Traffic Injury Prevention

Spatiotemporal Approaches to Analyzing Pedestrian Fatalities: The Case of Cali, Colombia

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Spatiotemporal Approaches to Analyzing Pedestrian Fatalities: The Case of Cali, Colombia

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Objective: Injuries among pedestrians are a major public health concern in Colombian cities such as Cali. This is one of the first studies in Latin America to apply Bayesian maximum entropy (BME) methods to visualize and produce fine-scale, highly accurate estimates of citywide pedestrian fatalities. The purpose of this study is to determine the BME method that best estimates pedestrian mortality rates and reduces statistical noise. We further utilized BME methods to identify and differentiate spatial patterns and persistent versus transient pedestrian mortality hotspots.

Methods: In this multiyear study, geocoded pedestrian mortality data from the Cali Injury Surveillance System (2008 to 2010) and census data were utilized to accurately visualize and estimate pedestrian fatalities. We investigated the effects of temporal and spatial scales, addressing issues arising from the rarity of pedestrian fatality events using 3 BME methods (simple kriging, Poisson kriging, and uniform model Bayesian maximum entropy). To reduce statistical noise while retaining a fine spatial and temporal scale, data were aggregated over 9-month incidence periods and census sectors. Based on a cross-validation of BME methods, Poisson kriging was selected as the best BME method. Finally, the spatiotemporal and urban built environment characteristics of Cali pedestrian mortality hotspots were linked to intervention measures provided in Mead et al.’s (2014) pedestrian mortality review.

Results: The BME space–time analysis in Cali resulted in maps displaying hotspots of high pedestrian fatalities extending over small areas with radii of 0.25 to 1.1 km and temporal durations of 1 month to 3 years. Mapping the spatiotemporal distribution of pedestrian mortality rates identified high-priority areas for prevention strategies. The BME results allow us to identify possible intervention strategies according to the persistence and built environment of the hotspot; for example, through enforcement or long-term environmental modifications.

Conclusions: BME methods provide useful information on the time and place of injuries and can inform policy strategies by isolating priority areas for interventions, contributing to intervention evaluation, and helping to generate hypotheses and identify the preventative strategies that may be suitable to those areas (e.g., street-level methods: pedestrian crossings, enforcement interventions; or citywide approaches: limiting vehicle speeds). This specific information is highly relevant for public health interventions because it provides the ability to target precise locations.

Keywords: pedestrian injuries, road safety, Bayesian maximum entropy, geographic analysis, Colombia

Introduction

Road traffic injuries in Colombia are the second cause of morbidity after cardiovascular disease and the second cause of mortality after homicides (Rodriguez et al. 2003; Villaveces et al. 2012). Pedestrians are the most vulnerable road users, comprising almost 68% of road traffic injuries (Rodriguez et al. 2003), and in Cali, the third largest city in Colombia, pedes-
trian fatalities account for 34.9% of all traffic-related mortality (Alcaldía Mayor de Cali 2012). Over the last 2 decades, the Colombian government has made substantial efforts to implement intervention strategies to diminish the elevated rates of road traffic mortality (Rodriguez et al. 2003; Villaveces et al. 2012). Long-term, high-investment prevention programs included upgrading road networks and introducing a mass transportation system. Less costly interventions included enhanced police efforts to reduce driving speeds and the number intoxicated drivers and a widespread media campaign promoting road safety (Rodriguez et al. 2003).

Geostatistical techniques have been used to describe the distribution of health outcomes through a wide variety of visual displays, including access to health care (Alegana et al. 2012; Gabrys et al. 2011; Gething et al. 2007; Hawthorne and Kwan 2012; Noor et al. 2004), prevalence of HIV/AIDS (Vanmeulebrouk et al. 2008), and incidence of influenza (Ferguson et al. 2005; Riley 2007) and malaria (Gething et al. 2010; Hanafi-Bojd et al. 2012; Soares Magalhaes et al. 2011). In traffic injury prevention, there are examples of risk estimations using mapping tools (Hijar-Medina 2000; Poulos et al. 2012; Prato et al. 2012; Rodriguez et al. 2003) in middle- or low-income countries. However, very few pedestrian mortality studies in Latin America have investigated the temporal and spatial characteristics of an environment simultaneously. Space–time analysis methods can efficiently identify hotspots and link their spatial and temporal extents. Using these methods, policy makers can better assign appropriate prevention measures by isolating and targeting risk areas according to their temporal persistence and spatial patterns (Allshouse et al. 2009; Choi et al. 2003; Hampton et al. 2011; Hanafi-Bojd et al. 2012; Law et al. 2004).

The Bayesian maximum entropy (BME) approach is a spatiotemporal analysis structure used to predict unknown values given a prior knowledge base of known observations (Serre et al. 2004). In public health analyses, BME models have several fundamental benefits over other space–time methods: (1) a recognized regression method effective under limiting conditions; (2) the ability to utilize a broad diversity of non-linear, non-Gaussian information bases that cannot be integrated by conventional methods; and (3) the incorporation of both known data and data modeled by various distributions, such as uniform or Poisson (Choi et al. 2003; Christakos 1990; de Nazelle et al. 2010).

The ability to incorporate known rates and data modeled by non-Gaussian distributions is especially important when researching rare outcomes, such as pedestrian fatalities. When analyzing rare outcomes, artificially elevated rates in low-population areas can occur when observed rates are calculated using population denominators. This “small number problem” can limit the identification of hotspots through an inappropriate interpretation of the rate distribution (Kennedy 1989; Kerry et al. 2010). Multiple methods, including Poisson kriging (PK) and uniform model Bayesian maximum entropy (UMBME), have been developed to more accurately assess true incidence rates, also known as latent rates (Hampton et al. 2011). These BME methods penalize areas with small populations to create a more accurate rate field (Goovaerts 2005; Goovaerts et al. 2005; Hampton et al. 2011).

Previous pedestrian mortality studies in Cali, Colombia, have not accounted for these low populations. This is problematic because observed rates based on population denominators are unreliable in areas with heavy industrial or governmental centers (military, sports, and university). This study is one of the first to apply existing BME methods to pedestrian mortality in Latin America. In our study, we used BME methods to reduce the small number problem and increase spatiotemporal resolution to best identify pedestrian mortality hotspots in Cali, Colombia. Our objective was to more accurately determine the temporal and spatial patterns of pedestrian mortality. Finally, we incorporated findings from Mead et al.’s (2014) review of pedestrian safety measures to suggest potential intervention strategies that could address these pedestrian mortality hotspots according to their spatial and temporal patterns and built environment characteristics.

**Methods**

**Mortality and Cali Census Data Sets**

The study population for this work includes all Cali residents in the time period 2008–2010. A pedestrian mortality case is defined as a person in the urban, incorporated areas of Cali, Colombia, killed by a motor vehicle between January 1, 2008, and December 31, 2010. The data for the study were acquired from the Cali Injury Surveillance System, a reliable and extensively used and validated source of information on fatal injury deaths (Gutierrez-Martinez et al. 2007; Instituto Cisalva 2011). For each mortality case we were provided with the following information: date, time, and street address of the event. During this time period, 356 deaths occurred and are included in the data set. The mortality sites were geocoded using a database from the GEOBIS EZU Software (Geobis International 2010) containing detailed information on the latitude and longitude of addresses in Colombian cities.

Colombian census information divides cities into geographic areas (communes or localities) and then divides communes into sectors, sections, and blocks. Census sections in Colombia (Departamento Administrativo Nacional de Estadistica 2009) are roughly equivalent in population size to the U.S. census tracts (1,500 to 8,000 persons; U.S. Census Bureau 2011). Fatalities were aggregated spatially by administrative boundaries: sections, sectors, and communes. The Cali Administrative Department of Municipal Planning provided a shape file of the Colombian Census for Cali city blocks, the smallest administrative area. The populations and boundaries of administrative categories used in the analysis were created by merging the areas of the 13,475 blocks and summing the population estimates in ArcGIS 10 (ESRI 2011) by the unique ID identifying the block’s section, sector, and commune. This resulted in 22 communes, 345 sectors, and 868 sections consistent with the Colombian census boundaries and population estimates.

Approximately 97% of the records (345 of 356) were successfully geocoded to a location. To reduce extreme outliers and a skewed analysis due to exceedingly inflated rates resulting from areas with small populations (Kennedy 1989),
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fatal events in sections with populations less than 100 were randomly moved to an adjacent section. If a suitable section could not be found within the commune the event was removed. In total, 17 cases were removed from the analysis data set for 3 reasons: (1) 11 cases could not be geocoded because of erroneous address data; (2) 5 events were removed because the fatal injury occurred outside of the urban perimeter; and (3) one case was removed because its section population was extremely low and no adjacent sections were suitable for relocation. Three cases were moved from their section to an adjacent section because the population was less than 100. The final data set yielded 339 unique events.

Each population estimate and the resulting mortality rate were moved to the geographic centroids of their corresponding administrative boundary (calculated using ArcGIS 10; ESRI 2011). To estimate population growth, the 1993 and 2005 census population estimates were linearly interpolated assuming positive growth and extrapolated to population denominators through 2010. Some sections (n = 118 of 868, 13.5%) were not developed until 1996; therefore, the mean citywide population growth was used for extrapolation.

Improving Accuracy of Pedestrian Mortality Estimates

Before applying the BME methods to reduce the small number problem, the effects of varying spatial and temporal aggregations were studied to select the finest space–time resolution while introducing minimal noise. Spatially, the data were aggregated to sections, sectors, and communes. Temporal aggregations with rolling time periods of 6, 9, and 12 months were also examined. The rolling time period creates a continuous temporal field.

The selection of the aggregation levels was performed through a visual analysis of exploratory, mean trend, and covariance analyses obtained at a range of spatial and temporal scales. The results of these analyses were used to determine whether similar spatial and temporal patterns were shown in each aggregation. Furthermore, the autocorrelation of the data sets was studied for losses demonstrating the introduction of variability or noise. Nine data sets with unique combinations of spatial (3 scales) and temporal (3 time periods) aggregations were created and compared.

The visual analysis of the exploratory, mean trend, and covariance analyses determined that fatal pedestrian events should be aggregated at 9-month incidence periods to reduce the small number problem while retaining the finest spatiotemporal scale. Table 1 shows minimal decreases in autocorrelation from the 12-month temporal aggregation to the 9-month aggregation. However, there is a large decrease in autocorrelation between the 9-month and the 6-month aggregation, demonstrating that the 6-month aggregation scale is likely too fine for this data set. Furthermore, the rate patterns were similar in the 9-month and 12-month temporal aggregations, adding additional evidence the 9-month aggregation is the most appropriate for the data set. The use of the 9-month temporal aggregation also allowed for the capture of seasonal patterns in rates without a loss in autocorrelation.

<table>
<thead>
<tr>
<th>Spatial Aggregation (using 9 Month Aggregation)</th>
<th>Spatial Covariance Range</th>
<th>(a)</th>
<th>Temporal Aggregation (using Section Aggregation)</th>
<th>Temporal Covariance Range</th>
<th>(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communes</td>
<td>53.3 Km</td>
<td>6 months</td>
<td>7 months</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sectors</td>
<td>5.3 Km</td>
<td>9 months</td>
<td>19 months</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sections</td>
<td>5.4 Km</td>
<td>12 months</td>
<td>22 months</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In space we chose census sections because there is an increase in spatial resolution and no loss in spatial autocorrelation range. Table 1 shows that there is a decrease in the covariance range between communes and sectors; however, this decrease is attributable to the area of communes, which are on average 30 times greater than sectors. The difference in area also affects the location of centroids where rate estimates are placed; thus, sectors will express a much smaller covariance range. Conversely, there is a minimal loss when comparing autocorrelation in census sectors and sections where sector areas and thus centroid distances are 10 times greater than section areas and centroid distances.

Once appropriate spatial and temporal aggregations were chosen, 3 BME geospatial techniques were selected for comparison: simple kriging, Poisson kriging, and uniform model Bayesian maximum entropy using BMELib 2.0b for MATLAB 7.8 (Serre 2002; Mathworks 2010). For additional information regarding BME methods and equations, please see the Appendix (see online supplement). In simple kriging (SK), the observed rates are used as exact (i.e., error free) measurements of the incidence rate, which are interpolated across space and time. The crude incidence rate at location $s_i$ and incidence period of duration $T$ (e.g., 9 months) centered at time $j$ is denoted as $R_{ij}$ and calculated as $R_{ij} = \frac{n_{ij}}{y_{ij}T}$, where $y_{ij}$ is the number of fatalities that occurred within the incidence area $i$ and incidence period $T$ centered at time $j$. $n_{ij}$ is the population at time $j$ and $T$ is the incidence period expressed in years (i.e., $T = 0.75$ years for a 9-month incidence). SK does not account for measurement error associated with the small number problem, because $R_{ij}$ calculated using a small population $n_{ij}$ is more error-prone than disease rates observed over larger populations.

Conversely, in PK (Goovaerts 2005; Monestiez et al. 2006), the true rate is described with a Gaussian probability distribution. In PK, the mean is equivalent to the rate, $R_{ij}$, as calculated in SK. The variance, $V_r^{ij}$ (also known as the measurement error variance), $V_r^{ij} = m_j/n_{ij}^2 T$ and $m_j = y_{ij}^\prime T$, where $m_j = \frac{x}{n_{ij} T}$. $V_r^{ij}$ is the total cases at the time period in Cali, Colombia, and $n_j$ is the population of Cali, Colombia, during the time period. As discussed in Goovaerts (2005), the measurement error variance increases as the population-year, $n_{ij} T$, decreases. PK addresses the small number problem by smoothing error-prone incidence rates in areas with small population-years.
The model assumption for UMBME is there exists a latent rate $X_{ij}$ such that the number of fatalities we expect is

$$R_{ij} - \frac{\alpha}{n_{ij} \times T} < X_{ij} \leq R_{ij} + \frac{\alpha}{n_{ij} \times T},$$

where $\alpha > 0.5$. (1)

The aim of UMBME is to obtain estimates across space of the latent disease rate $X$ defined in Eq. (1) given the observed rates $R_{ij}$ (Hampton et al. 2011). Hence, like PK, UMBME smooths error-prone incidence rates observed in incidence areas with small populations. The two methods differ in that PK aims to map a fatality risk using an unbounded measurement error, whereas UMBME aims to map a latent rate with a bounded measurement error strictly due to rounding error. Both methods are useful in correcting the small number problem (Hampton et al. 2011).

Cross-Validation of BME Methods

A cross-validation of the mean squared error (MSE) for the 3 BME methods (SK, PK, UMBME) was used to identify the most accurate method to model the mortality rates. In this process, an observed value was removed from the data set, and each BME method was used to reestimate that value. The observation was then returned to the data set and the next value was removed and its estimate was calculated. This was repeated for each data point and the difference between observed and reestimated values is used as the cross-validation error. These errors are then summarized as a function of the MSE. The estimator with the smallest MSE is considered the best predictor for the data set. To compare the MSE between the methods, the percentage change in the mean square error (PCMSE) is calculated by

$$PCMSE_{Method1} = 100 \left( \frac{MSE_{Method1} - MSE_{Method2}}{MSE_{Method2}} \right).$$

A negative PCMSE demonstrates the percentage improvement in the estimation accuracy from the first method to the second (de Nazelle et al. 2010).

The PK model was selected after cross-validation as the best estimator for the data set because it minimized the MSE and maximized the percentage improvement in mean squared error (where negative values indicate improvement).

Potential Intervention Strategies for Hotspot Spatial and Temporal Patterns

We were also provided with a large Cali urban built environment data set from the Cali Administrative Department of Municipal Planning. This urban data set contained shape files on road types (and numbers of lanes), residential areas, and major social and commercial centers (e.g., libraries, stadiums, universities, museums, etc.). We then linked the PK results to Mead et al. (2014) and the built urban environmental data to highlight a wide variety of evidence-based applications including environmental changes, enforcement activities, and potential areas for behavioral interventions that can be implemented from a BME analysis based on a hotspot’s temporal and spatial characteristics.

Results

Figure 1 shows that pedestrian mortality has a decreasing temporal mean trend from an average of 1.1 deaths/10,000 person-years at the start of the study period to 0.6 deaths/10,000 person-years at the end. This is consistent with surveillance data showing a general decrease in pedestrian mortality rates in Cali. The spatial mean trend shown in this figure also shows that fatalities are primarily occurring in the downtown area and in some middle- to high-income portions of the city. Other hotspots also occasionally appear in other city areas and have less space–time permanence.

The pedestrian mortality covariance models shown in Figure 2 reveal that hotspots have varying spatial extents. The covariance models also demonstrate that pedestrian fatalities are autocorrelated over relatively short distances ranging from approximately 0.25 to 1.1 km but persist over relatively long time durations (8 to 30 months).

The mean squared error results and percentage change in the mean square error for the 3 methods are shown in Table 2. The table shows that PK provided a large gain in accuracy over SK but only a small gain over UMBME.

The BME time series highlighted a notable area located downtown at the intersections of major roads, where pedestrian mortality was consistently elevated (area 1; Figure 3). The maps also showed smaller and more intermittent hotspots in an area at the intersection of secondary and major roads in areas located just south of the city’s downtown (area 2; Figure 3). These hotspots correspond to an area with a stadium, a university, and mixed commercial/residential zones...
and are highlighted in the center box in Figure 3. A third steadily occurring hotspot in the south of the city is located near 2 malls and a university campus (area 3; Figure 3). Finally, more transient hotspots are located along 2 large avenues in the eastern part of the city and have a north–south orientation (area 4; Figure 3).

Table 3 categorizes Cali’s pedestrian mortality hotspots according to their (1) temporal persistence and spatial extent determined by the PK analysis and (2) urban built environment characteristics. These hotspot characteristics are then linked to Mead et al.’s (2014) review on roadway pedestrian mortality interventions.

Discussion

Of the 3 BME methods tested, PK and UMBME provided a measure to reduce the small number problem and produced the most accurate results in the cross-validation. Additionally, in this study, PK was a better estimator than UMBME. This is likely because PK calculates more accurate rate estimates when the spatial autocorrelation in the data set is low (Hampton et al. 2011) as seen in this study, where hotspots are delineated to small geographic areas. Furthermore, in cases where the data set is Poisson distributed, PK is the most effective method (Hampton et al. 2011). Pedestrian mortality data are often modeled with a Poisson distribution (DiGuiseppi et al. 1997; Durkin et al. 1999; Roberts et al. 1992; Sonkin et al. 2006; Waller et al. 1989).

The PK BME analysis produced a highly accurate and fine-scale spatiotemporal visualization of pedestrian mortalities in Cali, Colombia. The mean trend analysis isolated areas in the city with high incidence throughout the time period. The space/time autocorrelation results showed that hotspots generally extend over small areas with subkilometer radii and persist over long durations of months to years, suggesting that the city could benefit from highly targeted interventions.

A limitation of this analysis is that injury fatalities are usually rare and using the most disaggregated data available might not be possible due to data scarcity. Another limitation is that though the kriging analysis provides a refined assessment of spatiotemporal risks of mortality, it is not inferential and hence causal associations cannot be obtained. For example, we may associate a high rate of pedestrian fatalities with the proximity of a particular venue or land use when in reality an unobserved factor explains the high fatality rates. This is a particular challenge when dealing with urban built environment administrative data because maps and infrastructure elements are not frequently updated over time.

Categorizing pedestrian mortality hotspots by their spatiotemporal characteristics has strong implications for multilevel pedestrian fatality interventions because these categories can inform the most appropriate type and scale of interventions while minimizing costs. The BME results found in this study can be extended to provide policy makers with additional and targeted information to choose between site-specific interventions such as in situ signage to

Table 2. Mean squared error (MSE) results for simple kriging, Poisson kriging, uniform model Bayesian maximum entropy, and the percentage change from simple to Poisson kriging in pedestrian fatal events in Cali, Colombia, 2008–2010

<table>
<thead>
<tr>
<th></th>
<th>MSE for simple kriging</th>
<th>MSE for Poisson kriging</th>
<th>MSE for uniform model BME</th>
<th>Percentage change from SK to PK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.98E-07</td>
<td>1.91E-07</td>
<td>1.93E-07</td>
<td>-3.66</td>
<td></td>
</tr>
</tbody>
</table>
alert pedestrians and motorists and broader informational campaigns. For persistent hotspots, spot-based, street-scale planning and engineering interventions such as narrowing lanes and improving pedestrian infrastructure is warranted (Mead et al. 2014). At broader scales, such as the neighborhood or the district level, measures such as traffic calming and awareness campaigns may also have an impact on reducing fatalities at specific locations (Mead et al. 2014). Citywide interventions can also include speed limit enforcement for all vehicles (Mead et al. 2014).

On a broader scale, additional BME analyses could be conducted to provide assessments of the impact of an intervention or action, whether localized or broadly implemented. Because resources are limited, not all hotspots are likely to be concurrently intervened and BME analyses can contribute to identifying priority areas. Monitoring the change in pedestrian mortality before and after an intervention and comparing the spatiotemporal characteristics of intervened areas with control areas can assess hotspot persistence to provide evidence of intervention effectiveness. Analyses can be implemented in random, crossover, and planned experimental designs for monitoring and evaluation. Varying monitoring and evaluation methods can also benefit from the clear display of results in time-lapse movies (PK of Cali pedestrian mortality can be seen at: www.unc.edu/depts/case/BMElab/studies/LF_PedMort_Cali.htm).

Furthermore, in conjunction with the results from Villaveces et al. (2012), the BME analysis can be used to generate hypotheses on the causes of incidence hotspots. For example the areas of persistent elevated pedestrian mortality in Cali correspond to 3 characteristics found in the Cali urban built environment data set and results from Villaveces et al. (2012): (1) highways with multiple lanes, which could correspond to a high density of motor vehicles; (2) high density of commercial and social activity points (universities, stadiums, malls) likely implying high pedestrian density; and (3) high risk exposures understood as the time taken by pedestrians to cross high-speed traffic, multiple lanes of traffic, or both (Villaveces et al. 2012). The convergence of all 3 factors in one location appears to lead to the highest risk and persistent pedestrian mortality hotspot seen in the downtown region of the city (area 1; Figure 3) where there is a convergence of major arteries, few walkable junctions, high density of cars, high-speed exposure, numerous pedestrians, and multiple interaction points for vehicles and pedestrians (Villaveces et al. 2012). Two areas in the city with a concentration of occupational, commercial, and educational activities also exhibit these risk factors (areas 2 and 3; Figure 3; Villaveces et al. 2012). Anecdotal experience suggests that there are few pedestrian bridges in these areas and, when available, pedestrians do not always use them (Hijar et al. 2003; Villaveces et al. 2012). More transient hotspots tend to express one or two of the above factors (for example, high speeds or multiple lanes) as is notable in the highway sections toward the east of the city (area 4; Figure 3).

In conclusion, BME methods such as PK, which have been used successfully in other public health areas, can also be used in novel ways for preventing pedestrian roadway mortalities in urban settings. BME analysis results can inform planners and policy makers regarding which areas to first target and interventions to consider initially. They can also support further research to test hypotheses. For example, regression analysis of environmental variables such as sidewalks, road type, and public lighting linked to pedestrian mortality may help determine whether these environmental factors explain pedestrian mortality.

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### Table 3. Potential interventions than can be informed using Bayesian maximum entropy analyses in preventing pedestrian fatality events in Cali, Colombia

<table>
<thead>
<tr>
<th>Intervention type (derived from Mead et al. 2014)</th>
<th>Cali locations (based on urban built environment data set)</th>
<th>Hotspot type (categorized from PK analysis)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Along the street</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Narrow lanes (lane diet)</td>
<td>Residential/secondary streets</td>
<td>Persistent/variable</td>
</tr>
<tr>
<td>2. Reduce lanes (road diet)</td>
<td>Residential/residential streets</td>
<td>Variable</td>
</tr>
<tr>
<td>3. Calm traffic (chokers, chicanes, speed humps, speed tables, raise crosswalks)</td>
<td>Residential and secondary streets</td>
<td>Variable</td>
</tr>
<tr>
<td>4. Add, widen, or improve sidewalks to get pedestrians off the road</td>
<td>Downtown/ universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>5. Add barriers or obstructions on existing sidewalks</td>
<td>Downtown</td>
<td>Persistent</td>
</tr>
<tr>
<td>Crossing the street</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Make crosswalks more visible</td>
<td>Downtown/universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>7. Make improvements to marked crosswalks</td>
<td>Downtown/universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>8. Improve signs, lights, and signals at crosswalks</td>
<td>Downtown/universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>9. Install or improve traffic signals</td>
<td>Downtown/universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>10. Consider overpasses and underpasses</td>
<td>Downtown/universities and large avenues</td>
<td>Persistent</td>
</tr>
<tr>
<td>11. Improve visibility at crosswalks</td>
<td>Citywide/Universities/large avenues</td>
<td>Variable</td>
</tr>
<tr>
<td>12. Extend curb toward road to decrease walking distance</td>
<td>Citywide/Universities/large avenues</td>
<td>Persistent/variable</td>
</tr>
<tr>
<td>13. Create crossing islands/medians</td>
<td>Universities/large avenues</td>
<td>Persistent/variable</td>
</tr>
<tr>
<td>14. Provide raised pedestrian crossing</td>
<td>Universities</td>
<td>Persistent</td>
</tr>
<tr>
<td>15. Time traffic signals to provide advance crossing time to pedestrians</td>
<td>Citywide</td>
<td>Variable</td>
</tr>
<tr>
<td>Transit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16. Stop location</td>
<td>Downtown</td>
<td>Persistent</td>
</tr>
<tr>
<td>17. Speed monitoring</td>
<td>Citywide</td>
<td>Variable</td>
</tr>
<tr>
<td>18. Enforce pedestrian laws</td>
<td>Citywide</td>
<td>Variable</td>
</tr>
<tr>
<td>19. Educate users of the space (pedestrians, motorists, and other users; e.g., street vendors, cyclists)</td>
<td>Citywide with downtown focus</td>
<td>Persistent</td>
</tr>
<tr>
<td>20. Consider issues related to personal safety (risk of violence)</td>
<td>Downtown/universities</td>
<td>Persistent</td>
</tr>
</tbody>
</table>
lance data set. The authors also thank Aaron Freeman Fox for providing an extensive editorial review of the document.

**Supplemental Materials**

Supplemental data for this article can be accessed on the publisher’s website.

**References**


Departamento Administrativo Nacional de Estadística [National Administrative Department of Statistics]. *Metodología Sistema de Información Geoesadestístico*. Bogotá: Colombia; Author; 2009.


