_{ij} = 1 \quad \forall i \in V_{zt} \quad (2)$$

$$\sum_{j \in V_{zt}} x_{jj} = 1 \quad (3)$$

$$x_{ij} \geq x_{jj} \quad \forall i, j \in V_{zt} \quad (4)$$

$$x_{ij} \in \{1, 0\} \quad \forall i, j \in V_{zt} \quad (5)$$

Objective (1) minimizes the total cost of responding to the incidents at nodes i from nodes j in a service district z in time period t . The decision to be made (x_{ij}) is to either respond ($x_{ij} = 1.0$) or not respond ($x_{ij} = 0.0$) to demand at i from response site j . Constraint (2) ensures that incidents at each node are served by a single response site. Constraint (3) states that one of the nodes be selected as the site from which the responses are to be launched. Constraints (4) state that a response cannot be launched from a node unless it has been selected as the response site. Constraints (5) ensure that the decision variables are binary and integer. Given only one node is to be selected as the response site, for each node, the total demand weighted cost of responding to all other nodes can be easily calculated to assess how well it would serve as the response site. The network median (and total cost of the associated response) can then be identified as the node with the lowest total demand weighted cost.

As an example, Fig. 1 illustrates a service zone containing 5363 network nodes, 31 of which represent the reported location of an incident warranting a response. Almost half of the incidents are located along the major highway traversing the lower portion of the zone with a majority of the remainder being located to the North/Northeast of the highway. The network median reflects the node from which the cost of responding to these incidents would be minimized.

Once the network median is found, the total demand weighted response time associated with responding to incidents from the median location can be compared with the actual response times observed for the same set of incidents. If a large relative difference between the modeled response time to the median and the actual response time is realized, then the response could be viewed as one in which resilience was in a degraded state. Larger relative differences between the actual and modeled response time to the incidents could point to a need for additional resources (e.g., planning, responders, etc.) for incident response in a region. Likewise, should small relative

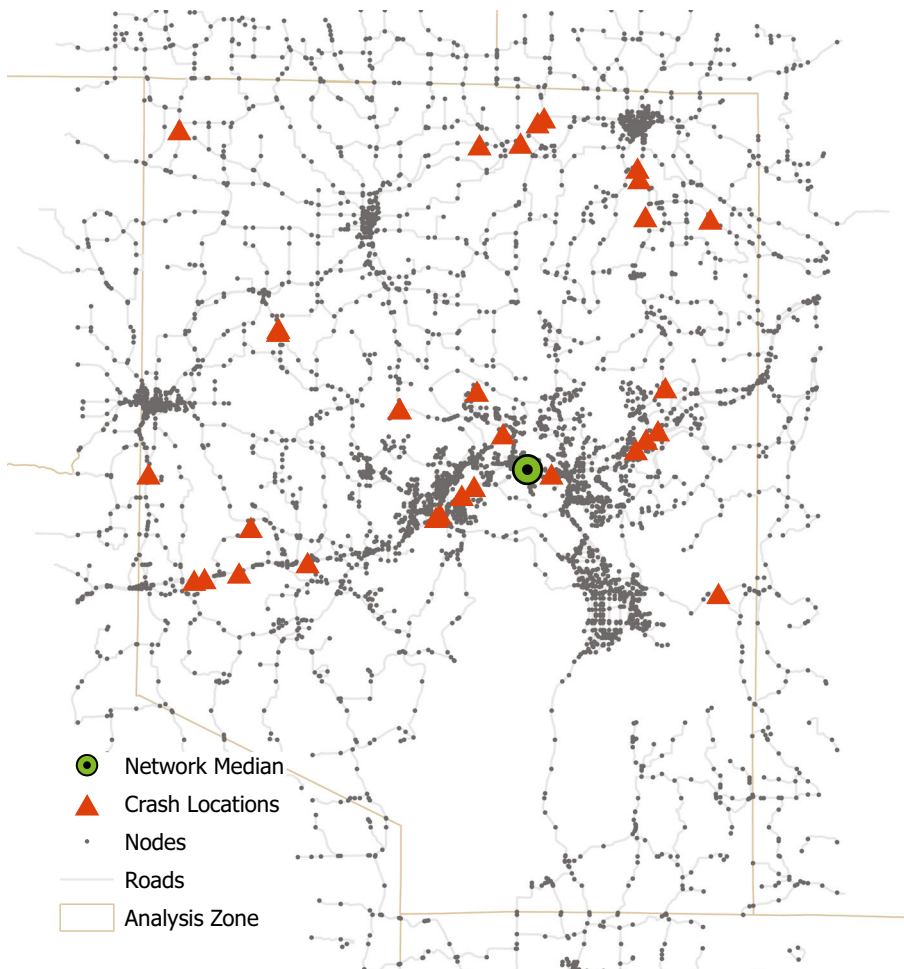


Fig. 1 Example network median

differences exist between the modeled response time from the median and the actual response time, the response could be interpreted as more efficient, offering a greater level of resilience.

The optimized response times can be compared with the actual response times over a series of time periods for each service zone to explore how resilience may vary over space and time. Further, the geographic movement of the median locations for service zones over time can be evaluated to assess the extent to which an optimal response location may change over time. This is analogous to the concept of measuring the “migration drift” of populations by tracking changes in the location of population mean centers over time (Plane and Rogerson 2015). As in Plane and Rogerson (2015), the distance between temporally sequential pairs of median locations can be used as a measure of their movement or drift. For instance, the geographic distance between the median location for incidents occurring in January and the median location of incidents in February can be computed. In this sense, for any service zone, a large amount of geographic drift over a set of time periods could indicate greater uncertainty as to where and when responders should be positioned to ensure efficient responses. Should the network medians exhibit less geographic drift over a period of time, a more consistent pattern of incidents may have been realized, one to which responders were able to better adapt.

4 State Highway Patrol Response to Vehicular Crashes

In order to explore the resilience of a transportation system to vehicular crashes, crash locations and associated response times in the state of Missouri (MO), United States (US) recorded by the Missouri State Highway Patrol (MSHP) are analyzed. The MSHP is a statewide police force responsible for public safety and law enforcement activity on Missouri’s highways (Revised Statutes of Missouri 1983). Responding to events on highways in Missouri is no small task given that there are nearly 64 k miles of Interstate, US, State and other highways in the state. Responsibility for MSHP activities is split among nine regional districts, referred to as Troops, each comprised of a number of smaller patrol zones (Fig. 2) within which officers (troopers) are assigned to conduct law enforcement and emergency response activities. In most cases, these zones conform to individual counties or in some cases pairs of adjacent counties, depending on the distribution of population and vehicular activity. Within the state, there are 78 patrol zones, which range in size from 283 sq. miles to nearly 1600 sq. miles. In most cases, at least one trooper is assigned to a patrol zone at any given time.

The MSHP utilizes an electronic crash reporting system called STARS (Statewide Traffic Accident Records System) (STARS 2019). Information about vehicular incidents, such as response times and incident locations, handled by the MSHP are entered electronically (and in some cases automatically). In many cases, urban areas having their own local police forces do not require the assistance of the MSHP in responding to incidents within their immediate jurisdiction. However, given increasing financial burdens on law enforcement agencies, the MSHP is increasingly asked to respond to crashes in areas where the local law enforcement capabilities are insufficient to meet the local demand. While local emergency responders are most often dispatched to

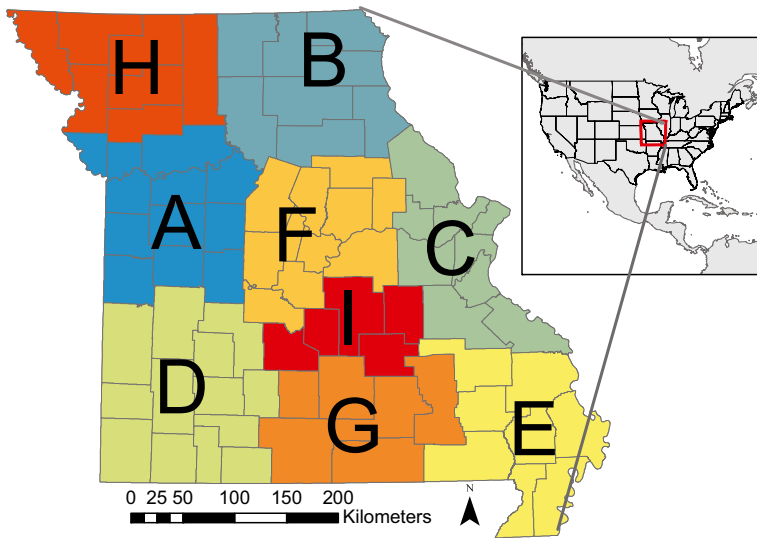


Fig. 2 MSHP regional Troop districts and patrol zones

vehicular crashes in urban areas, the MSHP responds to over 90% of all accidents on Interstate, US and State highways/routes in Missouri.

The MSHP documented 104,113 crashes occurring in the years 2015–2017. Approximately, 24% of the crashes are associated with Interstate highways, 15% with US highways, and 41% with State routes (numbered and lettered routes). Only a small proportion of the crashes reported by the MSHP were on smaller county roads (e.g., unpaved gravel) or city streets. Crashes were recorded every day in the three year period. Statewide on a daily basis, an average of 95 crashes were reported, with a minimum of 37 (some zones not reporting any crashes), and a maximum of 698 crashes per day (some zones reporting multiple crashes). Over the three years of reported data, nearly 57% of crashes were associated with clear weather conditions while cloudy conditions were associated with 23%. Precipitation was only associated with 10% of the reported crashes. Likewise, road conditions were reported to be dry in 77% of the crashes with wet road conditions reported in only 16% of the crashes. Top causes of crashes investigated during this period include vehicle overturning (6%), incidents involving animals (9%), collision with fixed objects (38%), and incidents involving other motor vehicles (41%).

The date and time of each crash incident is recorded in the STARS database as are response times rounded to the nearest minute. The reported response time reflects the difference between the time at which the crash occurred and the time at which a trooper arrived at the crash scene. Out of the 104,113 incidents, 8.8% did not have a reported response time. Unreported response times are largely associated with minor accidents for which an on-scene investigation was not conducted (e.g., collision with an animal). In such instances, the crash might have been reported later for insurance purposes, not necessitating a trooper visiting the scene. Approximately 0.28% of the crashes had response times greater than 24 h. Reasons for these extremely long response times are typically due to delayed reporting of a crash. For example, those involved in a crash may leave the scene, and then return the following day to report the crash. Fortunately, large

response times are not the norm and 90.7% of crashes had a response time of less than or equal to 250 min (4.1 h). The following analysis first examines crashes occurring within the 78 patrol zones that were visited by law enforcement with a reported response time of less than or equal to 250 min given that they could account for the possibility of higher response times due to periods of congestion, multiple accidents, difficult travel conditions, etc., but avoid incidents with response times likely due to very anomalous events. 94,144 (90.4%) of the crash records met this criteria, with a mean response time of 17.7 min (Fig. 3a). Aside from consideration of all crashes in the analysis of response times, variations in response time may vary for different categories of crashes, such as those involving injury (Lee and Fazio 2005). As such, a subset of the crash records, those in which personal injury was reported, are analyzed separately. There were 29,648 such crashes to which the MSHP responded over the three years, constituted approximately 28.5% of the records in the crash database (Fig. 3b).

A geospatially referenced vector dataset representing roads in the state of Missouri was used to represent the location of supporting infrastructure. Travel time (in minutes) was computed for each road segment based upon the posted speed limit and the assumption that responders could safely travel at slightly higher speeds (e.g., 1.1 times the posted speed limit). Using travel time as a measure of impedance, a network was built from the road dataset, consisting of 474,065 nodes and 1,131,647 arcs.

The records for the 94,144 crashes of all types (injury and non-injury), were first classified into 36, one month analysis periods (e.g., January 2015,..., December 2017). Over the set of analysis periods, there were an average of 34 crashes per month, per zone (min = 4, max = 151). For each of the 78 patrol zones, the average reported response time for crashes occurring in each of the 36 months was then calculated. To model an idealized average response time for each zone in an analysis period, the crashes occurring in that time period were added as nodes (with a weight equal to the number of crashes at the node) to the network, representing the locations needing assistance and all network nodes within the patrol zone were then considered candidate sites for the optimal response site. On average, there were 10,347 network nodes in each patrol zone (min = 3936, max = 45,521) over the 36 analysis periods. The network median (and associated modeled response time) for crashes of all types occurring in each of the 36 monthly analysis periods was identified for each of the 78 patrol zones (i.e., 36 medians for each zone, 2808 network medians in total) through enumeration as described earlier. The same process described above for all crashes was then repeated for the 29,648 crashes in which personal injury was reported. There were an average of 11 such crashes per month, per zone (min = 0, max = 47), yielding another 2800 network medians (no crashes involving an injury were investigated in 8 zone/months analyses). Finally, in order to measure geographic drift among the median sites m_i for each zone z ($m_i \in M_z$), a polyline was constructed from the temporally ordered set of median points (e.g., $[m_1, m_2, \dots, m_{|T|}]$). The length of the arcs between successive pairs of medians (e.g., (m_1, m_2)) can then be used as a measure of geographic drift.

5 Results and Discussion

Figure 4 illustrates the average reported response times for all crashes (injury and non-injury) in each patrol zone over the 36 analysis periods. 95.5% of the average monthly

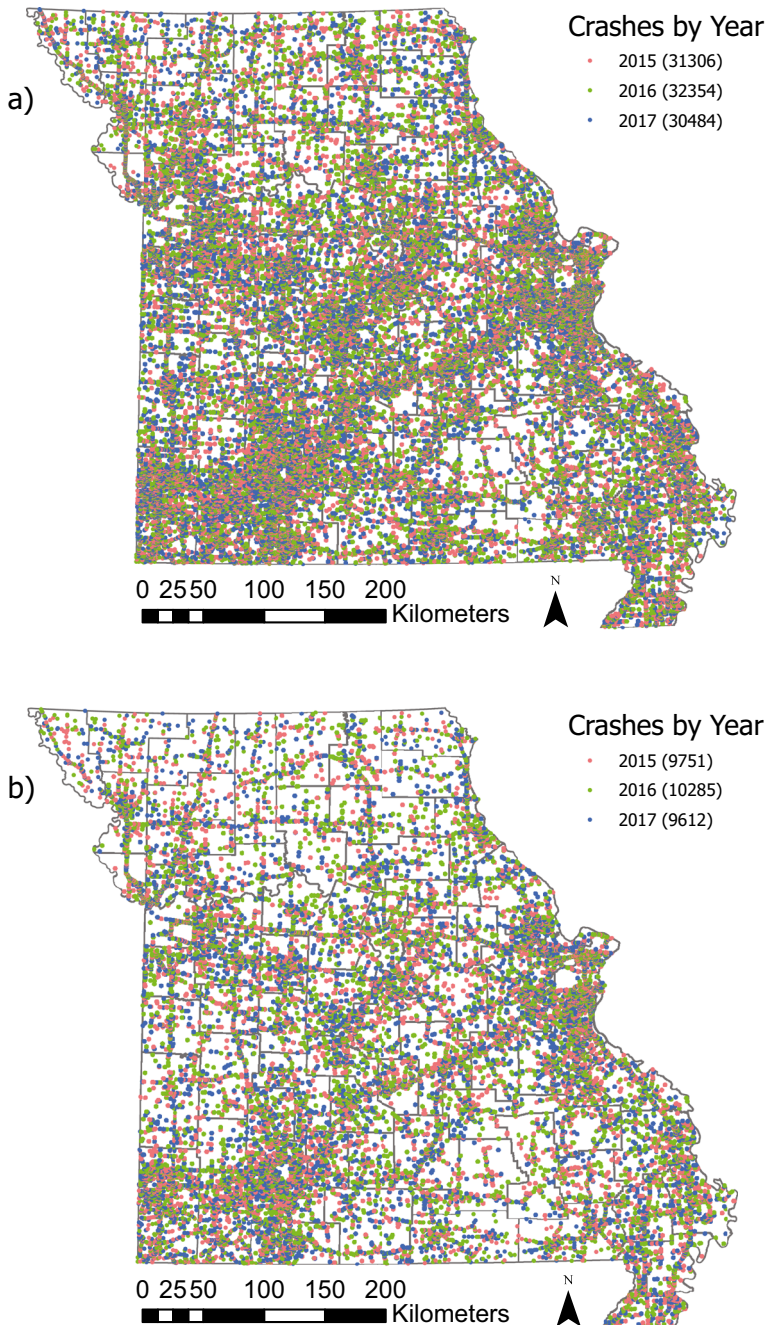


Fig. 3 Crashes to which the MSHP responded in years 2015–2017: **a)** all crashes, **b)** crashes involving personal injury

response times were less than 29.64 min. The zones with months in which average response time was in excess of 29.63 min are for the most part located in less populated, more rural portions of the state. 40.3% of the average monthly response

times were less than 16.93 min. In general, months with these lower average response times tend to be in patrol zones associated with greater quantities of high-capacity roadway (e.g., Interstate, US, and State highways) and/or are proximate to larger population centers. For many of these zones, the average monthly response times are under 16.93 min in a majority of the analysis periods. Approximately 55.2% of the average monthly response times are between 16.92 and 29.64 min. Average monthly response times in this range are typically associated with patrol zones in more rural counties.

The location of the medians computed based on the reported crashes in each time period exhibit notable clustering, especially those associated with patrol zones having more months of lower average response times. The monthly medians tend to be centered along a relatively well-defined corridor in many patrol zones, aligning with portions of the Interstate, US, and MO highway system. This is reasonable given that locations along roads of these classes support more traffic (and accidents) in addition to providing a higher level of accessibility to other locations within a patrol zone. A greater level of dispersion among monthly medians can be found in many (but not all) of the more rural patrol zones. Figure 5 depicts the relative difference between the average modeled and observed response time for each period within each patrol zone. Approximately 1.9% of the monthly average observed response times were actually less than or equal to what was modeled. Approximately 50% of monthly average observed response times represented less than a 60% increase over the average modeled

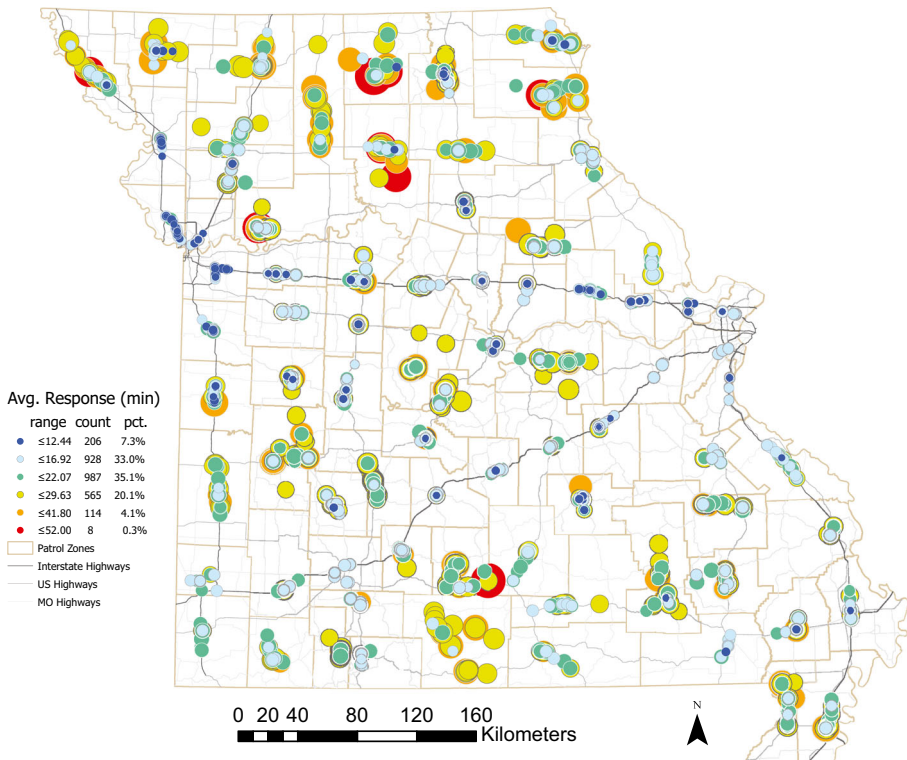


Fig. 4 Average observed response times and monthly medians (all crashes)

response times. Only 19.2% of the monthly average observed response times were more than 100% higher than the average modeled response times. This is quite notable given that the modeled response times were based upon knowledge of where the crashes occurred and then organizing an optimal response from a single location. Small relative differences between the observed and modeled response times could be viewed as periods of increased resilience in the adaptability of resources to respond to incidents. In some patrol zones, there are multiple periods in which there is a small relative difference between the observed and modeled response times, which could indicate more sustained resilience. Of particular interest are the many cases in which the average observed response times (Fig. 4) are moderate to high (e.g., greater than 22.07 min). In these instances, it could be tempting to attribute the higher response times to less efficient use of resources. However, when compared relative to the modeled response times in Fig. 5, many of the moderate to high response time months exhibit little relative difference from the modeled response times. Thus, it is possible that the responses could have in fact been very efficient, in light of a more challenging spatial distribution of crashes to serve. Larger relative differences between observed and modeled response times could be viewed as periods in which there was a greater mismatch between available resources and the spatial distribution of accidents, and hence, lower resilience. Of the instances in which the monthly observed response times were more than 100% that of the modeled response times, roughly 70% were associated with counties in which more than 25% of the population is classified as rural. On

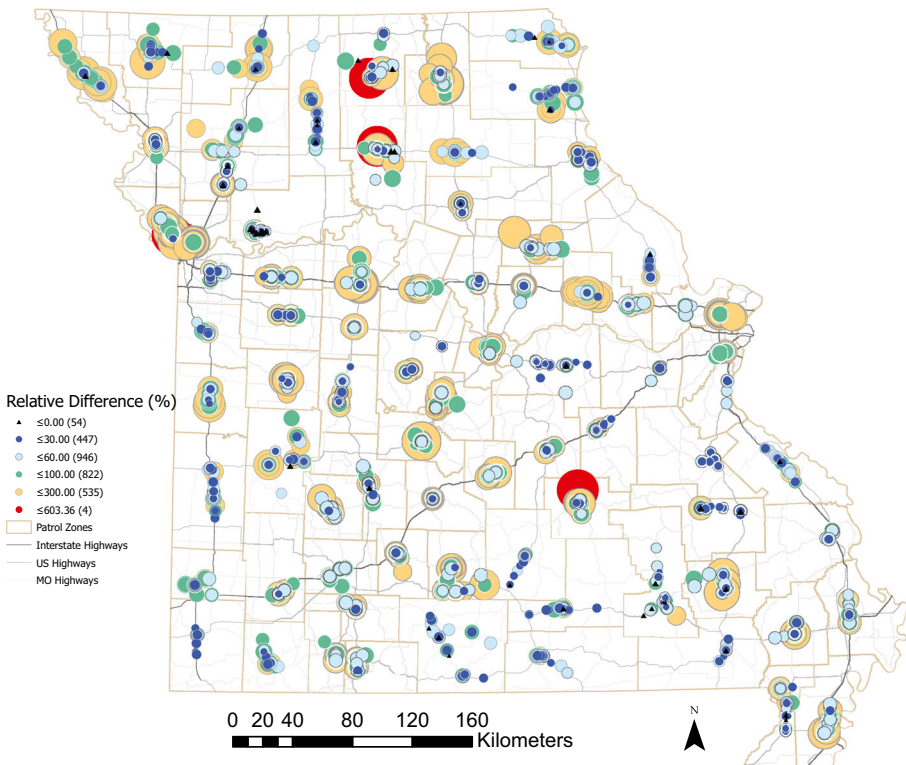


Fig. 5 Relative difference between modeled and observed response times (all crashes)

average over the analysis periods, zones in these portions of the state experienced approximately 1/3 the number of crashes than those in more urban areas. However, there is also much more roadway in these zones that the MSHP is responsible for patrolling than in zones hosting larger urban populations where other law enforcement agencies are also active.

Figure 6 depicts the 36 monthly network medians and average observed response times for crashes involving personal injury for each patrol zone. There are many more analysis periods (52.9%) in which the average observed responses are less than 16.3 min than those for the full set of crashes (injury and non-injury). Lower average observed response times are again predominately associated with zones hosting portions of high-capacity roadways and/or urban centers. Higher average response times tend to be associated with more rural portions of the state. The medians for the zones exhibit much more spatiotemporal variation than those computed for crashes of all types. Figure 7 illustrates the relative difference between the average modeled and observed response times for crashes involving an injury. In this case, approximately 10% of the observed average response times were less than or equal to those modeled. Around 52% of the average observed response times that were higher than those modeled were still within 60% of the modeled average response times. Most of the more extreme relative differences between the average observed and modeled response times tend to be in patrol districts that are more rural and do not host portions of the Interstate highway system.

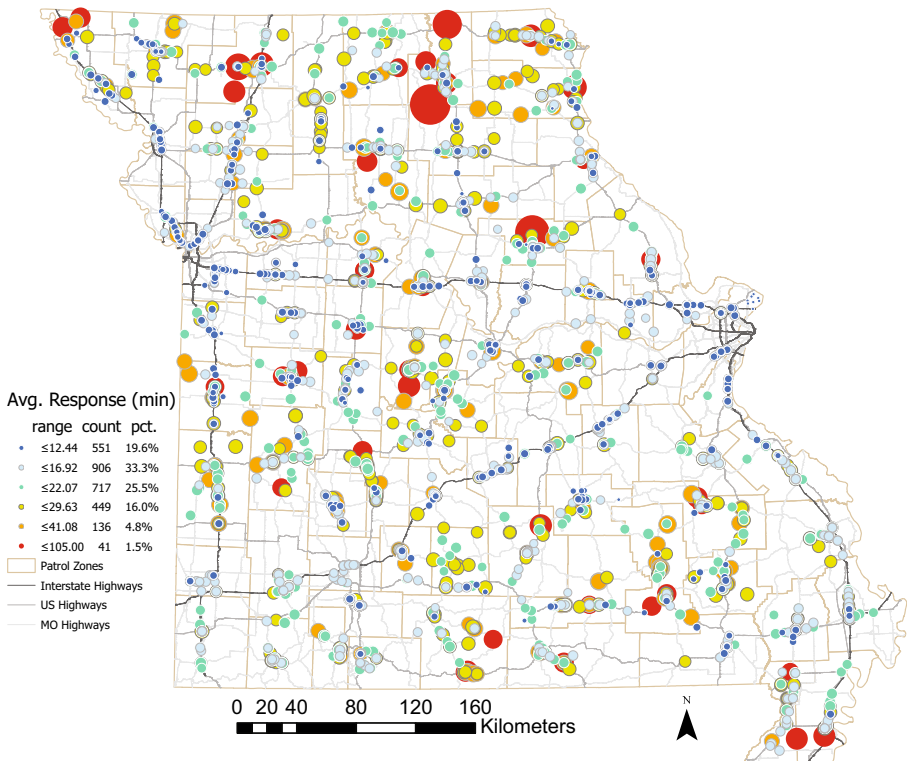


Fig. 6 Average observed response times and monthly median locations (injury only crashes)

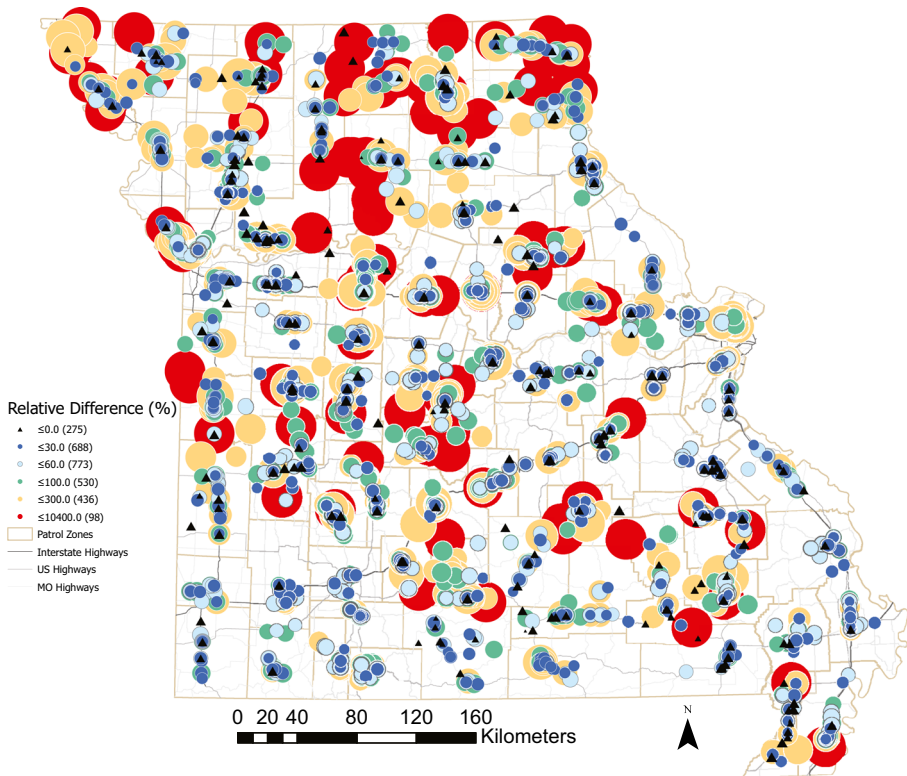


Fig. 7 Relative differences between modeled and observed response times (injury crashes)

Figure 8 illustrates the geographic drift in the network medians rendered for crashes of all types in each patrol zone over the 36 analysis periods. In 12 patrol zones, the median drifts less than 65 km over the 36 periods, approximately 1.8 km per month, indicating a relatively stable spatial distribution of crashes over time. In these cases, the drift among the medians tends to be geographically linear, corresponding with stretches of high capacity roadways central to other high capacity roadway in the zone. These instances are also mostly associated with lower average response times, suggesting that greater stability in the spatial distribution correlates with greater predictability of potential problems and the ability to better position response resources within the system. In cases where the median drifts between 65 to 127 km, there are still instances in which the spatiotemporal drift is relatively linear, again corresponding to patrol zones containing portions of high capacity roadways. This is particularly evident in areas of the state traversed by Interstate I-70 (East and West-bound movements through middle of state) and Interstate I-44 (Southwest and Northeast movements through lower half of state). However, instances also begin to appear in which the spatiotemporal drift is not completely linear, exhibiting changes in directionality over the analysis periods. As the monthly drift in the medians begins to move more than 127 km over the three years of crash data, the movement becomes much less linear, reflecting a more dramatic change in the distribution of crashes. The instances in which the spatial drift is more than 210 km or 5.8 km per month appear to be associated with patrol zones that are mostly rural with less high capacity infrastructure. The lower geographic stability of

crashes in these zones over time is likely attributable in part to traffic in the zones being less consolidated. Comparison of the geographic drift (Fig. 8) and average reported response times (Fig. 4) suggest that greater drift of the network median over time relates to higher average response times while lower median drift over time relates to lower average response times. Perhaps one explanation for this trend is that the spatial distribution of crashes is more predictable and/or stable in zones with lower drift and therefore lower response times are the norm with higher average response times occurring less frequently. Zones with greater drift may experience less predictable and/or stable spatial distributions of crashes over time, with higher average response times being more common and with lower average response times occurring less frequently. In other words, the need to effectively respond to crashes and to increase resilience can be thought of a goal-oriented or competitive process, which are known to give rise to negative spatial autocorrelation (Griffith and Arbia 2010).

The drift among the network median locations over time derived from crashes involving injury (Fig. 9) increases dramatically over that associated with all crashes (Fig. 8). On average, the drift associated with each patrol zone increased nearly 200%, a mean increase of 184 km. The drift for 11 zones even increases 250 to 2691%. This result suggests that the geographic distribution of crashes involving injury is much more variable over time in many of the patrol zones. While the distribution of the medians in Fig. 6 may suggest that the locations are geographically proximate to one another in some instances, the actual temporal sequence may involve considerable

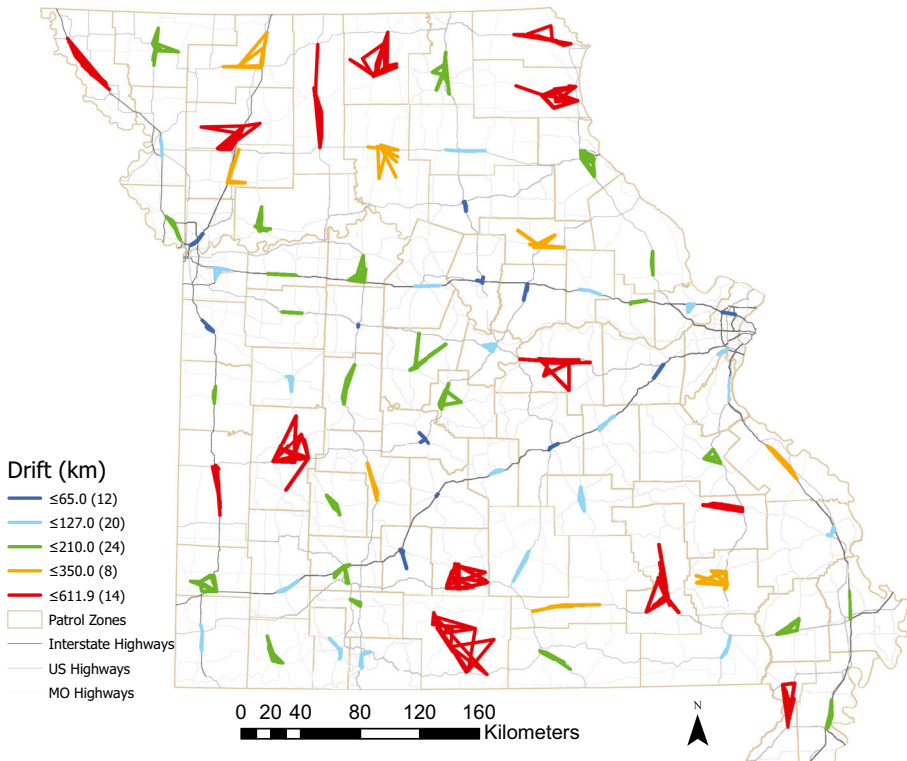


Fig. 8 Spatiotemporal drift among patrol zone network median locations (all crashes)

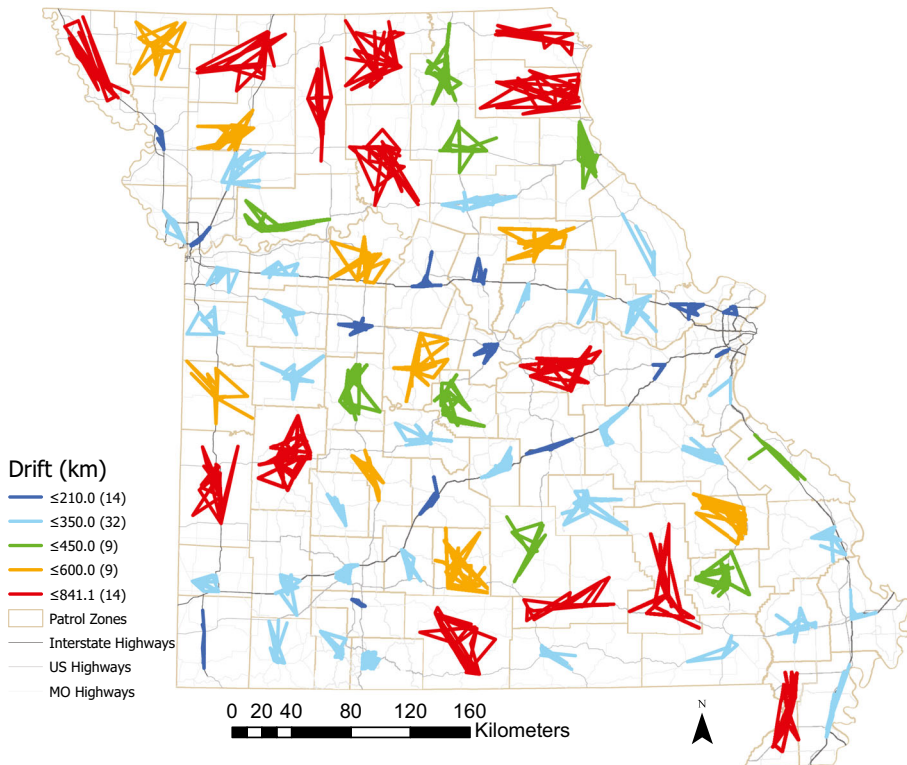


Fig. 9 Spatiotemporal drift among patrol zone network median locations (injury only crashes)

geographic deviations in location over time. Although higher geographic drift in the median locations was realized in all zones, again, patrol zones hosting portions of high-capacity roadway exhibit lower levels of drift over time as well as lower average response times.

6 Conclusions

This article examined the dynamics in resilience to transportation systems to disruptive incidents such as vehicular accidents. A quicker response from law enforcement personnel is an essential part of mitigating the effect of accidents on the operation and performance of transportation systems. As such, the time required for responders to arrive at the scene of an incident, can be used to characterize resilience. In many cases, responses to incidents in a transportation system may not always originate from a fixed facility, such as is often the case with law enforcement personnel. Therefore, their ability to effectively respond depends in part on the location of their activities in the portions of the system to which they are assigned. Given the characteristics of transportation systems can vary considerably throughout a region as well as over time, the nature of system resilience could vary as well.

To investigate these issues, the network median location for incidents occurring within a particular timeframe was used to represent an origin of an optimized response.

The actual time involved in responding to incidents within the timeframe can then be compared with that modeled from the median location. In cases where the modeled response time is relatively close to that observed, greater system resilience could exist. In instances where the modeled response time is much lower than that observed, resilience might be viewed as degraded. Aside from assessing the efficiencies within a single time period, changes in resilience among different time periods can be evaluated as well. Further, changes in the location of the network medians over time can be analyzed to better understand the level of geographic drift in terms of the need for resilience (e.g., placement of response resources) that exists in the system.

The developed approach was applied to evaluate resilience to vehicular crashes in a statewide highway system comprised of multiple traffic patrol zones. Crashes occurring over a three year period were analyzed by month for every traffic patrol zone in the state. It was found that the average modeled response times correlated with the average actual response times rather well for analysis periods in many of the patrol zones. These cases could indicate situations in which responders were able to better anticipate the location of incidents and adjust their activities within the system accordingly. While in some cases, the observed response times may appear to be large, their relative difference from the modeled response times was rather low. This corroboration between the observed and modeled response times indicates that the higher response times are likely attributable to the characteristics of the transportation system and the spatial distribution of the incidents rather than an inefficient response. In other words, the geography of the patrol zones can play a huge role in the time required for a responder to arrive at the scene of an accident. As such, assessment of response times without some consideration of local conditions (e.g., as addressed by modeling the network medians) could easily lead to alternative interpretations.

It was also found that for different patrol zones, the location of the network medians change over the analysis periods in a variety of ways. When considering all types of crashes (injury and non-injury), the medians for some patrol zones exhibited very little movement over time, drifting on average a few km per month. For other patrol zones though, medians regularly drift over a wide area, moving a dozen km or more per month. When focusing on a specific subgroup of accidents, the dynamics of geographic drift can change significantly. For example, when considering only accidents involving personal injury, the location of the medians over time exhibited much less stability, with the monthly drift for the medians in most response zones ranging from 8 to 26 km.

Evaluating resource utilization with respect to resilience in a large networked system certainly has its limitations. That is, in determining how to best respond to an incident, there are many factors that can come into play. For instance, responders could be driven to minimize total demand weighted travel cost as was investigated here. However, other objectives and constraints are certainly involved in the complex decisions made by emergency responders. In other words, resource utilization in contexts such as emergency response is inherently multiobjective. Further, the underlying network conditions (e.g., congestion, construction, weather, etc.) that can influence both accidents as well as the responses can be very dynamic and difficult to incorporate in evaluations of resource utilization. While the network median was used here to provide comparative context to the characteristics of an observed response, other optimization methods could also be applied in a similar spirit. Should the number of responders assigned to

each service zone be known for a particular time, a multi-facility location model could possibly be employed versus a single facility version like the one used here. While a multi-facility approach would illustrate the value of strategic location for responders, zone-based allocation policies are the reality for many response services, especially those also charged with law enforcement. Further, in cases where multiple responders may be assigned to a response zone, they are likely to be assigned to either a sub-zone or to be closely deployed per safety/backup protocols.

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