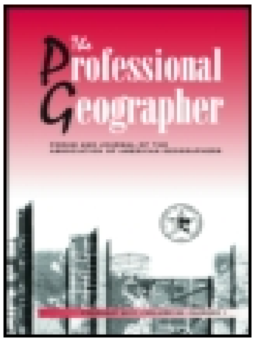

The Professional Geographer

ISSN: 0033-0124 (Print) 1467-9272 (Online) Journal homepage: http://www.tandfonline.com/loi/rtpg20

Characterizing and Predicting Traffic Accidents in Extreme Weather Environments

Richard M. Medina, Guido Cervone & Nigel M. Waters

Characterizing and Predicting Traffic Accidents in Extreme Weather Environments

Richard M. Medina
University of Utah

Guido Cervone
Pennsylvania State University

Nigel M. Waters
University of Calgary

Motorists are vulnerable to extreme weather events, which are likely to be exacerbated by climate change throughout the world. Traffic accidents are conceptualized in this article as the result of a systemic failure that includes human, vehicular, and environmental factors. The snowstorm and concurrent accidents that occurred in the Northeastern United States on 26 January 2011 are used as a case study. Traffic accident data for Fairfax County, Virginia, are supplemented with Doppler radar and additional weather data to characterize the spatiotemporal patterns of the accidents resulting from this major snowstorm event. A kernel density smoothing method is implemented to identify and predict patterns of accident locations within this urban area over time. The predictive capability of this model increases over time with increasing accidents. Models such as these can be used by emergency responders to identify, plan for, and mitigate areas that are more susceptible to increased risk resulting from extreme weather events. **Key Words: extreme weather events, geographic information systems, predictive model, traffic accidents.**

汽车驾驶者对于极端气候事件而言相当脆弱，而极端气候事件则可能因全世界的气候变迁而加剧。本文将交通事故概念化为包含人类、交通工具与环境因素的系统性失败之结果。本文运用美国东北部于2011年一月二十六号的暴风雪与同时发生的意外事故作为案例研究。维吉尼亚州费尔法克斯郡的交通事故数据，以都普勒雷达和额外的气象数据补充之，以描绘此次重大暴风雪事件所导致的事故之时空模型特徵。本研究实施核密度平滑方法，以指认并预测这个城市区域中，随着时间改变的事件地点模式。此一模型的预测能力，随着时间中事故的增加而增强。紧急状况的回应者，可运用诸如此类的模型，指认、规划并缓解对于极端气候事件导致的风险增加更为敏感的区域。 **关键词：极端气候事件，地理信息系统，预测模型，交通事故**。

Los motoristas son vulnerables a eventos atmosféricos extremos, los cuales son susceptibles de exacerbación por el cambio climático global. En este artículo los accidentes de tránsito se conceptualizan como resultado de una falla sistémica que incluye factores humanos, vehiculares y ambientales. La tormenta de nieve y los accidentes concurrentes que ocurrieron en el Nordeste de los Estados Unidos el 26 de enero de 2011 se utilizan como estudio de caso. Los datos de accidentes de tránsito del Condado de Fairfax, en Virginia, se complementaron con radar Doppler y datos meteorológicos adicionales para caracterizar los patrones espaciotemporales de los accidentes resultantes de este evento meteorológico mayor. Se implementó un método de suavización de la densidad del núcleo para identificar y predecir patrones de localizaciones de accidentes a través del tiempo dentro de esta área urbana. La capacidad predictiva de este modelo aumenta con el paso del tiempo al incrementarse los accidentes. Modelos de esta clase pueden usarse por los servicios de respuesta a emergencias para identificar, planear y atenuar efectos en áreas que sean más susceptibles a incrementar el riesgo resultante de eventos meteorológicos extremos. **Palabras clave: eventos meteorológicos extremos, sistemas de información geográfica, modelo predictivo, accidentes de tránsito.**

Weather-related traffic accidents contribute a large proportion of the total traffic accidents in the United States, and with the potential for increased weather variability and populations to urban areas in the future, efforts to better understand and mitigate these hazards are of great importance. The U.S. Department of Transportation estimates that 23 percent of annual traffic accidents are weather related. This amounts to about 1.312 million of the estimated total (about 5.870 million). In the ten-year period between 2002 and 2012, the annual average for injuries was 480,338 and for deaths was 6,253 (U.S. Department of Transportation 2015). A 2014 report prepared for the U.S. Department of Transportation, Federal Highway Administration outlined "key gaps in the integration of climate change considerations

The Professional Geographer, 0(0) 2016, pages 1–12 © 2016 American Association of Geographers.
Initial submission, January 2016; revised submission, March 2016; final acceptance, March 2016.
Published by Taylor & Francis Group, LLC.

into transportation engineering" (Hyman et al. 2014, 1). Based on the assessments made in this report, studies such as this one can assist transportation planning efforts, namely, with translating climate and accident data to "terms that resonate with transportation practitioners" (Hyman et al. 2014, 5), evaluating various costs and benefits of potential and implemented infrastructural or environmental changes, and decision making. Informed mitigation processes through the understanding of spatiotemporal accident patterns and resulting risk can help reduce the number of casualties by implementing more effective planning designs (Nunn and Newby 2015).

Weather can negatively affect travel and transportation by increasing hazard potential, especially in the case of extreme weather events (Stamos et al. 2015). This is, of course, a spatiotemporal problem (Whitelegg 1987). Consider that the risk of traffic accidents for commuters can be worse during rush hours, in regions that experience more or higher impact hazardous events, and at times of the year when seasonal variation can lead to greater hazard. The relative increase in commuting hazard is due to direct effects of the events (e.g., unstable road conditions, poor visibility), infrastructural limitations (e.g., poor lighting, unsafe roads, inadequate cleanup), poor vehicle performance (e.g., bad brakes, two-wheel drive, or inappropriate tires in snow conditions), and counteradaptive changes in human behavior (e.g., speeding, bad decisions resulting from inexperience; S. P. Satterthwaite 1976; Golob and Recker 2001).

As areas are affected by extreme weather, poor infrastructural and environmental conditions increase the risk for commuters. This includes insufficient lighting, dangerous roads (e.g., slopes, potholes, debris), and latent, insufficient, or lacking response (e.g., late, poor, or no snow clearing during and after a storm). Commuters can minimize the hazardous effects of extreme weather events by reducing speeds, altering routes, or avoiding the commute completely, but these behaviors are dependent on knowledge of the situation, previous experience, reaction times, and personality characteristics (Legree et al. 2003). These behaviors can also lead to increased hazard if poor or inexperienced decisions are made on the road.

The negative effects of storms are not uniform over urban areas. Social, physical, and infrastructural vulnerabilities cause some regions to be more hazardous than others. Although traffic accident analyses using network-based statistics are popular (see Yamada and Thill 2007; Eckley and Curtin 2013), in some cases it might be more beneficial to focus on traffic systems that include the environment, interactions, and related infrastructure. Urban areas are systems within which hazard risk is spatially and temporally variable, as is the potential for disaster (Jarup 2000). Negative effects to parts of an urban system can lead to cascading failures that can result in diminished accessibility by emergency responders. In this way, vulnerability to traffic accidents is dependent on more than the road alone (Whitelegg 1987; Nunn and Newby 2015).

This research focuses on the spatiotemporal patterns of extreme weather events and potential vulnerabilities of densely populated urban areas to motorists. It examines a 2011 storm that greatly affected the northeastern United States and resulted in excessive traffic accidents in Fairfax County, a busy part of the Washington, DC, metro area. The objective of this research is to identify changing accident patterns over space and time and design a method to predict, with reasonable accuracy, regions of greatest hazard impact on commuters. This is possible as traffic accidents are in part a function of (1) spatially dependent infrastructure failures and environmental conditions and (2) human behavior that is affected by perceptions of risk, which vary during extreme weather events. The first step in anticipating where traffic accidents will occur and reducing risk is understanding where weaknesses and vulnerabilities exist within urban systems.

As we write, the Washington, DC, urban region is forecast to have another major snowstorm of more than a foot of snow. The National Weather Service (2016) reported that since 1884 such catastrophic snowstorms have occurred sixteen times in the Washington, DC, area, an average of one every eight years. Climate change, however, might increase their frequency.

Weather and Traffic Accidents

Three main systemic processes will likely increase human vulnerabilities to weather-based traffic accidents in the future. First, climate change is expected to increase instances of extreme weather events. This will result in more hazardous days throughout the year in many areas. These events are on the rise in many parts of the world and include increased precipitation, storm intensity, and flooding (Seneviratne et al. 2012; Walsh et al. 2014), all of which greatly affect commuter safety. Second, there is a global rural-to-urban migration trend. Developing regions are projected to see a 100 percent increase in urban dwellers between 2010 and 2050, and developed regions are projected to see a 22 percent increase (United Nations 2011). Finally, aging or crumbling infrastructures can lead to more hazardous road conditions, especially in the face of extreme weather events.

There have been many studies of the causes and effects of traffic accidents. Some of these studies have attempted to predict traffic accidents or correlate them with human behavior. Among the behavioral factors investigated are social deviance (Lawton et al. 1997; Meadows, Stradling, and Lawson 1998), personality (Sümer 2003), sleep patterns and obesity (Terán-Santos et al. 1999; Stoohs et al. 1994), and cell phone use (Strayer, Drews, and Johnston 2003; Strayer, Drews, and Crouch 2006). Other studies focus on infrastructural characteristics, such as speed and speed limit effects on accidents (Aljanahi, Rhodes, and Metcalfe 1999), lighting conditions (Golob and Recker 2003), and geometric design and pavement conditions (Karlaftis 2002). The relationships between environmental variables and traffic accidents have been studied from different perspectives, including focuses on wildlife effects (Putmam 1997; Alexander and Waters 2014) and weather factors, such as visibility. There is ample evidence that weather factors, particularly precipitation, can lead to traffic accidents (see Campbell 1971; Codling 1974; S. P. Satterthwaite 1976; Sherretz and Farhar 1978; Smith 1982; Veith 1983; Brotsky and Hakkert 1988; Palutikof 1991; Andreescu and Frost 1998). Few studies focus on specific hazardous weather events and the traffic accidents they facilitate. Those rare studies, including Edwards (1996), Amundsen and Ranes (2000), and Hijar et al. (2000), would have benefited from computational approaches, such as those discussed in this article. Given present dangers and impending climate changes, weather event–based transportation hazards should be a critical concern.

The 26 January 2011 Winter Storm Affecting the Northeast United States

On Wednesday, 26 January 2011, the Northeast United States experienced a storm in which the entire area from Washington, DC, to Pennsylvania and southern New York was eventually inundated with snow. This area includes many regions of high-density population and increased social vulnerabilities to natural hazards (Cutter and Finch 2008). Figure 1 illustrates the extent of this storm in a NASA MODIS satellite image from 27 January 2011.

Ground Doppler weather radar data were used to determine the spatial distribution of the storm. Figure 2 shows four frames from the radar data: 13h00, 15h00, 17h00, and 19h00. This illustrates the quick movement of the storm in a northeast direction. The greatest amount of precipitation (shown in dark red) is seen roughly about the area of Point Lookout on the Chesapeake Bay at 15h00. This also marks the time when the largest precipitation downfall was observed over the study area, Fairfax County, Virginia.

Due to the timing and intensity of the 2011 storm, there was a high impact on commuters in the Washington, DC, metropolitan area. The large number of accidents can be partially attributed to the sizable amount of snowfall, its accumulation due to the cold temperatures, and the timing of the storm, which coincided with the afternoon rush hour, leading to poor commuting conditions throughout the region. Furthermore, in January in this area the sun sets early, so that by the beginning of the storm, visibility was reduced in many areas. In cases where large storms are anticipated, the number of accidents might not be as high, as sufficient time is given for work and school cancelations and motorists are deterred from making their usual trips (de Freitas 1975; S. P. Satterthwaite 1976). This storm was unexpected. Many motorists were left stranded and others abandoned their vehicles on the roads to seek shelter. The western suburbs of Washington, DC, including Fairfax County, were some of the most affected areas. Approximately 400,000 homes were without power in the Washington, DC, area and 18.5 cm of snow accumulated at Dulles International Airport, west of Washington, DC. The precipitation totals were lower than other storms in 2009 and 2010 but, as mentioned previously, the timing and intensity of this storm made it one of the most detrimental in the region's history (National Oceanic and Atmospheric Administration 2011).

Figure 3 shows the precipitation (bars) and accumulated precipitation (line) for the Washington, DC, metropolitan area as a function of time for 26 January 2011,

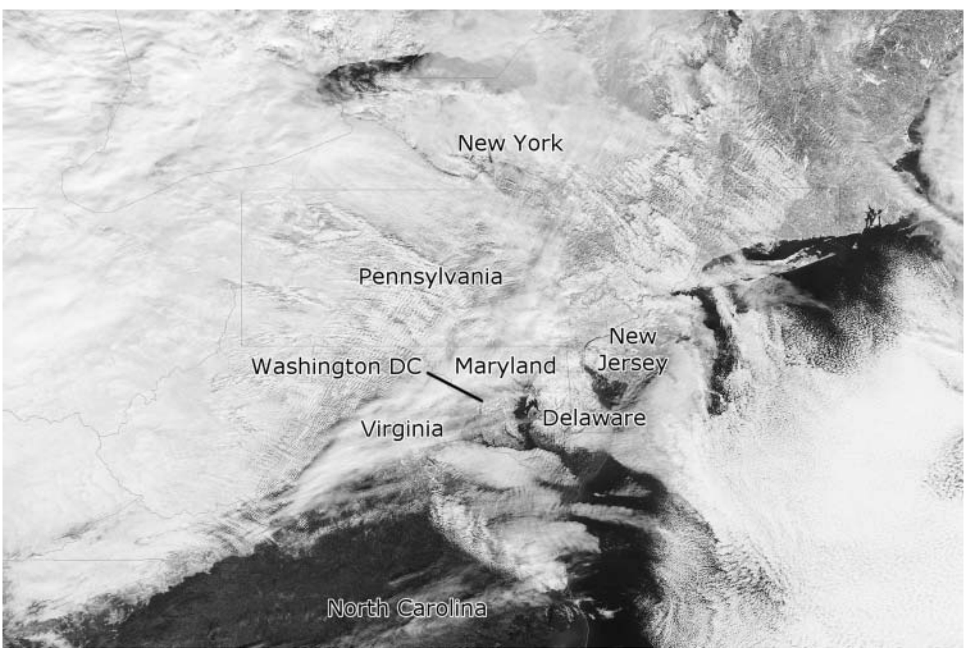

Figure 1 *NASA MODIS Image from 10:55 am EST, 27 January 2011.*

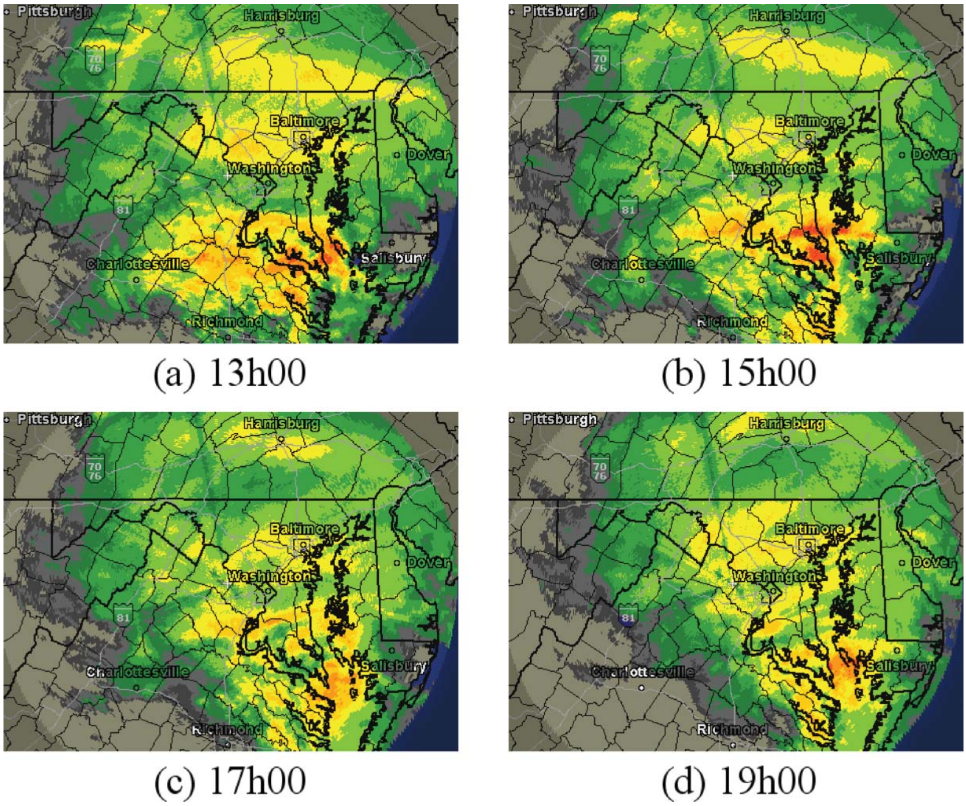

Figure 2 *Ground Doppler weather radar visualizations of the 2011 Washington, DC, metropolitan area storm. (Color figure available online.)*

categorized by rain, light snow, and heavy snow. The heavy snow peak occurred at approximately 15h00 (3:00 pm), at the beginning of the afternoon rush hour. During this peak time, heavy snowfall was measured to be over 1.5 cm per hour and accumulation increased drastically in the area.

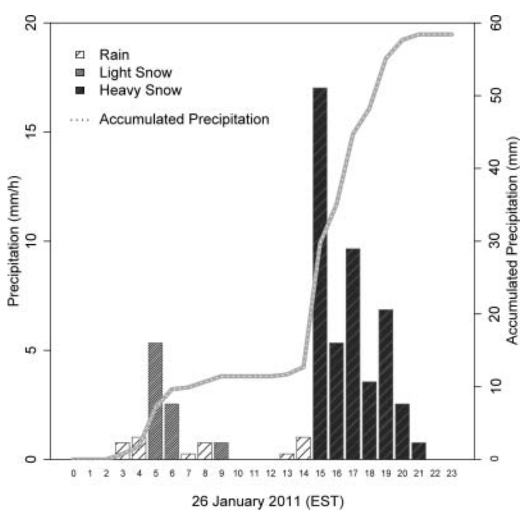

Figure 3 *Precipitation profiles for the 26 January 2011 storm.*

Although a high number of accidents were reported in Fairfax County, the area in and surrounding Washington, DC, received a modest amount of snow, whereas areas in New York received as much as 48 cm. Part of the reason that a comparably small amount of snow caused so much distress is due to the lack of familiarity of Washington, DC, motorists with snowy conditions and also the paucity of infrastructure (e.g., snowplows) necessary to quickly mitigate the situation with snow removal.

During the storm, local police departments were unprepared to answer the massive amount of calls from disabled or injured motorists. The police report written for this event includes overall statistics for the period of the storm (e.g., number of calls, police, fire, and emergency medical service [EMS] dispatches, and radio transmissions) between the police headquarters

Table 1 *Number of calls, dispatches, and transmissions directly related to the storm*

Type of communication	Number
911 calls	1,558
Admin line calls	1,316
Police dispatched	1,318
Fire-rescue dispatches	523
Emergency medical service dispatches	110
Radio transmissions	21,985

and the emergency responders. A summary of these statistics is given in Table 1.

Over the eight-hour period of the storm, there was an approximate 317 percent increase in telephone calls, a 68 percent increase in computer-aided dispatch (CAD) events, and a 140 percent increase in radio transmissions. Increases in communication of this magnitude can lead to cascading failures in urban area response systems (Comfort 2006).

There was no timely suitable warning for this event with respect to its effects in the Washington, DC, metro area. The potential for predicting storm intensity varies from region to region because of environmental uncertainties. In the greater Washington, DC, area uncertainties are high due to the common convergence of cold, dry Arctic and warm, moist maritime air masses. This leads to difficulties in predicting extreme weather events. There have been many occasions when extreme weather preparations have been either overtly excessive or completely inadequate in response to specific events in this area. For example, in February 2013 a major storm was forecast in the area, causing schools and businesses to close, but the storm passed with little to no impact.

Data and Methods

Weather Data

Weather data were retrieved from Weather Underground (The Weather Channel 2015) using the meteorological station located at Dulles Airport in Fairfax County. The measurements available include the precipitation rate and accumulated precipitation, wind speed and direction, air and surface temperature, pressure, and dew point. Only a single station is available in Fairfax County, so ground Doppler radar data are used to address the spatial distribution of precipitation, not to quantify the amount of precipitation but to assess which areas were affected most. In addition, Doppler radar data are also used to determine the trajectory of the storm and which areas were affected first.

GIS Data and Processing

The geographic information systems (GIS) data used for this study include roads, speed limits, and zoning for Fairfax County, which were acquired from the Fairfax County government online.[1] Public infrastructural data such as these are available from many local government offices. This ensures the possible repeatability of this type of study. The data are rasterized such that they are represented in 100 × 100 m cells where the top speed limit and majority of zoning within each cell determine their values. The entire county of Fairfax was used as a study area, but it is important to note that an area in the center of the county, Fairfax City, is excluded, as it is an independent city (shown in Figure 4).

Accident Data

Accident data were obtained through a Freedom of Information Act request to the Fairfax County Police Department for all traffic accident dispatches from 00hr00/12:00 am, 25 January 2011 to 15hr00/3:00 pm, 27 January 2011. The data contain information for 1,016 traffic accidents, categorized as minor (TRAFDMI), intermediate (TRAFHZ), and severe (ACCIPP) depending on the number and type of injuries and damage, as discussed previously. Each accident is associated with a specific date and time, the street address or intersection where it occurred, its severity category, and optional remarks. The accident geolocation was generated using the Google Application Programming Interface, automatically identifying the specific longitude and latitude corresponding to the street address or intersection filed in the police report. A visual inspection of the geolocated results is performed by overlaying all accidents on Google Earth maps and, furthermore, by verifying accidents further than 10 m from a road and all clusters of events that occurred within less than thirty minutes at the same intersection or address. To combine the accident data with the rasterized GIS data, all accidents closest to each 100 × 100 m cell centroid become properties of those specific cells. Thus, the entire resolution for all data in the study is 100 × 100 m.

Spatiotemporal Descriptives and a Predictive Model

The goal is to analyze the spatiotemporal distribution of the accidents and urban environmental interactions associated with a major storm event and to develop a predictive model to forecast areas where accidents are more likely to occur. This study begins with visual depictions of descriptive statistics to characterize the extreme weather event–based accidents. This includes graphing the number of accidents in the area over time and evaluating urban patterns for accidents.

To develop a predictive model of accidents over time, a smoothing of the point data is performed using a kernel estimator, where K is the kernel function and h is the bandwidth.

$$\hat{f}(x) = \frac{1}{nh} \sum{}_{i=1}^{n} K\left(\frac{x - x_i}{h}\right).$$

Here the bandwidth used is defined by Silverman's rule of thumb (Silverman 1986) with Scott's (1992) factor of 1.06.

$$h = 1.06An^{-1/5},$$

where A = min(standard deviation, interquartile range/1.34).

At discrete relative time steps (i.e., the time required for the county to aggregate n accidents), the function f is computed and used as a predictor for the regions

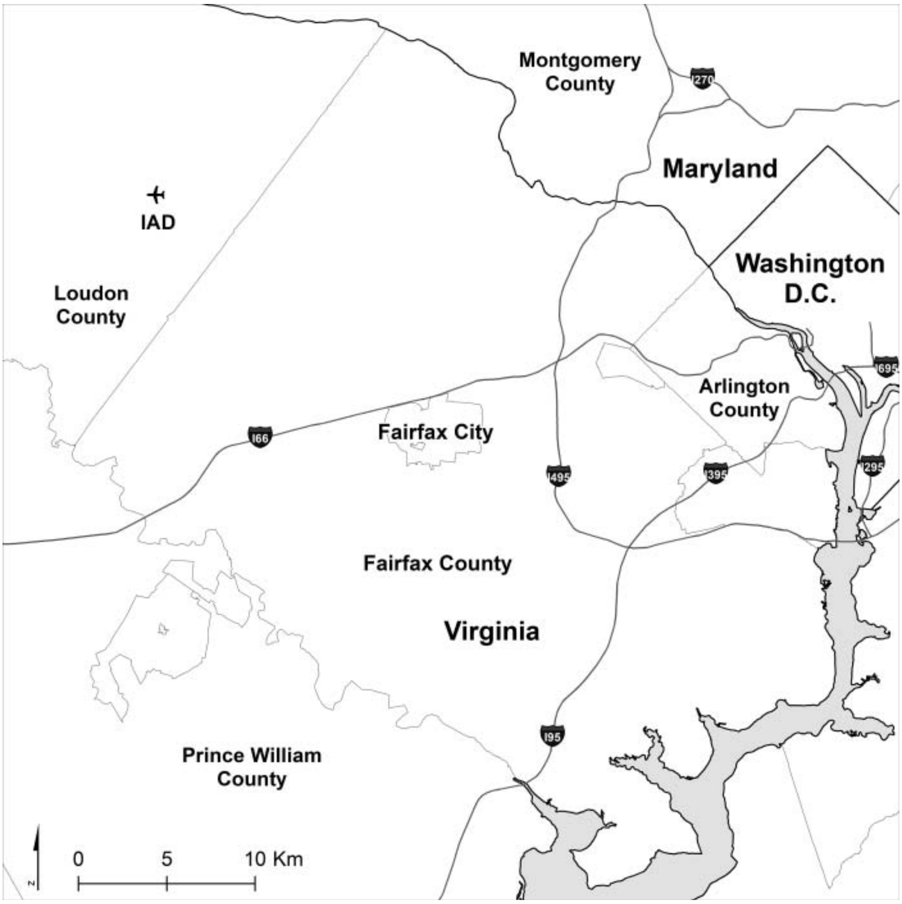

Figure 4 *Fairfax County and City in Northern Virginia.*

where accidents are more likely to occur. The smoothing is performed in two dimensions, spatial (longitude and latitude) and at discrete accident time steps (200 accidents, 300 accidents, etc.). Thus, the predictive model is based on both the location and temporal sequence of the accidents. The smoothing is performed with a memory of all accidents occurring in sequence to the current time because of the relatively short time domain (two days) and relatively high number of accidents. For longer time domains (e.g., spanning several days) it is advised to forget the locations of the oldest accidents and thus constrain the prediction to the areas that were most affected last, so that the model can more easily detect changing patterns.

Traffic Accident Patterns in Fairfax County During the 2011 Storm

The bar graph in Figure 5 illustrates the number of accidents as a function of time. Each bar corresponds to a one-hour period. The peak is reached between 20h00 on 26 January 2011 and 04h00 on the following day. It is important to remember, however, that the data do not report when accidents occurred but when a first responder was dispatched or was sent to investigate, so there is an inevitable lag. Several of the accidents reported late at night or in the early morning might have occurred at any time during a period of several hours. It is assumed that the accident record on 25 January 2011 (Wednesday) is representative of normal accident rates for a typical work day.

Figure 6 shows the temporal distribution of accidents in Fairfax County by severity before, after, and during the storm. The legend lists three categories of accident severity levels—injuries involved (ACCIPP), traffic hazards (TRAFHZ), and disabled motorists/incapacitated vehicles (TRAFDMI) or severe, intermediate, and minor, respectively. The peak effects of the storm on motorists in Fairfax County are easy to approximate (occurring at about 15hr00/3:00 pm). The most severe accidents (ACCIPP) dipped and spiked at the beginning of the storm, and the least severe (TRAFDMI) accidents had the largest spike. The spike in intermediately severe accidents (TRAFHZ) began about the same time as the other two categories, but spiked later. Their increased trend ended about the same time as the intermediately severe accidents (TRAFDMI). It was expected that the most hazardous accidents would occur much less frequently than the less hazardous ones.

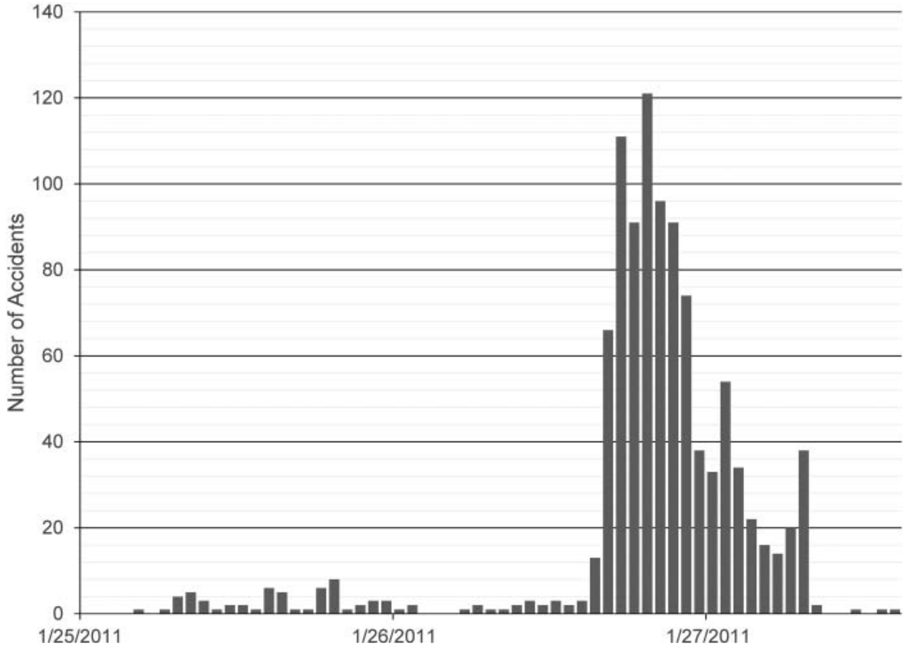

Figure 5 *Number of accidents as a function of time for 25–27 January 2011.*

Figures 7 and 8 show the speed limits and zoning for the streets where most accidents occurred. These figures illustrate the transition of accidents on the drive home during rush hour. There is a clear pattern in which accidents began occurring on roads with higher speed limits (35–45 mph), but during the peak of the storm, accidents occurred roughly on all roads, ranging from those with slower speed limits (<25 mph) to the higher speed limits (>45 mph). The large majority of accidents throughout the storm were occurring in residential areas, and accidents increased over time for regions of no zoning. The designation *no zoning* in this data set refers to areas in which the zoning field is left blank and includes freeways and other major roads throughout the county. Accidents within commercial zones did not amount to a large enough sample to be shown, but those accidents occurring in the no zoning category could well be surrounded by commercial or other zones.

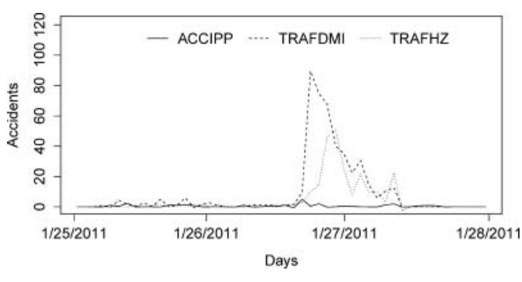

Figure 6 *Temporal distribution of accidents by severity during the 26–27 January 2011 Washington, DC, storm. Note: ACCIPP = injuries involved; TRAFDMI = disabled motorists/incapacitated vehicles; TRAFHZ = traffic hazards.*

Predicting Extreme Weather Event–Driven Traffic Accidents

A kernel density analysis was performed to determine the areas of increased likelihood of accidents. Figure 9 illustrates this progressive kernel smoothing method and predictive model. The top three graphics were computed using 100 (Figure 9A), 300 (Figure 9B), and 500 (Figure 9C) accident time steps, the regions of accident occurrence changing substantially. In the bottom three images, realized with 700 (Figure 9D), 900 (Figure 9E), and 1,000 (Figure 9F) accidents, the relative locations remain constant, indicating clustering of areas likely to experience accidents. Approximate locations of accidents were less likely to be predicted correctly at the beginning of the storm due to the distribution of accidents. Toward the end of the storm, accident locations became much more predictable, where they are clustered along major roads and highly populated residential neighborhoods. The regions that evolve into high accident areas over time might be attractors to accidents within the urban system characterized by their potential for hazard.

Figure 10 shows the final accident data smoothing superimposed over a map of Fairfax and surrounding counties in northern Virginia. The majority of the accidents occurred in densely populated areas on the eastern side of the county along the rim of the Beltway, including McLean, Falls Church, and Annandale. The other two areas of higher accident activity can be observed on the western side of the county corresponding to Centerville, Chantilly, and Reston, which also represent densely populated residential areas. Interestingly, several of the accidents are located nearby major Metro stops.

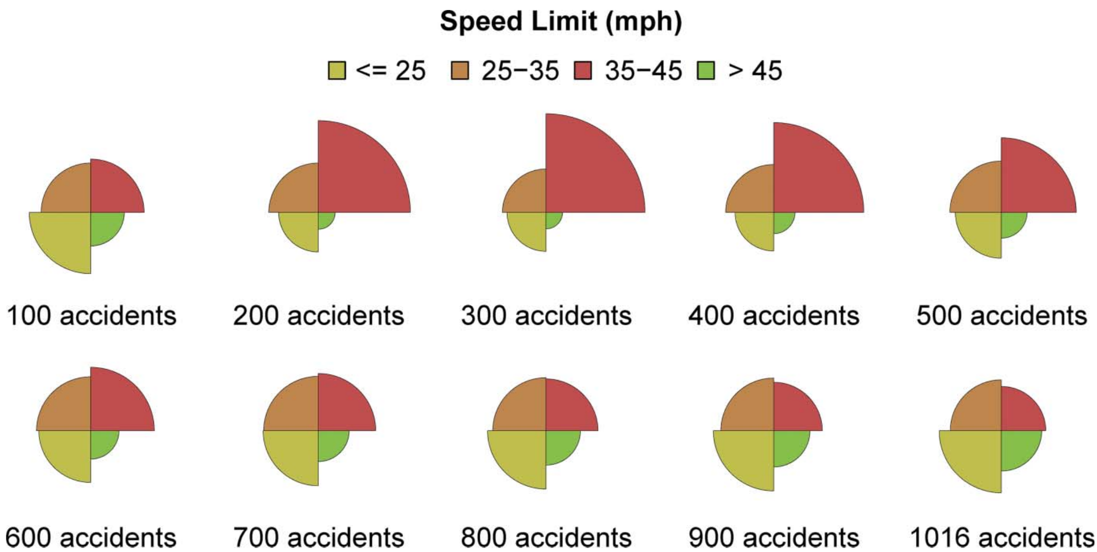

Figure 7 *Speed limits (mph) and accidents during the 26 January 2011 storm. (Color figure available online.)*

The predictive model is based on the previous kernel density smoothing function. Results of accuracy for prediction are shown in Figure 11, where the dotted red line delineates Fairfax County, Virginia. The model estimates where accidents are going to occur based on previous occurrences. After approximately fifty accidents, the general locations of half of the future accidents can be reasonably predicted, and after 200 accidents, the predictive accuracy quickly approaches 100 percent in an asymptotic relationship.

The model's ability to correctly predict the location of future accidents is consistent with the findings that specific locations, governed by their road type, speed limit, and zoning are governing variables. Over the period of the study there was no spatial change in meteorology or precipitation patterns that would have skewed the distribution of the accidents. In this study, the hazard can be considered static, as the snow affected the entire region equally. The model can be easily extended to take into account spatial variation of the snow over time.

Conclusions

This study characterizes traffic accident behavior in a densely populated urban system and provides a

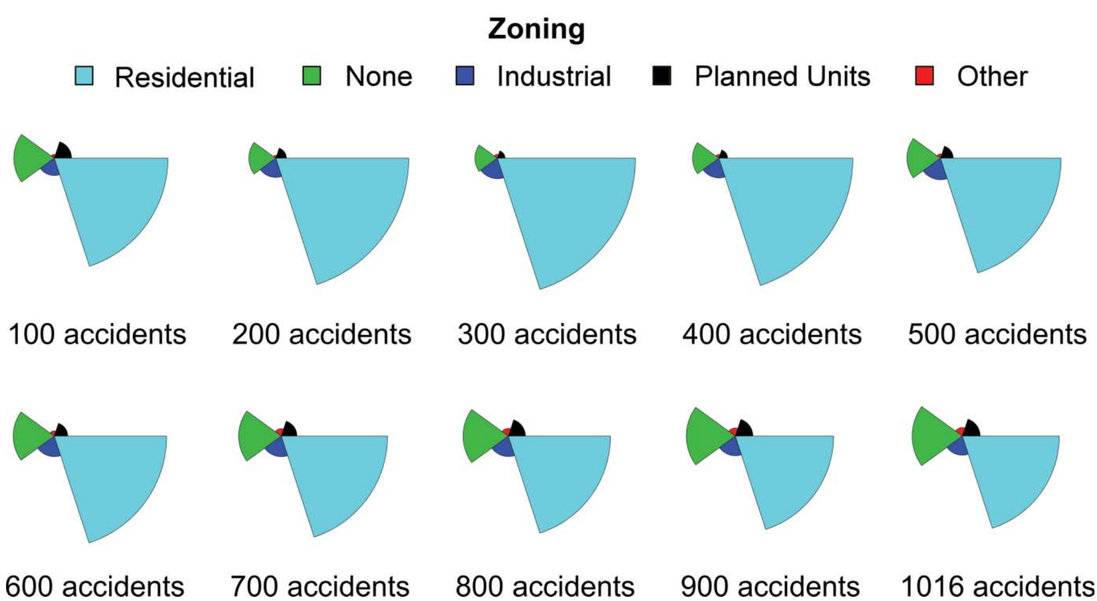

Figure 8 *Zoning and accidents during the 26 January 2011 storm. (Color figure available online.)*

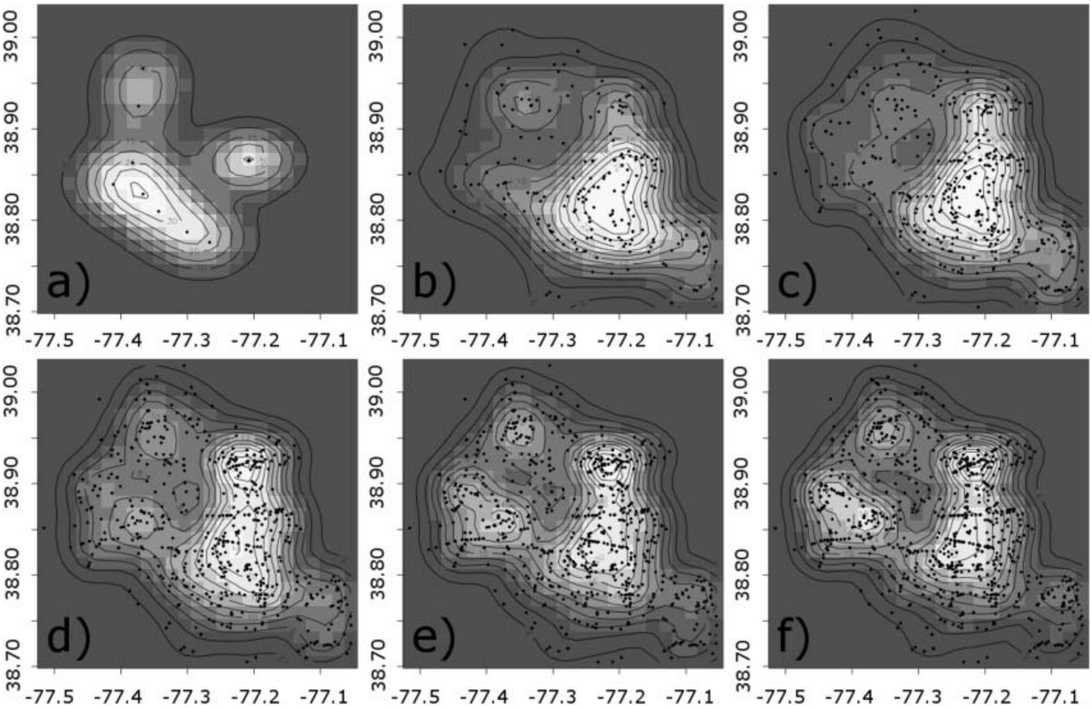

Figure 9 *Predictive model of accident likelihood in the Fairfax County urbanized area.*

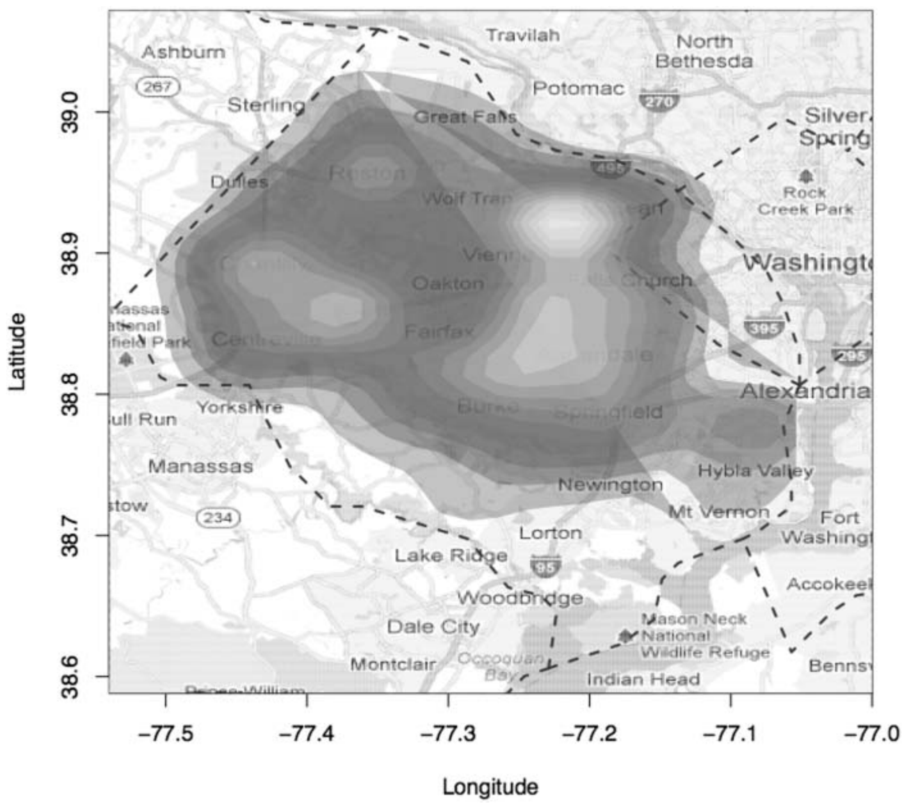

Figure 10 *Kernel density estimates for all 1,016 accidents.*

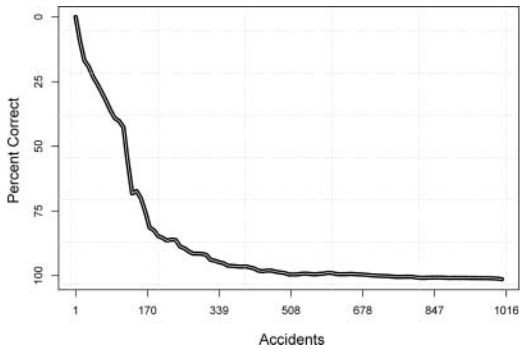

Figure 11 *Prediction error over time for accident locations.*

methodology to identify the most vulnerable regions of this system with respect to extreme weather-related traffic accidents. Given accident data, studies such as this can help planners pinpoint areas that require attention to reduce accidents and can aid emergency responders in quickly understanding and adapting to the emerging patterns in accident behavior. In this study, accident patterns did shift early. After the fiftieth accident the locations of the remaining majority of future accidents were predictable by the model, and the predictability increased as more accidents occurred.

Increased vulnerabilities for motorists in the future can be offset by a stabilization of weather and climate (e.g., reduction of potential impact from climate change), less dependence on personal automobile transportation in urban areas (e.g., transit-oriented development; Ewing and Cervero 2001), and the redistribution of monetary and other resources to urban infrastructures (Jarvis 2005). It is important to consider that some urban systems might have the ability to adapt to changing climate and demographics. The ability to do so is located in political and engineering arenas (D. Satterthwaite 2008). Monetary and planning resources could be directed to helping minimize the effects of weather on infrastructure and motorists. For example, closure of offices, more effective street lighting, consideration of speed limits, advancements in urban planning for new areas, and road conditions can all be implemented in areas affected by weather and commuting hazards. Future trends might see many more people working from home (i.e., telecommuting), which would also reduce commuting vulnerabilities. This will only reduce urban hazards, however, not eliminate them. Waiting to act in anticipation of these offsetting factors could be dangerous. Models that identify and forecast locations and times of relatively more dangerous urban areas have the potential to save lives.

There were obvious patterns of accidents during this 2011 extreme weather event in the Washington, DC, metro area. Although we do not want to assume that this is also the case for other urban areas experiencing extreme weather throughout the country and the world, it is likely. The patterns, areas, and hot spots identified are only relevant to the snow event in Fairfax County. This methodology can be applied to other areas under similar circumstances, but the specific findings here can only be applied to Fairfax County, Virginia. Each urban area might have its own accident pattern signature that, once known, can help planners build safer cities. With growing populations in urban areas, increased numbers of extreme weather events, and crumbling infrastructures in the United States, there will likely be increases in the number of accidents, their severity, or both. The goal should be to reduce this by building safer infrastructure and environment, lowering first responder response times, and increasing preparation and mitigation efforts. It is possible that with real-time data (e.g., all accidents reported at the time of response or before to a central office for analysis) emergency responder offices could use a method such as this one to anticipate where areas of higher accident activity will be located, given that the system has had enough time to evolve to its equilibrium.

Note

[1] These data can be accessed at http://www.fairfaxcounty.gov/maps/.

Literature Cited

Alexander, S., and N. Waters. 2014. Road ecology. In *Encyclopedia of transportation: Social science and policy*, ed. M. Garrett, 1162–65. Thousand Oaks, CA: Sage.

Aljanahi, A. A. M., A. H. Rhodes, and A. V. Metcalfe. 1999. Speed, speed limits and road traffic accidents under free flow conditions. *Accident Analysis and Prevention* 31:161–68.

Amundsen, F. H., and Ranes, G. 2000. Studies on traffic accidents in Norwegian road tunnels. *Tunnelling and Underground Space Technology* 15 (1): 3–11.

Andreescu, M. P., and D. B. Frost. 1998. Weather and traffic accidents in Montreal, Canada. *Climate Research* 9 (3): 225–30.

Brodsky, H., and A. S. Hakkert. 1988. Risk of a road accident in rainy weather. *Accident Analysis & Prevention* 20 (3): 161–76.

Campbell, M. E. 1971. The wet-pavement accident problem: Breaking through. *Traffic Quarterly* 25 (2): 209–14.

Codling P. J. 1974. Weather and road accidents. In *Climatic resources and economic activity*, ed. D. Holding and C. Holding, 205–22. London: Newton Abbot.

Comfort, L. K. 2006. Cities at risk: Hurricane Katrina and the drowning of New Orleans. *Urban Affairs Review* 41 (4): 501–16.

Cutter, S. L., and C. Finch. 2008. Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences* 105 (7): 2301–06.

de Freitas, C. R. 1975. Estimation of the disruptive impact of snowfalls in urban areas. *Journal of Applied Meteorology* 14:1166–73.

Eckley, D. C., and K. M. Curtin. 2013. Evaluating the spatiotemporal clustering of traffic accidents. *Computers, Environment and Urban Systems* 37:70–81.

Edwards, J. B. 1996. Weather-related road accidents in England and Wales: A spatial analysis. *Journal of Transport Geography* 4 (3): 201–12.

Ewing, R., and R. Cervero. 2001. Travel and the built environment: A synthesis. *Transportation Research Record: Journal of the Transportation Research Board* 1780 (1): 87–114.

Golob, T., and W. Recker. 2001. Relationship among urban freeway accidents, traffic flow, weather and lighting conditions. Report No. UCB-ITS-PWP-2001-19. Institute of Transportation Studies, University of California, Berkeley.

Golob, T. F., and W. W. Recker. 2003. Relationships among urban freeway accidents, traffic flow, weather, and lighting conditions. *Journal of Transportation Engineering* 129 (4): 342–53.

Hijar, M., C. Carrillo, M. Flores, R. Anaya, and V. Lopez. 2000. Risk factors in highway traffic accidents: A case control study. *Accident Analysis & Prevention* 32 (5): 703–09.

Hyman, R., R. Kafalenos, B. Beucler, and M. Culp. 2014. Transportation engineering approaches to climate resilience: Assessment of key gaps in the integration of climate change considerations into transportation engineering. Fairfax, VA: ICF International.

Jarup, L. 2000. The role of geographical studies in risk assessment. In *Spatial epidemiology: Methods and applications*, ed. P. Elliot, J. Wakefield, N. Brest, and D. Briggs, 415–33. New York: Oxford University Press.

Jarvis, H. 2005. Moving to London time: Household co-ordination and the infrastructure of everyday life. *Time & Society* 14 (1): 133–54.

Karlaftis, M. G. 2002. Effects of road geometry and traffic volumes on rural roadway accident rates. *Accident Analysis and Prevention* 34 (3): 357–65.

Keay, K., and I. Simmonds. 2006. Road accidents and rainfall in a large Australian city. *Accident Analysis & Prevention* 38 (3): 445–54.

Lawton, R., D. Parker, S. G. Stradling, and A. S. Manstead. 1997. Predicting road traffic accidents: The role of social deviance and violations. *British Journal of Psychology* 88 (2): 249–62.

Legree, P. J., T. S. Heffner, J. Psotka, D. E. Martin, and G. J. Medsker. 2003. Traffic crash involvement: Experiential driving knowledge and stressful contextual antecedents. *Journal of Applied Psychology* 88 (1): 15.

Meadows, M. L., S. G. Stradling, and S. Lawson. 1998. The role of social deviance and violations in predicting road traffic accidents in a sample of young offenders. *British Journal of Psychology* 89 (3): 417–31.

National Oceanic and Atmospheric Administration. 2011. Mid Atlantic winters: Snow, wind, ice and cold. http://www.erh.noaa.gov/lwx/winter/DC-Winters.htm (last accessed 16 March 2013).

National Weather Service. 2016. Snowfall and cold. http://www.weather.gov/lwx/winter_storm-pr#Noreasters (last accessed 21 January 2016).

Nunn, S., and W. Newby. 2015. Landscapes of risk: The geography of fatal traffic collisions in Indiana, 2003 to 2011. *The Professional Geographer* 67 (2): 269–81.

Palutikof, J. P. 1991. *Road accidents and weather. Highway meteorology*. London: E & FN Spon.

Putmam, R. J. 1997. Deer and road traffic accidents: Options for management. *Journal of Environmental Management* 51 (1): 43–57.

Satterthwaite, D. 2008. Climate change and urbanization: Effects and implications for urban governance. In *United Nations Expert Group meeting on population distribution, urbanization, internal migration and development*, 309–34. New York: United Nations.

Satterthwaite, S. P. 1976. An assessment of seasonal and weather effects on the frequency of road accidents in California. *Accident Analysis & Prevention* 8 (2): 87–96.

Scott, D. W. 1992. *Multivariate density estimation: Theory, practice, and visualization*. New York: Wiley.

Seneviratne, S. I., N. Nicholls, D. Easterling, C. M. Goodess, S. Kanae, J. Kossin, and Y. Luo, et al. 2012. Changes in climate extremes and their impacts on the natural physical environment. In *Managing the risks of extreme events and disasters to advance climate change adaptation*, ed. C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, et al., 109–20. New York: Cambridge University Press.

Sherretz, L. A., and B. C. Farhar. 1978. An analysis of the relationship between rainfall and the occurrence of traffic accidents. *Journal of Applied Meteorology* 17 (5): 711–15.

Silverman, B. W. 1986. *Density estimation for statistics and data analysis* (vol. 26). London and New York: CRC Press.

Smith, K. 1982. How seasonal and weather conditions influence road accidents in Glasgow. *The Scottish Geographical Magazine* 98 (2): 103–14.

Stamos, I., E. Mitsakis, J. M. Salanova, and G. Aifadopoulou. 2015. Impact assessment of extreme weather events on transport networks: A data-driven approach. *Transportation Research Part D* 34:168–78.

Stoohs, R. A., C. Guillenminault, A. Itoi, and W. C. Dement. 1994. Traffic accidents in commercial long-haul truck drivers: The influence of sleep-disordered breathing and obesity. *Sleep* 17 (7): 619–23.

Strayer, D. L., F. A. Drews, and D. J. Crouch. 2006. A comparison of the cell phone driver and the drunk driver. *Human Factors* 48 (2): 381–91.

Strayer, D. L., F. A. Drews, and W. A. Johnston. 2003. Cell phone-induced failures of visual attention during simulated driving. *Journal of Experimental Psychology: Applied* 9 (1): 23–32.

Sümer, N. 2003. Personality and behavioral predictors of traffic accidents: Testing a contextual mediated model. *Accident Analysis & Prevention* 35 (6): 949–64.

Terán-Santos, J., A. Jiménez-Gómez, J. Cordero-Guevara, and Cooperative Group Burgos-Santander. 1999. The association between sleep apnea and the risk of traffic accidents. *The New England Journal of Medicine* 340 (11): 847–51.

United Nations. 2011. Introduction. In *Population distribution, urbanization, internal migration and development: An international perspective*, 1–5. New York: United Nations, Department of Economic and Social Affairs, Population Division.

U.S. Department of Transportation. 2015. *How do weather events impact roads?* Washington, DC: Federal Highway Administration. http://www.ops.fhwa.dot.gov/weather/q1_roadimpact.htm (last accessed 9 April 2015).

Walsh, J., D. Wuebbles, K. Hayhoe, J. P. Kossin, K. Kunkel, G. L. Stephens, R. Somerville, et al. 2014. Our changing climate. In *Climate change impacts in the United States: The Third National Climate Assessment*, ed. J. M. Mellilo, T. Richmond, and G. W. Yohe, 19–67. Washington, DC: U.S. Global Change Research Program.

The Weather Channel. 2015. Weather underground. http://www.wunderground.com/ (last accessed 9 March 2016).

Whitelegg, J. 1987. A geography of road traffic accidents. *Transactions of the Institute of British Geographers* 12 (2): 161–76.

Yamada, I., and J.-C. Thill. 2007. Local indicators of network-constrained clusters in spatial point patterns. *Geographical Analysis* 39 (3): 268–92.

RICHARD M. MEDINA is an Assistant Professor in the Department of Geography at the University of Utah, Salt Lake

City, UT 84112. E-mail: richard.medina@geog.utah.edu. His research interests include anthropogenic hazards and geographic information systems.

GUIDO CERVONE is Associate Director of the Institute for CyberScience and Associate Professor in the Department of Geography at Pennsylvania State University, University Park, PA 16802. E-mail: cervone@psu.edu. His research interests include geoinformatics, machine learning, and remote sensing. His research focuses on the development and application of computational algorithms for the analysis of spatiotemporal remote sensing, numerical modeling, and social media "big data" related to environmental hazards and renewable energy.

NIGEL M. WATERS is a Professor Emeritus in the Department of Geography at the University of Calgary, Calgary, Alberta, Canada T2N 1N4. E-mail: nwaters@ucalgary.ca. His research interests include transportation GIS and spatial modeling.