Title

Comparative Analysis of Modeling Techniques for Fatal Car Accidents in Downtown Los Angeles: A Spatial Point Process Perspective

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Comparative Analysis of Modeling Techniques for Fatal Car Accidents in Downtown Los Angeles: A Spatial Point Process Perspective

A thesis submitted in partial satisfaction

of the requirements for the degree

Master of Applied Statistics and Data Science

by

Paulė Dargis

2024

ABSTRACT OF THE THESIS

Comparative Analysis of Modeling Techniques
for Fatal Car Accidents in Downtown Los Angeles:
A Spatial Point Process Perspective

by

Paulė Dargis
Master of Applied Statistics and Data Science
University of California, Los Angeles, 2024
Professor Frederic R. Paik Schoenberg, Chair

Methods for evaluating the fit of spatial point process models using residual analysis are explored to study fatal car accidents in Downtown Los Angeles (DTLA). Residual diagnostics include spatial residual plots, quantile-quantile (Q-Q), and residual density plots to summarize residual distributions. Comparative analysis focuses on homogeneous and different structures of the inhomogeneous Poisson point process models, incorporating covariates such as freeway proximity `cub_distance` and environmental conditions `Smoke.or.Haze`. Goodness-of-fit metrics and K-function analyses assess clustering and dispersion patterns, particularly in high-traffic regions, relevant to the covariates involved.

Results highlight improvements in model performance when spatial covariates are included. Residual analyses reveal that homogeneous models fail to capture local clustering, while models with covariates reduce unexplained variability and align residual distributions more closely with theoretical expectations. K-function results show that combining covari-

ates effectively balances clustering and dispersion patterns, particularly at smaller distances.

The study is only an introduction to applying locational and environmental factors to enhance the ability of point process models to explain spatial variability in fatal accidents. These findings provide a foundation for improving urban safety planning and traffic policy design. Residual diagnostics and spatial analysis indicate that future models could benefit from additional covariates, thinning techniques, and spatio-temporal extensions to capture evolving accident patterns and further improve model fits.

The thesis of Paulė Dargis is approved.

Michael Tsiang

Davis Anthony Zes

Chad J. Hazlett

Frederic R. Paik Schoenberg, Committee Chair

University of California, Los Angeles

2024

To my Mother and Father . . .

and Sister and Brother

who—among so many other things—

saw to it that I live a good life

Be Jūsu... Aš Būčiau Niekas

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ACKNOWLEDGMENTS

I want to express my gratitude to all the professors I had the pleasure of studying under at UCLA. Their expertise and encouragement have been instrumental in shaping this study. I would like to emphasize my gratitude to Professor Tsiang for my first true introduction to coding.

I particularly want to thank Professor Schoenberg for introducing geostatistics to me and expanding my view of how statistics can be applied in ways I did not know were possible. I also wish to thank Professor Zes for providing invaluable knowledge of data management, which has been instrumental in organizing the information used in this study. This experience has taught me that proper organization of thought is essential to being a competent data scientist.

This study represents an introductory exploration into modeling fatal car accidents in Downtown Los Angeles, and I recognize it is only the beginning. I hope this research serves as a foundation for future studies that aim to develop more robust and comprehensive approaches to understanding and mitigating traffic fatalities.

Finally, I am grateful to my family and friends for their endless support, as well as for their perpetual patience and understanding during the countless nights devoted to this project. Simply without them, none of this would have been possible.

CHAPTER 1

Introduction

Figure 1.1: Overlay a Satallite Image of Downtown Los Angeles using ggmap

According to the World Health Organization, about 1.19 million people are killed in car accidents every year[Wor24]. Life in Los Angeles, it is impossible not to notice the massive car culture[Lev23]. With the structure of the culture, it could be assumed that it will only grow. As of August 2024, new vehicle sales are currently 33% above where they were last year at the same time, while used vehicle sales are up 21% [Spe24]. Numerous geospatial studies have identified various factors contributing to road traffic accidents, including adverse weather conditions[Als24][APF23]. However, the Poisson Point Process used on car accident fatalities is not as widely available, but the application of the process may reveal factors on fatalities that were not considered before.

Analyzing spatial point processes with new, constantly updating available data[Dep24] allows us to explore the activity of fatalities in Downtown Los Angeles. This study also allows the use of temporal factor indexes by grouping the time of an event into either day, evening, or night. These marks would compare behaviors resulting in the time of the day. Anastassios Karaganis and Angelos Mimis have done similar analyses [KM06] to observe accidents involving day and night.

Incorporating covariates gives use of the spatial intensity as a function of explanatory variables[BCS12]. This provides insights into how specific factors influence accident occurrence, a core goal of spatial point process modeling. Testing models with different covariates, one at a time and combined, helps isolate these variables' individual and combined effects on accident risk.

By examining the impact of factors such as climate conditions and proximity to freeway entrances, future adapted studies from this paper can inform targeted interventions, such as improving infrastructure near high-risk areas or implementing weather-related safety measures.

CHAPTER 2

Methodology

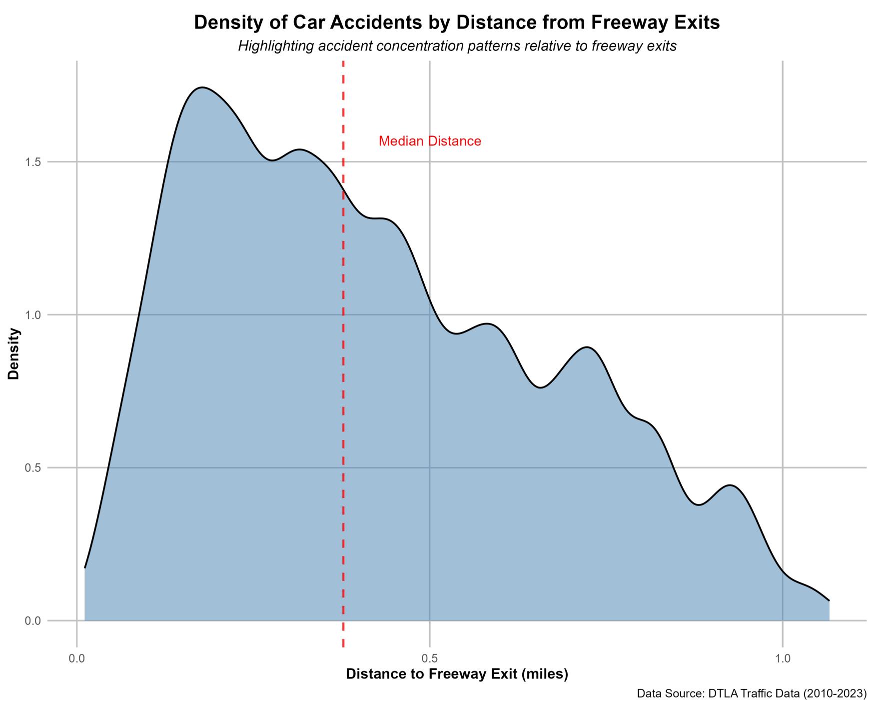

Figure 2.1: Density plot showing accident concentration patterns relative to freeway exits.

2.1 Overview

This study focuses on the comparative analysis of point process modeling techniques to understand the spatial patterns of fatal car accidents in Downtown Los Angeles (DTLA). Statistically, traffic accidents are defined as a process that is indexed by the exact location. The analysis employs statistical methods to assess model performance, evaluate spatial variability, and extract actionable insights.

The homogeneous Poisson Point Process assumes complete spatial randomness [BCS12], meaning all points (accidents) have an equal probability of occurring anywhere in the study area. That is, N is a Poisson process if $N(A_1), \ldots, N(A_k)$ are independent Poisson random variables for any disjoint, measurable subsets $A_1, \ldots, A_k$ of S [Sch11]. The points of a point process are typically nearly identical other than by their times and locations. This serves as a baseline to test whether the distribution of accidents deviates from randomness.

Climate factors and freeway information are extracted, combined, and prepared to use as covariates to compare in the models. This study also prepares future studies to compare accidents during different parts of the day by extracting the time and grouping them by day, evening, and night. When additional important information is stored along with each event point, the result may be viewed as a marked point process [Sch11]. However, this study will focus on the basic spatial point process models.

2.1.1 Statistical Methods and Techniques

This study systematically evaluates the efficacy of incorporating spatial and climate covariates into point process models. Residual diagnostics for fatal car accidents in DTLA reveal that homogeneous models fail to capture local clustering. Incorporating covariates such as freeway proximity and environmental factors improves model performance, reducing unexplained variability and aligning residuals with theoretical expectations. Q–Q plots and K-function analysis further demonstrate the effectiveness of covariates in balancing clustering and dispersion patterns, particularly at smaller distances.

2.1.1.1 Point Process:

To model spatial heterogeneity, the inhomogeneous process with intensity function:

$$\lambda(u, x) = b(u), \quad u \in W,$$

allows intensity to vary across the study region. The inhomogeneous also extends the homogeneous model by incorporating spatial covariates to account for variability in intensity [BCS12].

2.1.1.2 Residual Analysis:

The spatial point process models make use of residual plots and influence diagnostics to identify unusual or influential observations. Under a homogeneous Poisson process, the theoretical K-function is:

$$K(h) = \pi h^2,$$

indicating complete spatial randomness [VS06]. These residuals can be used to assess the model fit, particularly in regions where intensity is low, and require $\hat{\lambda}(x_i, X) > 0$ for all $x_i \in X$[BCS12]. The residuals apply to any point process model that has a conditional intensity [BCS12].

Residual diagnostics includes Q–Q plots to validate the interpoint interaction component of a model. These plots compare empirical quantiles of the smoothed residual field $s(u)$ with expected empirical quantiles under the fitted model. For the j-th quantile, the expected quantile e_j is calculated as:

$$e_j = \frac{1}{N} \sum_{n=1}^{N} s_{(j)}^{(n)},$$

where $s_{(j)}^{(n)}$ represents the j-th order statistic from the simulated data under the model. A Q–Q plot of $s_{(j)}$ against e_j provides a graphical assessment of model adequacy [BCS12]. Skewness is used to measure asymmetry, while kurtosis measures the peakedness of residual distributions[Kim13].

2.1.1.3 Goodness-of-Fit:

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) balance model fit and complexity:

$$\text{AIC} = -2 \log L + 2k, \quad \text{BIC} = -2 \log L + k \log n,$$

where L is the likelihood, k is the number of parameters, and n is the sample size. These metrics assist in selecting models with optimal performance while avoiding overfitting [Kle08].

2.1.2 Framework

A flowchart is included below to help understand the structure of this study.

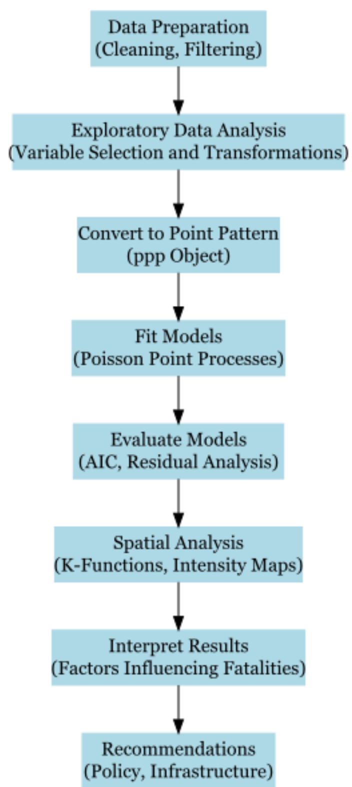

Figure 2.2: Workflow of the Analysis

2.2 Data Collection and Description

2.2.1 LAPD

The primary dataset for this study was sourced from the Los Angeles Police Department (LAPD) through their publicly available repository of traffic collision data spanning from 2010 to the present [Dep24]. This dataset provides records of traffic accidents in Los Angeles county, including geographic, temporal, and descriptive variables (through 4 digit MO Codes). Geocoding is used to extract latitude and longitude coordinates from the `Location` field to enable spatial analysis. Observations with invalid or missing data, coordinates equal to zero and missing `MO.Codes`, were removed and filtered to ensure data quality. `Time.Occurred` field was converted from military time to a standardized `HH:MM:SS` format for temporal analysis. The `TimeOfDay` field defines Day as the time 6:00am-5:59pm, Evening 6:00pm-10:59pm, and Night 11:00pm-5:59am.

2.2.1.1 MO Codes

The LAPD dataset includes a field for `MO.Codes`, which provides detailed descriptions of accident circumstances and contributing factors, however this information is hidden in the form of 4 digits that need additional information to decode. A separate codebook [Los24] was used to interpret these codes and create binary indicator variables for modeling. The fatality variable is indicated by the presence of MO code `3027` (*T/C - (K) Fatal Injury*)to classify accidents as fatal or non-fatal. MO code `3036` (*T/C - At Intersection - Yes*) identified accidents occurring at intersections. MO code `3036` (*T/C - At Intersection - Yes*) identified accidents occurring at intersections. Indicators were created for variables such as `DUI.Felony` (`3038`), `Speeding.Involved` (`3040`), and `Hit.Run.Felony` (`3029`) for behavioral indicators. MO codes were also used to distinguish between accident types, such as `Veh.vs.Ped` (`3003`), `Veh.vs.Veh` (`3004`), and `Veh.vs.Bike` (`3009`).

A comprehensive list of binary indicators created from MO codes is provided in the Appendix. This preprocessing step enhanced the dataset's interpretability and allowed for more finite modeling of accident characteristics.

2.2.2 Spatial Filtering

The study area is represented as a rectangular spatial window bounded by the geographic boundaries of Downtown Los Angeles (Latitude: 34.030–34.070, Longitude: -118.275 to -118.225). Minimum distance to freeway exits was calculated using the Haversine formula, enabling investigation into the proximity of accidents to freeway exits.

2.2.3 Climate Information

Climate data for Downtown Los Angeles is sourced from the National Oceanic and Atmospheric Administration (NOAA) using the Global Historical Climatology Network (GHCND) dataset [Inf24]. This dataset was divided into four periods (2010–2012, 2012–2016, 2016–2020, and 2020–2024) and subsequently merged to create a comprehensive record of weather conditions for the study period. Climate variables were renamed for clarity, `WT01` to `Fog`, `WT02` to `Heavy.Fog`, and `WT08` to `Smoke.or.Haze`. Missing values in weather condition indicators were replaced with zeros to ensure consistency. Date Formatting: The `DATE` column was converted to a standardized `Date.Occurred` format to facilitate merging with the LAPD dataset. The climate data merged with the accident data allows the incorporation of environmental factors into the accident risk analysis.

2.2.3.1 Final Dataset Summary

The final dataset includes variables capturing spatial, temporal, environmental, and behavioral factors. Not all the explained variables were used in the modeling. However, factors were decided not to be removed for potential future use. This dataset provides only a basis for applying myriad statistical modeling techniques.

The final dataset incorporates variables spanning spatial, temporal, environmental, and behavioral factors. Spatial variables include `min_distance_to_freeway_exit`, `Latitude`, `Longitude`, and `Intersection`, while temporal attributes, `Date.Occurred`, `DayOfWeek`, `TimeOfDay`, and `Time.Occurred`, provide a detailed account of precise time factors. Behavioral factors are captured through variables like `Speeding.Involved`, `DUI.Felony`, and `Hit.Run.Felony`. Environmental conditions are reflected in variables such as `Fog`, `Heavy.Fog`, and `Smoke.or.Haze`. The response variable, `Fatality`, denotes whether a fatality occurred, serving as the focal point of analysis.

2.3 Feature Engineering

Feature engineering involves preparing data for modeling by selecting and transforming variables that capture significant relationships. This step enhances model performance and interpretability, particularly for analyses involving spatial and environmental factors.

2.3.1 Variable Selection and Transformations

Variable selection identified predictors most relevant to understanding fatal accidents. The process combined exploratory data analysis, domain knowledge, and statistical tests. The response variable in the data is the binary `Fatality`. Environmental (`Smoke.or.Haze`) and spatial variables (`min_distance_to_freeway_exit`) are selected as the predictors.

2.3.1.1 Transformations

Transformations were applied to capture non-linear relationships and simplify spatial and temporal dependencies. The variable `min_distance_to_freeway_exit` was cubed to create the `cub_distance` variable to reflect potential non-linear effects. Multiple transformations, including square root and cube root, were tested. However, the log transformation was highlighted, indicating its suitability for the data.

$$\text{cub\_distance} = (\text{min\_distance\_to\_freeway\_exit})^3$$

2.4 Modeling Applications

2.4.1 Point Pattern Object

Spatial data was prepared by converting latitude and longitude coordinates into a point pattern object (`ppp`) within a predefined observation window (`owin`). The observation window was constructed using the range of coordinates:

$$\texttt{xrange} = [-118.2749, -118.2255], \quad \texttt{yrange} = [34.03, 34.07]$$

The observation window and point pattern object were defined as follows:

$$\texttt{window} = \text{owin(xrange, yrange)}, \quad \texttt{fatal\_ppp} = \text{ppp(x = Longitude, y = Latitude, window = window)}$$

2.4.2 Homogeneous Poisson Point Process

The homogeneous Poisson point process assumes a constant intensity of events across the study area, meaning the likelihood of an event occurring is uniform regardless of location. This model was implemented using the `spatstat` package in R. The homogeneous Poisson point process model was fitted to the point pattern object using maximum likelihood estimation. The fitted intensity (λ) was found to be uniform across the study area, with the following value:

$$\lambda = 61,740.89 \text{ events per square unit.}$$

To assess the assumption of Complete Spatial Randomness (CSR), diagnostics were performed, including spatial functions (F-function, G-function, and K-function). These results reject the null hypothesis of CSR, indicating significant spatial heterogeneity in the point pattern. The diagnostics and predicted intensity suggest significant spatial heterogeneity in the point pattern, which violates the assumption of spatial uniformity under the homogeneous Poisson model. While the homogeneous model provides a baseline, these findings support the need for more sophisticated models may account for clustering and spatial variations in event intensity.

F-Function (Empty Space Function): Mean empirical $F(r)$ was 0.7354, closely aligned with the theoretical mean (0.7374). However, at shorter distances, deviations from CSR were observed, suggesting clustering. At larger distances, the empirical $F(r)$ reached its maximum of 1.0, indicating that most random locations are within some distance of observed points (Figure 2.3).

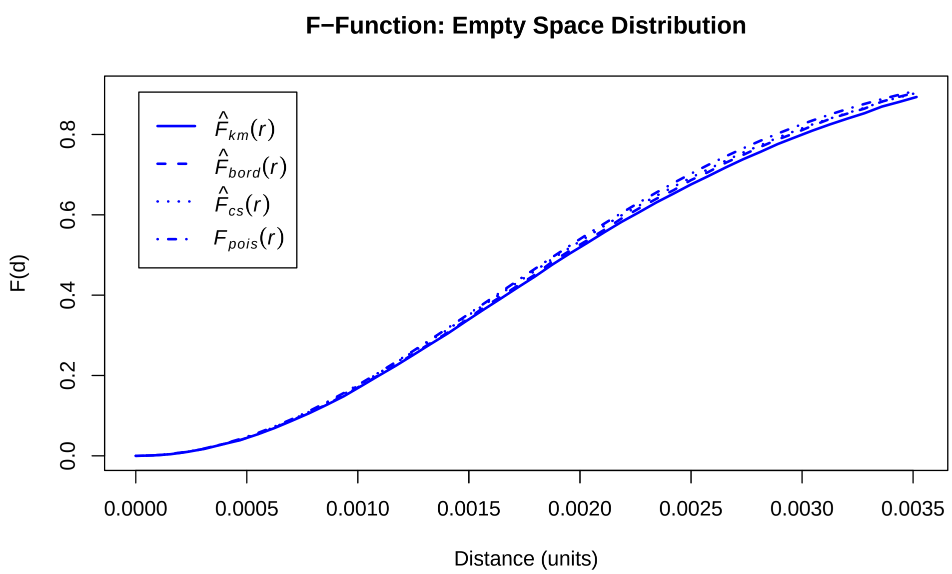

Figure 2.3: F-Function (Empty Space Function). The empirical $F(r)$ aligns closely with the theoretical $F(r)$, but deviations at shorter distances indicate clustering.

G-Function (Nearest Neighbor Function): Mean empirical $G(r)$ was 0.7228, slightly below the theoretical mean (0.7383), indicating closer proximity between points than expected under CSR. The empirical $G(r)$ reached its maximum of 1.0, confirming that all observed points have a nearest neighbor within certain small distances (Figure 2.4).

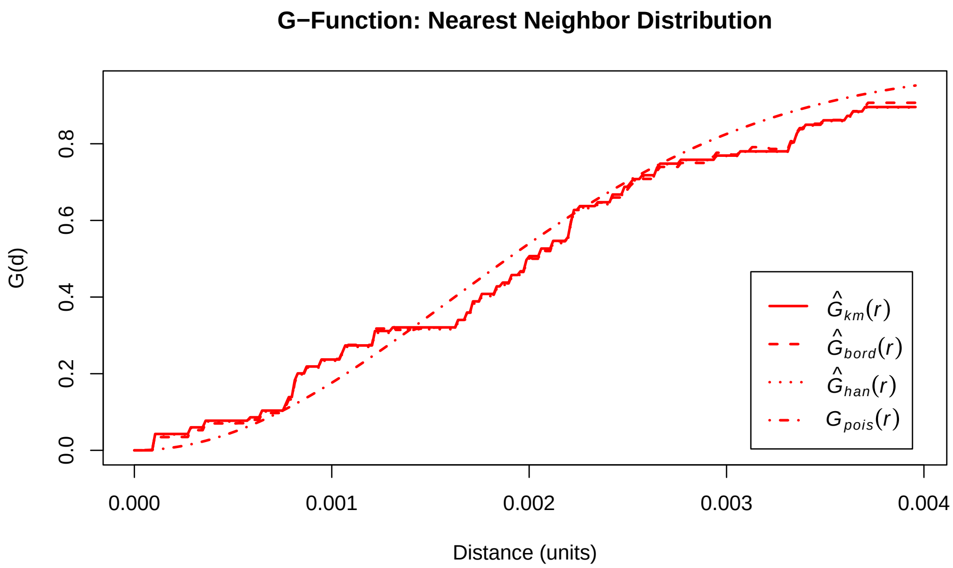

Figure 2.4: G-Function (Nearest Neighbor Function). The empirical $G(r)$ indicates closer proximity between points than expected under CSR, suggesting clustering.

K-Function (Ripley's K): Mean empirical $K(r)$ was 1.303×10^{-4}, exceeding the theoretical mean (1.048×10^{-4}), indicating significant clustering across spatial scales. The maximum $K(r)$ was 3.76×10^{-4}, further confirming clustering at larger distances (Figure 2.5).

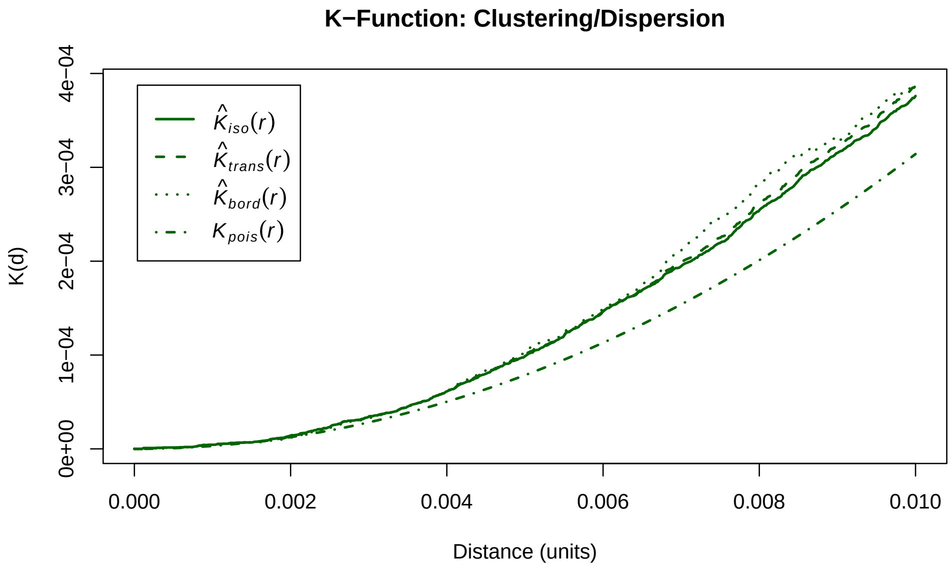

Figure 2.5: K-Function (Ripley's K). The empirical $K(r)$ exceeds the theoretical $K(r)$, confirming significant clustering across spatial scales.

2.4.3 Inhomogeneous Poisson Process Model (First-Order Effects)

The inhomogeneous model can explain the first-order spatial trends but may require additional covariates (e.g., traffic density, proximity to freeways) for improved accuracy.

Model Specification An inhomogeneous Poisson process was fitted using the trend formula:

$$\log \lambda(x, y) = \beta_0 + \beta_1 x + \beta_2 y$$

Intensity function, $\lambda(x, y)$ represents the expected number of events per unit area at location (x, y). β_0 is the intercept (baseline log-intensity). β_1 and β_2 are the coefficients capturing the linear effects of x (longitude) and y (latitude), respectively.

The model was fitted using the `ppm` function in the `spatstat` package with the Berman-Turner approximation. Quadrature points were used to approximate the intensity across the study area, with a grid of 32×32 dummy points. The total window area was 0.001976 square units.

The fitted log-intensity with fitted coefficients is:

$$\log \lambda(x, y) = -146.098 - 4.490x - 10.980y$$

The large negative intercept indicates a very low baseline intensity of fatal accidents in the study area. Negative coefficients for both x (longitude) and y (latitude) suggest a decreasing trend in accident intensity as one moves toward higher longitude and latitude within the specified window.

2.4.4 Inhomogeneous Poisson Process With Freeway Covariate

This model investigates the relationship between the intensity of fatal car accidents and proximity to freeway exits, measured using the covariate `cub_distance` (cubed distance to the nearest freeway exit). The log-intensity function includes spatial coordinates (x, y) and the covariate `cub_distance`.

Model Specification: The log-intensity function is given by

$$\log \lambda(x, y) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 \texttt{cub\_distance}$$

The fitted model produced coefficients where the baseline log-intensity was $\beta_0 = -91.63$. Longitude ($\beta_1 = -3.78$) and latitude ($\beta_2 = -10.12$) showed negative but non-significant associations ($p > 0.05$), while `cub_distance` had a highly negative coefficient ($\beta_3 = -14,655.13$) with a wide confidence interval ($[-44,134.60, 14,824.35]$), indicating a non-significant effect ($p > 0.05$). These results suggest that proximity to freeway exits does not independently explain variations in accident intensity. While `cub_distance` was hypothesized to influence fatal accident intensity, its lack of statistical significance highlights the need for further investigation with additional covariates or alternative transformations to better understand spatial variations in fatal accidents.

2.4.5 Marked Inhomogeneous Poisson Process With Climate Covariate

This model evaluates the impact of adverse environmental conditions (`Smoke.or.Haze`) on the intensity of fatal car accidents. The log-intensity function incorporates spatial coordinates (x, y) and binary covariate `Smoke.or.Haze`.

Model Specification: The log-intensity function is given by

$$\log \lambda(x, y) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 \texttt{Smoke.or.Haze}$$

The fitted model produced a baseline log-intensity of $\beta_0 = 3911.12$, with longitude showing a positive and significant association ($\beta_1 = 27.46, p < 0.05$), and latitude exhibiting a negative and significant association ($\beta_2 = -19.04, p < 0.05$). The covariate `Smoke.or.Haze` had a significant negative coefficient ($\beta_3 = -9.78, p < 0.01$), indicating that the presence of smoke or haze reduces the likelihood of fatal accidents. This reduction in accident intensity likely reflects behavioral adaptations by drivers under adverse environmental conditions. The inclusion of `Smoke.or.Haze` in the model highlights the influence of environmental factors on accident intensity and supports the hypothesis that adverse conditions can lead to behavioral changes that reduce accident risk. These findings demonstrate the importance of incorporating environmental covariates into spatial modeling to better understand the factors affecting accident intensity.

2.4.6 Inhomogeneous Poisson Process With Multiple Covariates

For this model, geographic coordinates were used(x, y) and two covariates: `cub_distance` and `Smoke.or.Haze` .

Model Specification The log-intensity function for the model is defined as:

$$\log \lambda(x, y) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 \texttt{cub\_distance} + \beta_4 \texttt{Smoke.or.Haze}$$

The baseline log-intensity of fatal accidents in the absence of spatial effects or covariates is represented by $\beta_0 = 4349.718$. Longitude ($\beta_1 = 31.373$) is positively associated with accident intensity, indicating higher intensity in areas with greater x-coordinates, while latitude ($\beta_2 = -18.316$) has a negative association, reflecting lower intensity at higher y-coordinates. The covariate `cub_distance` ($\beta_3 = -18722.051$) shows a strong negative association, suggesting that locations farther from freeway exits have significantly lower accident intensity, although this effect is not statistically significant ($p = 0.225$). Conversely, `Smoke.or.Haze` ($\beta_4 = -10.554$) has a statistically significant negative coefficient ($p < 0.01$), indicating reduced accident intensity in areas with smoke or haze. The statistical significance of the spatial coordinates (x, y) and `Smoke.or.Haze` further supports their influence on fatal accident intensity, while the non-significance of `cub_distance` suggests its weaker or confounded effect. Predicted intensity values range from 22,212.19 to 126,151.29 events per unit area, with a mean of 62,180.16 and a standard deviation of 19,835.27, highlighting substantial spatial variability in fatal accident occurrence.

The inclusion of multiple covariates provided nuanced insights into spatial patterns of fatal car accidents. (`Smoke.or.Haze`) emerged as a significant predictor, indicating that adverse environmental conditions might reduce accident intensity, potentially due to altered traffic behavior.(`cub_distance`) exhibited a weaker, non-significant association, suggesting that proximity to freeway exits may be less influential than hypothesized or confounded by other factors.

2.5 Descriptive Statistics

This section presents a summary of model performance, residual diagnostics, and spatial intensity characteristics for the fitted Poisson process models. The results provide insights into the effectiveness of each model and the influence of the included covariates.

2.5.1 Model Comparison

Table 2.1 summarizes the Akaike Information Criterion (AIC) values for all fitted models. The model incorporating `Smoke.or.Haze` alone achieved the lowest AIC (-2450.63), indicating the best fit. The model with both covariates (`cub_distance` and `Smoke.or.Haze`) performed slightly worse (-2450.17), suggesting that `cub_distance` does not substantially improve model fit.

Table 2.1: AIC Comparison of Models

Model	**AIC**
Homogeneous PPP	-2445.49
Inhomogeneous PPP	-2443.94
cub_distance Only	-2442.92
Smoke.or.Haze Only	-2450.63
Both Covariates	-2450.17

2.5.2 Coefficient Summary

Table 2.2 provides the estimated coefficients, standard errors, confidence intervals, and statistical significance for key predictors across the models. The table summarizes the coefficients, standard errors (SE), confidence intervals (CI), and significance levels for two spatial models: one with only the `Smoke.or.Haze` covariate and another with both `cub_distance` and `Smoke.or.Haze`. The `Smoke.or.Haze` covariate consistently shows strong negative effects, with significant coefficients in both models. In the combined model, spatial coordinates (x and y) also significantly influence outcomes, highlighting the spatial variability of accidents. However, the `cub_distance` variable shows a large but nonsignificant negative effect, suggesting limited impact in this analysis.

Table 2.2: Model Coefficient Summary

Model	Predictor	Estimate	SE	CI 95% (Low)	CI 95% (High)	Significance
Smoke.or.Haze Only	y	-19.04	8.69	-36.08	-2.00	*
Smoke.or.Haze Only	`Smoke.or.Haze`	-9.78	3.35	-16.34	-3.22	**
Both Covariates	Intercept	4349.72	1756.54	906.97	7792.47	*
Both Covariates	x	31.37	14.19	3.56	59.19	*
Both Covariates	y	-18.32	8.97	-35.89	-0.75	*
Both Covariates	`cub_distance`	-18,722.05	15,402.82	-48,911.03	11,466.93	
Both Covariates	`Smoke.or.Haze`	-10.55	3.56	-17.52	-3.58	**

2.5.3 Residual Diagnostics

Residual diagnostics assess the model's fit to the data. Table 3.1 summarizes the mean and standard deviation of residuals for each model. The residuals for the model with both covariates have the largest standard deviation, indicating slightly higher variability.

Table 2.3: Residual Summary

Model	Mean Residuals	SD Residuals
Homogeneous PPP	5.62×10^{-21}	0.00131
Inhomogeneous PPP	-2.40×10^{-7}	0.00131
cub_distance Only	9.89×10^{-8}	0.00131
Smoke.or.Haze Only	-5.46×10^{-7}	0.00131
Both Covariates	6.40×10^{-7}	0.00132

The summary of the residuals indicates that the discrete mass (observed points) and continuous mass (background intensity) nearly cancel out, resulting in a total mass close to zero (0.0007). This balance suggests the model's predictions align well with the observed data. Further comparison between models are explained in Chapter 3.

2.5.4 Spatial Intensity Analysis

Table 2.4 summarizes the predicted intensity metrics for each model. The model with `Smoke.or.Haze` alone produced the highest maximum intensity ($139,195.92$), while the model with both covariates provided the widest range of predicted intensity ($22,212.19$ to $126,151.29$).

Table 2.4: Predicted Intensity Summary

Model	**Min Intensity**	**Max Intensity**	**Mean Intensity**
Homogeneous PPP	61,740.89	61,740.89	61,740.89
Inhomogeneous PPP	44,035.41	84,846.55	61,743.71
cub_distance Only	29,592.50	77,210.32	61,773.66
Smoke.or.Haze Only	24,070.40	139,195.92	62,120.32
Both Covariates	22,212.19	126,151.29	62,180.16

The `Smoke.or.Haze` model achieved the highest maximum intensity. Adding `cub_distance` broadened the range of predicted intensity but did not significantly alter the mean intensity. The homogeneous model predicted a constant intensity across the study area, as expected.

CHAPTER 3

Model Performance and Interpretation

3.1 Variable-Performance Comparison

The predicted intensity plots Figure 3.1 for the models incorporating both covariates and the weather-related covariate (`Smoke.or.Haze`) show similar spatial patterns. In contrast, the plot using the freeway entrance distance covariate (`cub_distance`) exhibits distinct differences. These differences highlight the following information about model fits:

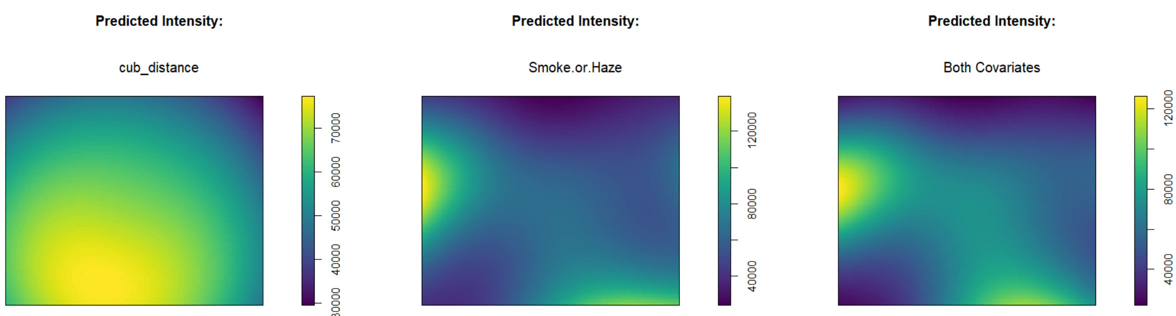

Figure 3.1: Predicted accident intensity maps for models incorporating `cub_distance` (left), `Smoke.or.Haze` (middle), and both covariates (right).

The spatial intensity is evenly distributed across the study area for the climate covariate model, indicating that environmental factors like smoke or haze contribute to overall accident risk but do not localize specific hotspots. This covariate captures broad-scale patterns but may lack specificity for localized clustering.

The intensity is higher near freeway exits, suggesting that proximity to freeway infrastructure is a key determinant of localized accident hotspots. This covariate effectively captures micro-level clustering.

The combined model blends the broad-scale effects of `Smoke.or.Haze` and the localized effects of `cub_distance`. The resulting intensity map shares similarities with the weather covariate plot, suggesting that `Smoke.or.Haze` dominates the combined model's spatial patterns. However, the combined model reduces unexplained clustering near freeway exits, this could be indication of an improved overall fit.

3.2 Residual Analysis

Residual analysis was performed to assess the goodness-of-fit for each model. Spatial residual plots and Q-Q plots were used as diagnostic tools. The spatial distribution of residuals for each model is shown in Figure 3.2. Red indicates areas of over-prediction, while blue signifies under-prediction.

The *Homogeneous*, serving as the overarching baseline, shows relatively uniform residual patterns but fails to account for local variations in intensity, particularly in areas of high clustering. In contrast, the *Inhomogeneous PPP* and models incorporating covariates exhibit reduced clustering of residuals, indicating improved fit in specific regions. The model with *Smoke.or.Haze Only* and the model with *Both Covariates* show noticeable improvements in capturing spatial variations, although some over- and under-prediction remain in extreme regions.

The Q-Q plots in Figure 3.3 provide a visual comparison of residual alignment with theoretical quantiles for each model. A perfect fit would align all points with the 1:1 line.

The *Homogeneous PPP* shows the greatest deviation from the theoretical quantiles, reflecting its limitations in capturing variability.*Inhomogeneous PPP* shows moderate improvement, although deviations remain in the tails. Models with covariates only *Smoke.or.Haze*,

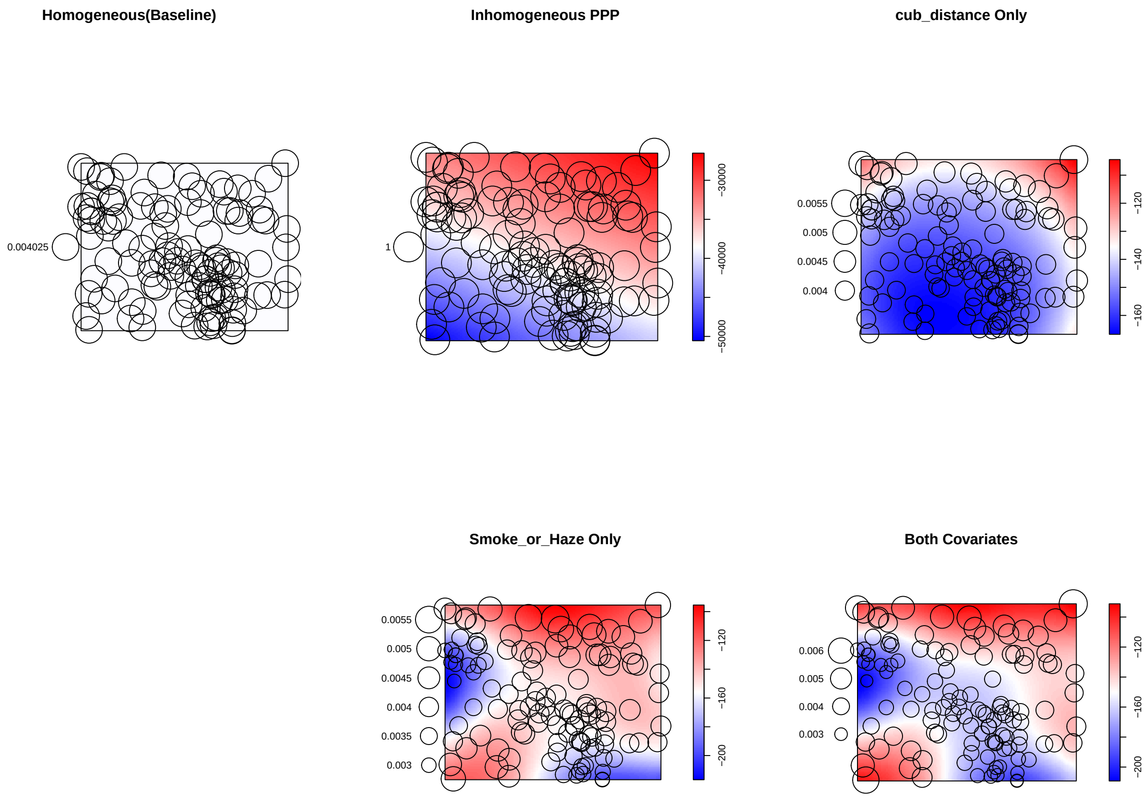

Figure 3.2: Comparison of Spatial Residuals for Different Models. Red and blue indicate over- and under-prediction, respectively.

only *cub_distance*, and Both Covariates align more closely with theoretical quantiles, particularly in central regions, suggesting better adherence to the normality assumption.

Mean residuals for all models are close to zero, suggesting unbiasedness overall. Standard deviations of residuals are similar across models, with minor variations, indicating comparable dispersion. Notably, the *Both Covariates* model achieves the smallest maximum residual value (0.0066), indicating better handling of extreme values compared to other models. Table 3.1 summarizes the residual statistics for each model.

Further insights are drawn from the skewness and kurtosis of residuals, as shown in Table 3.2. All models exhibit positive skewness indicating longer right tails in the residual

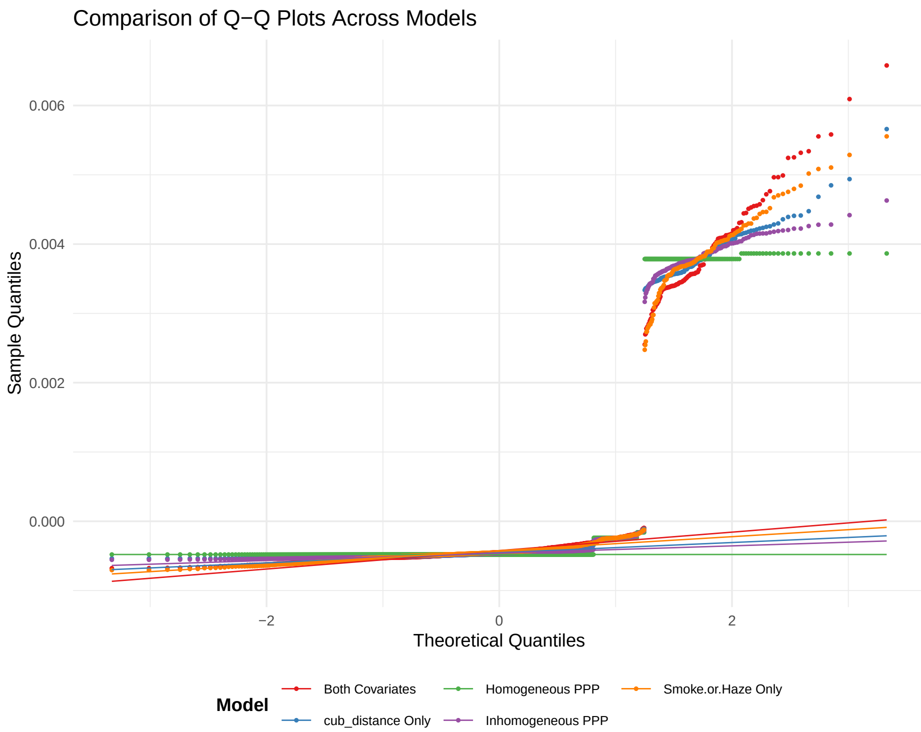

Figure 3.3: Comparison of Q-Q Plots Across Models. The overlay plot highlights differences in performance relative to theoretical quantiles.

Table 3.1: Summary Statistics of Residuals by Model

Model	**Mean**	**Median**	**SD**	**Min**	**Max**
Both Covariates	6.40×10^{-7}	-0.00045	0.00132	-0.00068	0.00658
Homogeneous PPP	5.62×10^{-21}	-0.00048	0.00131	-0.00048	0.00386
Inhomogeneous PPP	-2.40×10^{-7}	-0.00046	0.00131	-0.00056	0.00463
Smoke.or.Haze Only	-5.46×10^{-7}	-0.00045	0.00131	-0.00070	0.00555
cub_distance Only	9.89×10^{-8}	-0.00047	0.00131	-0.00054	0.00566

distributions. Similarly, kurtosis values are high suggesting heavy tails and potential outliers.

Finally, the Kolmogorov-Smirnov test results (Table 3.3) reveal that all models significantly deviate from a normal distribution ($p < 10^{-190}$). However, the models with covariates

Table 3.2: Skewness and Kurtosis of Residuals by Model

Model	**Skewness**	**Kurtosis**
Both Covariates	2.71	8.88
Homogeneous PPP	2.54	7.50
Inhomogeneous PPP	2.56	7.65
Smoke.or.Haze Only	2.64	8.27
cub_distance Only	2.59	7.85

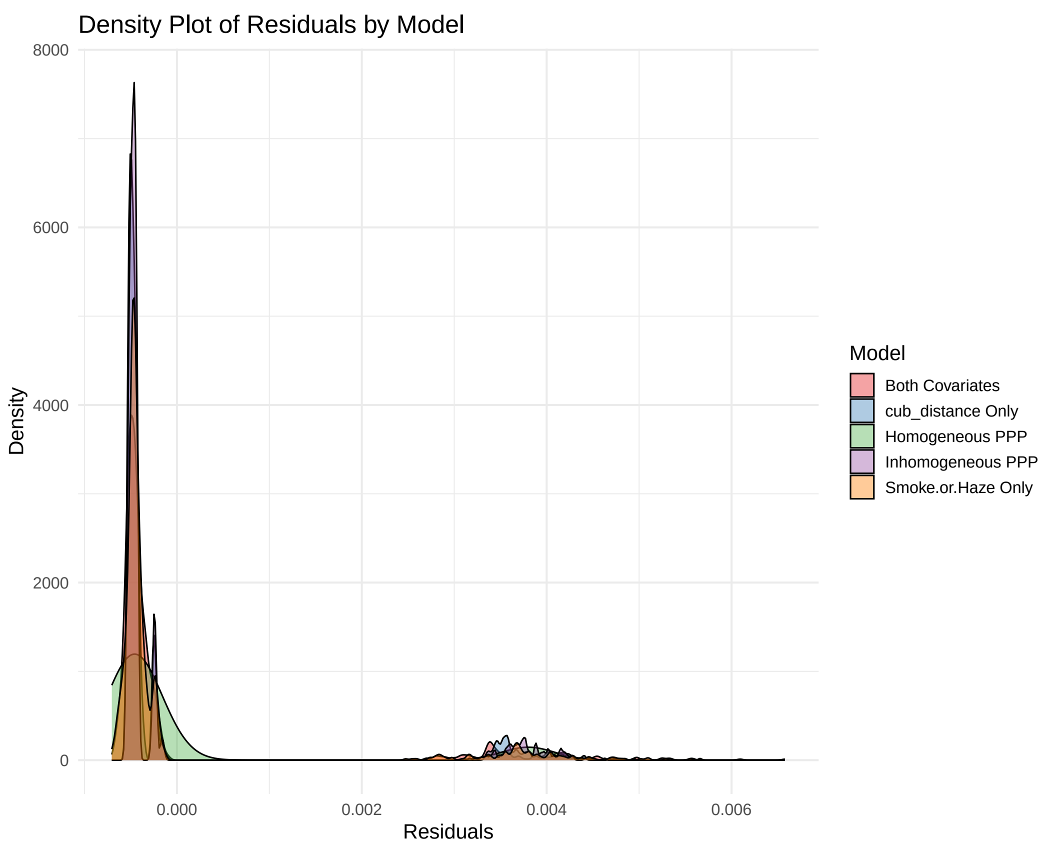

Figure 3.4: Density Plot of Residuals by Model Highlighting the Heavy Tails in the Models.

generally show smaller deviations compared to the baseline.

The residual analysis highlights that incorporating covariates improves model performance over the baseline. While residuals for all models deviate from normality, covariate-

Table 3.3: Kolmogorov-Smirnov Test Results for Residuals

Model	**KS p-value**
Both Covariates	4.18×10^{-191}
Homogeneous PPP	1.53×10^{-206}
Inhomogeneous PPP	7.73×10^{-199}
Smoke.or.Haze Only	1.35×10^{-193}
cub_distance Only	3.12×10^{-196}

based models achieve better alignment and reduced extremes in spatial predictions.

3.3 K-Function Comparison

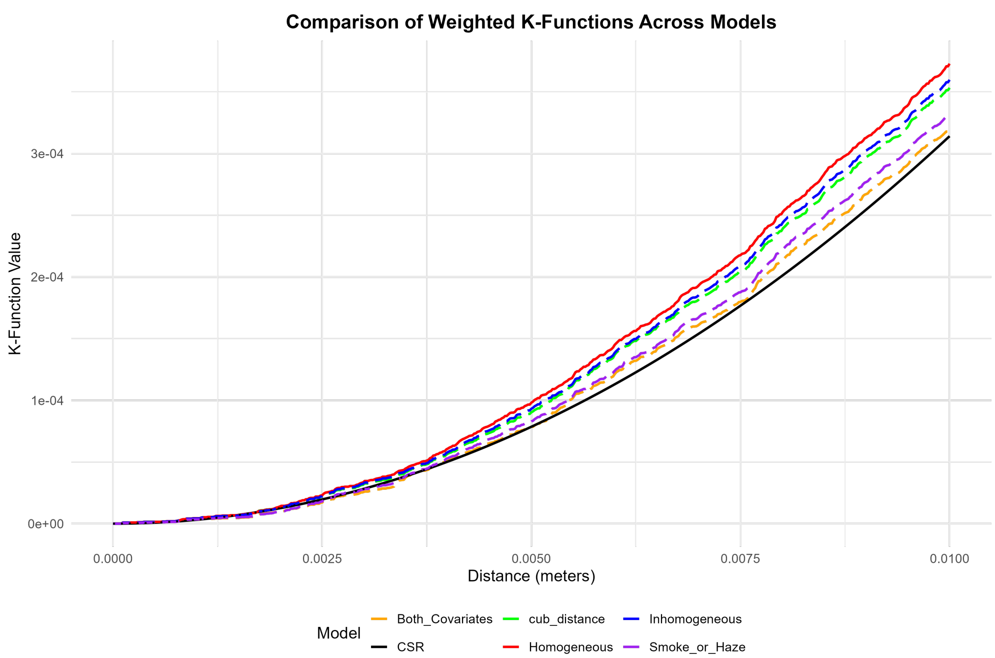

Figure 3.5: Comparison of weighted K-functions for various models. Points above the CSR baseline (solid black) indicate clustering.

The K-function analysis provides insights into the spatial interaction patterns. The observed K-function values for each model are compared against the baseline of Complete Spatial Randomness (CSR). Table 3.4 summarizes the number of distances where the K-function for each model deviates above or below the CSR baseline.

Model	**Above CSR**	**Below CSR**
Homogeneous PPP	496	16
Inhomogeneous PPP	490	22
Inhomogeneous PPP with `cub_distance`	491	21
Inhomogeneous PPP with `Smoke.or.Haze`	389	123
Inhomogeneous PPP with Both Covariates	352	160

Table 3.4: Summary of K-function deviations from CSR for different models.

The homogeneous PPP model shows clustering above CSR at 496 distances and dispersion below CSR at 16 distances. Including only the spatial trends in first order model slightly reduces clustering but increases dispersion. This improvement indicates the value of accounting for basic spatial variation. Inclusion of the `cub_distance` covariate yields a similar performance to the spatial trend model. The comparable results suggest that proximity to freeway exits partially explains accident patterns but does not fully capture the observed clustering. The inclusion of environmental factors like `Smoke.or.Haze` leads to a notable reduction in clustering but introduces a significant increase in dispersion. This suggests that environmental covariates account for clustering at smaller scales but may introduce over-dispersion in other areas. Combining both covariates (`cub_distance` and `Smoke.or.Haze`) results in the most balanced model, with the fewest clustering distances and the highest dispersion. This indicates that the combined model effectively reduces unexplained clustering, particularly at smaller distances, but may over-adjust for clustering at larger scales. Figure 3.5 provides the visual for the weighted K-functions for all models, with the CSR envelope included for reference.

CHAPTER 4

Conclusion

4.1 Interpretability and Applicability

Results of the residual analysis and Weighted-K analysis highlight that the models should be built upon and that improvement continues as the model becomes more complex, accounting for freeway proximity and environmental conditions. These findings validate the applicability of covariant-based models for urban safety planning. They highlight the importance of considering locational and environmental factors in traffic accident analysis, offering actionable insights for policymakers.

4.2 Limitations of the Study

While the study contributes valuable insights, it is important to acknowledge its limitations. Beginning with the model assumptions, the Poisson point process (PPP) models assume independence between events, which might not hold in the presence of temporal or spatial dependencies, such as accidents clustered due to adverse weather conditions or during specific times of the day. The analysis also focused on two covariates (*Smoke.or.Haze* and *cub_distance*). Including additional variables, such as traffic density, may further enhance model performance.

The analysis relies on data collected by law enforcement and external sources, which may contain reporting biases, missing values, or inaccuracies. This could affect the data quality and completeness of events—for instance, environmental covariates such as *Smoke.or.Haze* are interpolated and may not fully capture localized weather conditions at the time of accidents. Spatial covariates such as *cub_distance* are derived from aggregated values, which might lead to overgeneralization and loss of finer spatial details.

The geographic focus on DTLA may limit the flexibility of the findings to other areas, even within Los Angeles, as urban dynamics vary significantly across neighborhoods. This study primarily addressed spatial patterns, with no emphasis on temporal dynamics. Incorporating temporal variability could yield a more comprehensive understanding of car accident fatalities in DTLA.

Lastly, residual normality remained a challenge across all models, as indicated by the Kolmogorov-Smirnov test results.

4.3 Future Work and Recommendations

Future studies should consider some expansions and enhanced modeling techniques to the models and datasets used in this study. Expanding the range of covariates by including additional factors like traffic flow, weather conditions, and infrastructure characteristics would allow for a more comprehensive understanding of accident determinants. Incorporating spatio-temporal analysis, such as integrating spatio-temporal point process models or marked point processes, could capture the dynamic nature of accidents over time and improve the prediction of evolving patterns. Additionally, advanced techniques like machine learning and hybrid modeling approaches may address residual deviations and enhance model flexibility.

Comparing alternative modeling approaches, including hierarchical Bayesian models and machine learning techniques, would help evaluate their predictive accuracy and explanatory power relative to the methods employed in this study.

Broadening the geographic scope of the analysis by applying the methods to other neighborhoods within Los Angeles or other cities would assess the generalizability and transferability of the observed patterns. Such comparative analyses could identify region-specific trends and provide a foundation for targeted interventions aimed at improving road safety.

Exploring the policy implications of traffic safety measures, such as improved bicycle lanes, stricter speed regulation enforcement, and enhanced signage, could offer actionable insights into reducing accident rates.

By addressing these limitations and adapting the models, the study could reduce traffic fatalities and improve urban road safety in DTLA, a city populated by so many, with vehicles of potential life-altering events at every corner. Future research can advance the field of traffic accident modeling, providing deeper insights and enhancing the effectiveness of safety interventions.

APPENDIX A

Mo.Code Desc

0100 Suspect Impersonate

0101 Aid victim

0102 Blind

0103 Crippled

0104 Customer

0105 Delivery

0106 Doctor

0107 God

0108 Infirm

0109 Inspector

0110 Involved in traffic/accident

0112 Police

0113 Renting

0114 Repair Person

0115 Returning stolen property

0116 Satan

0117 Salesman

0118 Seeking someone

0119 Sent by owner

0120 Social Security/Medicare

0121 DWP/Gas Company/Utility worker

0122 Contractor

0123 Gardener/Tree Trimmer

0200 Suspect wore disguise

0201 Bag

0202 Cap/hat

0203 Cloth (with eyeholes)

0204 Clothes of opposite sex

0205 Earring

0206 Gloves

0207 Handkerchief

0208 Halloween mask

0209 Mask

0210 Make up (males only)

0211 Shoes

0212 Nude/partly nude

0213 Ski mask

0214 Stocking

0215 Unusual clothes

0216 Suspect wore hood/hoodie

0217 Uniform

0220 Suspect wore motorcycle helmet

0301 Escaped on (used) transit train

0302 Aimed gun

0303 Ambushed

0304 Ate/drank on premises

0305 Attacks from rear

0306 Crime on upper floor

0307 Defecated/urinated

0308 Demands jewelry

0309 Drive-by shooting

0310 Got victim to withdraw savings

0311 Graffiti

0312 Gun in waistband

0313 Hid in building

0314 Hot Prowl

0315 Jumped counter/goes behind counter

0316 Makes victim give money

0317 Pillowcase/suitcase

0318 Prepared exit

0319 Profanity Used

0320 Quiet polite

0321 Ransacked

0322 Smashed display case

0323 Smoked on premises

0324 Takes money from register

0325 Took merchandise

0326 Used driver

0327 Used lookout

0328 Used toilet

0329 Vandalized

0330 Victims vehicle taken

0331 Mailbox Bombing

0332 Mailbox Vandalism

0333 Used hand held radios

0334 Brandishes weapon

0335 Cases location

0336 Chain snatch

0337 Demands money

0338 Disables Telephone

0339 Disables video camera

0340 Suspect follows victim/follows victim home

0341 Makes vict lie down

0342 Multi-susps overwhelm

0343 Orders vict to rear room

0344 Removes vict property

0345 Riding bike

0346 Snatch property and runs

0347 Stalks vict

0348 Takeover other

0349 Takes mail

0350 Concealed victim's body

0351 Disabled Security

0352 Took Victim's clothing or jewelry

0353 Weapon Concealed

0354 Suspect takes car keys

0355 Demanded property other than money

0356 Suspect spits on victim

0357 Cuts or breaks purse strap

0358 Forces Entry

0359 Made unusual statement

0360 Suspect is Other Family Member

0361 Suspect is neighbor

0362 Suspect attempts to carry victim away

0363 Home invasion

0364 Suspect is babysitter

0365 Takeover robbery

0366 Ordered vict to open safe

0367 Was Transit Patrol

0368 Suspect speaks foreign language

0369 Suspect speaks spanish

0370 Frisks victim/pats down victim/searches victim

0371 Gang affiliation questions asked/made gang statement

0372 Photographed victim/took pictures of victim

0373 Handicapped/in wheelchair

0374 Gang signs/threw gang signs using hands

0375 Removes cash register

0376 Makes victim kneel

0377 Takes vict's identification/driver license

0378 Brings own bag

0379 Turns off lights/electricity

0380 Distracts Victim

0381 Suspect apologizes

0382 Removed money/property from safe

0383 Suspect entered during open house/party/estate/yard sale

0384 Suspect removed drugs from location

0385 Suspect removed parts from vehicle

0386 Suspect removed property from trunk of vehicle

0387 Weapon (other than gun) in waistband

0388 Suspect points laser at plane/helicopter

0389 Knock-knock

0390 Purse snatch

0391 Used demand note

0392 False Emergency Reporting

0393 911 Abuse

0394 Susp takes UPS, Fedex, USPS packages

0395 Murder/Suicide

0396 Used paper plates to disguise license number

0397 Cut lock (to bicycle, gate, etc.

0398 Roof access (remove A/C, equip, etc.)

0399 Vehicle to Vehicle shooting

0400 Force used

0401 Bit

0402 Blindfolded

0403 Bomb Threat, Bomb found

0404 Bomb Threat, no bomb

0405 Bound

0406 Brutal Assault

0407 Burned Victim

0408 Choked/uses choke hold/Strangulation/Suffocation

0409 Cover mouth w/hands

0410 Covered victim's face

0411 Cut/stabbed

0412 Disfigured

0413 Drugged

0414 Gagged

0415 Handcuffed/Metal

0416 Hit-Hit w/ weapon

0417 Kicked

0418 Kidnapped

0419 Pulled victims hair

0420 Searched

0421 Threaten to kill

0422 Threaten Victims family

0423 Tied victim to object

0424 Tore clothes off victim

0425 Tortured

0426 Twisted arm

0427 Whipped

0428 Dismembered

0429 Vict knocked to ground

0430 Vict shot

0431 Sprayed with chemical

0432 Intimidation

0433 Makes victim kneel

0434 Bed Sheets/Linens

0435 Chain

0436 Clothing

0437 Flexcuffs/Plastic Tie

0438 Rope/Cordage

0439 Tape/Electrical etc...

0440 Telephone/Electric Cord

0441 Wire

0442 Active Shooter/Armed person who has used deadly physical force on other persons & aggressively continues while having access to more victim's

0443 Threaten to harm victim (other than kill)

0444 Pushed

0445 Suspect swung weapon

0446 Suspect swung fist

0447 Suspect threw object at victim

0448 Grabbed

0449 Put a weapon to body

0450 Suspect shot at victim (no hits)

0500 Sex related acts

0501 Susp ejaculated outside victim

0502 Fecal Fetish

0503 Fondle victim

0504 Forced to disrobe

0505 Forced to fondle suspect

0506 Forced to masturbate suspect

0507 Forced to orally copulate suspect

0508 Hit victim prior, during, after act

0509 Hugged

0510 Kissed victims body/face

0511 Masochism/bondage

0512 Orally copulated victim

0513 Photographed victim

0514 Pornography

0515 Put hand, finger or object into vagina

0516 Reached climax/ejaculated

0517 Sadism/Sexual gratification obtained by infliction of physical or mental pain on ot

0518 Simulated intercourse

0519 Sodomy

0520 Solicited/offered immoral act

0521 Tongue or mouth to anus

0522 Touched

0523 Unable to get erection

0524 Underwear Fetish

0525 Urinated

0526 Utilized Condom

0527 Actual Intercourse

0528 Masturbate

0529 Indecent Exposure

0530 Used lubricant

0531 Suspect made sexually suggestive remarks

0532 Suspect undressed victim

0533 Consentual Sex

0534 Suspect in vehicle nude/partially nude

0535 Suspect asks minor's name

0536 Suspect removes own clothing

0537 Suspect removes victim's clothing

0538 Suspect fondles self

0539 Suspect puts hand in victim's rectum

0540 Suspect puts finger(s) in victim's rectum

0541 Suspect puts object(s) in victim's rectum

0542 Orders victim to undress

0543 Orders victim to fondle suspect

0544 Orders victim to fondle self

0545 Male Victim of sexual assault

0546 Susp instructs vict to make certain statements

0547 Suspect force vict to bathe/clean/wipe

0548 Suspect gives victim douche/enema

0549 Suspect ejaculates in victims mouth

0550 Suspect licks victim

0551 Suspect touches victim genitalia/genitals over clothing

0552 Suspect is Victim's Father

0553 Suspect is Victim's Mother

0554 Suspect is Victim's Brother

0555 Suspect is Victim's Sister

0556 Suspect is Victim's Step-Father

0557 Suspect is Victim's Step-Mother

0558 Suspect is Victim's Uncle

0559 Suspect is Victim's Aunt

0560 Suspect is Victim's Guardian

0561 Suspect is Victim's Son

0562 Suspect is Victim's Daughter

0563 Fetish, Other

0601 Business

0602 Family

0603 Landlord/Tenant/Neighbor

0604 Reproductive Health Services/Facilities

0605 Traffic Accident/Traffic related incident

0701 THEFT: Trick or Device

0800 BUNCO

0901 Organized Crime

0902 Political Activity

0903 Hatred/Prejudice

0904 Strike/Labor Troubles

0905 Terrorist Group

0906 Gangs

0907 Narcotics (Buy-Sell-Rip)

0908 Prostitution

0909 Ritual/Occult

0910 Public Transit (Metrolink/Train Station,Metro Rail Red,Line Subway Station, Metro Rail Blue Line Station,adjacent transit parking lots, tracks or tunnels MTA(RTD), and other municipal lines.

0911 Revenge

0912 Insurance

0913 Victim knew Suspect

0914 Other Felony

0915 Parolee

0916 Forced theft of vehicle (Car-Jacking)

0917 Victim's Employment

0918 Career Criminal

0919 Road Rage

0920 Homeland Security

0921 Hate Incident

0922 ATM Theft with PIN number

0923 Stolen/Forged Checks (Personal Checks)

0924 Stolen/Forged Checks (Business Checks)

0925 Stolen/Forged Checks (Cashier's Checks)

0926 Forged or Telephonic Prescription

0927 Fraudulent or forged school loan

0928 Forged or Fraudulent credit applications

0929 Unauthorized use of victim's bank account information

0930 Unauthorized use of victim's credit/debit card or number

0931 Counterfeit or forged real estate documents

0932 Suspect uses victim's identity in reporting a traffic collision

0933 Suspect uses victim's identity when arrested

0934 Suspect uses victim's identity when receiving a citation

0935 Misc. Stolen/Forged documents

0936 Dog Fighting

0937 Cock Fighting

0938 Animal Neglect

0939 Animal Hoarding

0940 Met online/Chat Room/on Party Line

0941 Non-Revocable Parole (NRP)

0942 Party/Flier party/Rave Party

0943 Human Trafficking

0944 Bait Operation

0945 Estes Robbery

0946 Gang Feud

1000 Suspects offers/solicits

1001 Aid for vehicle

1002 Amusement

1003 appraise

1004 Assistant

1005 Audition

1006 Bless

1007 Candy

1008 Cigarette

1009 Directions

1010 Drink (not liquor)

1011 Employment

1012 Find a job

1013 Food

1014 Game

1015 Gift

1016 Hold for safekeeping

1017 Information

1018 Liquor

1019 Money

1020 Narcotics

1021 Repair

1022 Ride

1023 Subscriptions

1024 Teach

1025 Train

1026 Use the phone or toilet

1027 Change

1028 Suspect solicits time of day

1100 Shots Fired

1101 Shots Fired (Animal) - Animal Services

1201 Absent-advertised in paper

1202 Aged (60 & over) or blind/crippled/unable to care for self

1203 Victim of crime past 12 months

1204 Moving

1205 On Vacation/Tourist

1206 Under influence drugs/liquor

1207 Hitchhiker

1208 Illegal Alien

1209 Salesman, Jewelry

1210 Professional (doctor, Lawyer, etc.)

1211 Public Official

1212 LA Police Officer

1213 LA Fireman

1214 Banking, ATM

1215 Prostitute

1216 Sales

1217 Teenager(Use if victim's age is unknown)

1218 Victim was Homeless/Transient

1219 Nude

1220 Partially Nude

1221 Missing Clothing/Jewelry

1222 Homosexual/Gay

1223 Riding bike

1224 Drive-through (not merchant)

1225 Stop sign/light

1226 Catering Truck Operator

1227 Delivery person

1228 Leaving Business Area

1229 Making bank drop

1230 Postal employee

1231 Taxi Driver

1232 Bank, Arriving at

1233 Bank, Leaving

1234 Bar Customer

1235 Bisexual/sexually oriented towards both sexes

1236 Clerk/Employer/Owner

1237 Customer

1238 Handicapped

1239 Transgender

1240 Vehicle occupant/Passenger

1241 Spouse

1242 Parent

1243 Co-habitants

1244 Victim was forced into business

1245 Victim was forced into residence

1247 Opening business

1248 Closing business

1251 Victim was a student

1252 Victim was a street vendor

1253 Bus Driver

1254 Train Operator

1255 Followed Transit System

1256 Patron

1257 Victim is Newborn-5 years old

1258 Victim is 6 years old thru 13 years old

1259 Victim is 14 years old thru 17 years old

1260 Deaf/Hearing Impaired

1261 Mentally Challenged/Retarded/Intellectually Slow

1262 Raped while unconscious

1263 Agricultural Target

1264 Pipeline

1265 Mailbox

1266 Victim was security guard

1267 Home under construction

1268 Victim was 5150/Mental Illness

1269 Victim was armored car driver

1270 Victim was gang member

1271 Victim was Law Enforcement (not LAPD)

1272 Victim was at/leaving medical/retail/non-retail cannabis location

1273 Home was being fumigated

1274 Victim was Inmate/Incarcerated

1275 Vacant Residence/Building

1276 Pregnant

1277 Gardner

1278 Victim was Uber/Lyft driver

1279 Victim was Foster child

1280 Victim was Foster parent

1281 Victim was Pistol-whipped

1300 Vehicle involved

1301 Forced victim vehicle to curb

1302 Suspect forced way into victim's vehicle

1303 Hid in rear seat

1304 Stopped victim vehicle by flagging down, forcing T/A, etc.

1305 Victim forced into vehicle

1306 Victim parking, garaging vehicle

1307 Breaks window

1308 Drives by and snatches property

1309 Susp uses vehicle

1310 Victim in vehicle

1311 Victim removed from vehicle

1312 Suspect follows victim in vehicle

1313 Suspect exits vehicle and attacks pedestrian

1314 Victim loading vehicle

1315 Victim unloading vehicle

1316 Victim entering their vehicle

1317 Victim exiting their vehicle

1318 Suspect follows victim home

1401 Blood Stains

1402 Evidence Booked (any crime)

1403 Fingerprints

1404 Footprints

1405 Left Note

1406 Tool Marks

1407 Bullets/Casings

1408 Bite Marks

1409 Clothes

1410 Gun Shot Residue

1411 Hair

1412 Jewelry

1413 Paint

1414 Photographs

1415 Rape Kit

1416 Saliva

1417 Semen

1418 Skeleton/Bones

1419 Firearm booked as evidence

1420 Video surveillance booked/available

1501 Other MO (see rpt)

1601 Bodily Force

1602 Cutting Tool

1603 Knob Twist

1604 Lock Box

1605 Lock slip/key/pick

1606 Open/unlocked

1607 Pried

1608 Removed

1609 Smashed

1610 Tunneled

1611 Shaved Key

1612 Punched/Pulled Door Lock

1701 Elder Abuse/Physical

1702 Elder Abuse/Financial

1801 Susp is/was mother's boyfriend

1802 Susp is/was victim's co-worker

1803 Susp is/was victim's employee

1804 Susp is/was victim's employer

1805 Susp is/was fellow gang member

1806 Susp is/was father's girlfriend

1807 Susp is/was priest/pastor

1808 Susp is/was other religious confidant

1809 Susp is/was rival gang member

1810 Susp is/was roommate

1811 Susp is/was victim's teacher/coach

1812 Susp is/was foster parent/sibling

1813 Susp is/was current/former spouse/co-habitant

1814 Susp is/was current/former boyfriend/girlfriend

1815 Susp was student

1816 Suspect is/was known gang member

1817 Acquaintance

1818 Caretaker/care-giver/nanny

1819 Common-law Spouse

1820 Friend

1821 Spouse

1822 Stranger

1823 Brief encounter/Date

1824 Classmate

1900 Auction Fraud/eBay/cragslist,etc. (Internet based theft)

1901 Child Pornography/In possession of/Via computer

1902 Credit Card Fraud/Theft of services via internet

1903 Cyberstalking (Stalking using internet to commit the crime)

1904 Denial of computer services

1905 Destruction of computer data

1906 Harrassing E-Mail/Text Message/Other Electronic Communications

1907 Hate Crime materials/printouts/e-mails

1908 Identity Theft via computer

1909 Introduction of virus or contaminants into computer system/program

1910 Minor solicited for sex via internet/Known minor

1911 Theft of computer data

1912 Threatening E-mail/Text Messages

1913 Suspect meets victim on internet/chatroom

1914 Unauthorized access to computer system

1915 Internet Extortion

1916 Victim paid by wire transfer

2000 Domestic violence

2001 Suspect on drugs

2002 Suspect intoxicated/drunk

2003 Suspect 5150/mentally challenged or disturbed

2004 Suspect is homeless/transient

2005 Suspect uses wheelchair

2006 Suspect was transgender

2007 Suspect was homosexual/gay

2008 In possession of a Ballistic vest

2009 Suspect was Inmate/Incarcerated

2010 Suspect was Jailer/Police Officer

2011 Vendor (street or sidewalk)

2012 Suspect was costumed character (e.g., Barney, Darth Vader, Spiderman, etc.)

2013 Tour Bus/Van Operator

2014 Suspect was Uber/Lyft driver

2015 Suspect was Foster child

2016 Suspect was Train Operator

2017 Suspect was MTA Bus Driver

2018 Cannabis related

2019 Theft of animal (non-livestock)

2020 Mistreatment of animal

2021 Suspect was Aged (60+over)

2022 Suspect was Hitchhiker

2023 Suspect was Prostitute

2024 Suspect was Juvenile

2025 Suspect was Bisexual

2026 Suspect was Deaf/hearing impaired

2027 Suspect was Pregnant

2028 Suspect was Repeat/known shoplifter

2029 Victim used profanity

2030 Victim used racial slurs

2031 Victim used hate-related language

2032 Victim left property unattended

2033 Victim refused to cooperate w/investigation

2034 Victim was asleep/unconscious

2035 Racial slurs

2036 Hate-related language

2037 Temporary/Vacation rental (AirBnB, etc)

2038 Restraining order in place between suspect and victim

2039 Victim was costumed character (e.g., Barney, Darth Vader, Spiderman, etc.)

2040 Threats via Social Media

2041 Harassment via Social Media

2042 Victim staying at short-term vacation rental

2043 Victim is owner of short-term vacation rental

2044 Suspect staying at short-term vacation rental

2045 Suspect is owner of short-term vacation rental

2046 Suspect damaged property equal to or exceeding $25,000

2047 Victim was injured requiring transportation away from scene for medical reasons

2048 Victim was on transit platform

2049 Victim was passenger on bus

2050 Victim was passenger on train

2051 Suspect was passenger on bus

2052 Suspect was passenger on train

9999 Indistinctive MO

2100 Observation/Surveillance

2101 Counter Surveillance efforts

2102 Questions about-security procedures

2103 Appears to take measurements

2104 Photography (pics or video footage)

2105 Draws diagrams or takes notes

2106 Abandons suspicious package/item

2107 Abandons vehicle restricted area

2108 Enters restricted area w/o authorization

2109 Testing or Probing of Security

2110 Contraband at security check point

2111 Susp purchase of legal materials

2112 Acquires restricted items/information

2113 Acquires illegal explosive/precur agents

2114 Acquires illegal chemical agent

2115 Acquires illegal biological agents

2116 Acquires illegal rediological material

2117 Uses explosives for illegal purposes

2118 Uses chemical agent illegally

2119 Uses biological agent illegally

2120 Uses radiological material illegally

2121 Acquires uniforms without legit reason

2122 Acquires official vehicle without legit reason

2123 Pursues training/education with suspect motives

2124 Large unexplained sum of currency

2125 Multiple passports/ID's/travel documents

2126 Expressed or Implied threats

2127 Brags about affiliation with extremist organization

2128 Coded conversation or transmission

2129 Overt support of terrorist network

2130 Uses Facsimile/Hoax explosive device (susp offer/solicts)

2131 Uses Facsimile/Hoax dispersal device (susp offer/solicts)

2135 Sensitive event schedules(susp offer/solicts)

2136 VIP appearance or travel schedules (susp offer/solicts)

2137 Security schedules (susp offer/solicts)

2138 Blueprints/building plans (susp offer/solicts)

2139 Evacuation or emergency plans (susp offer/solicts)

2140 Security plans (susp offer/solicts)

2141 Weapons or ammunition (susp offer/solicts)

2142 Explosive materials(susp offer/solicts)

2143 Illicit chemical agents (susp offer/solicts)

2144 Illicit biological agents (susp offer/solicts)

2145 Illicit radiological material (susp offer/solicts)

2146 Other sensitive materials (susp offer/solicts)

2150 Coded/ciphered literature/correspondence

2151 Sensitive event schedules (susp in possession)

2152 VIP appearance or travel schedules (susp in possession)

2153 Security schedules (susp in possession)

2154 Blueprints/building plans (susp in possession)

2155 Evacuation or emergency plans (susp in possession)

2156 Security plans (susp in possession)

2157 Weapons or ammunition (susp in possession)

2158 Explosive materials (susp in possession)

2159 Illicit chemical agents (susp in possession)

2160 Illicit biological agents (susp in possession)

2161 Illicit radiological material (susp in possession)

2162 Other sensitive materials (susp in possession)

2163 Facsimile/Hoax explosive device (susp in possession)

2164 Facsimile/Hoax dispersal device (susp in possession)

2170 Associates with known/susp terrorist

2171 Corresponds w/suspected terrorist

2172 In photos w/suspected terrorists

2173 Organization supports overthrow/violent acts

2180 Bomb/explosive device

2181 Biological agent

2182 Chemical agent

2183 Radiological matter

2184 Military ordinance

2185 Incendiary device

2186 Pyrotechnics

2187 Facsimile/Hoax device

2190 Financing terrorism

2191 Victim's religion

2192 Victim's national origin

2193 Influencing societal action

2194 Furthering objectives by force

2197 SSI - Food/Agriculture

2198 Pipeline

2199 SSI - Postal/Shipping/Mailbox

2200 SSI - Government Facilities/Bldg.

2201 Church

2202 Synagogue

2203 University

2204 School

2205 Sports Venue

2206 Theater

2207 Amusement Park

2208 Shopping Mall

2209 Convention Center

2210 Mass Gathering Location

2211 Bridge

2212 High-Rise Building

2213 Airport

2214 Freight Train

2215 Train Tracks

2216 SSI - Chemical storage/Manufacturing plant

2217 SSI - Telecommunication Facility/Location

2218 SSI - Energy Plant/Facility

2219 SSI - Water Facility

2220 Sewage Facility/Pipe

2221 SSI - Nuclear Facility, Reactors, Materials & Waste

2222 SSI - Dam/Reservoir

2223 SSI - National Monuments/Icon/Cultural significance

2224 Tactical significance

2225 SSI - Healthcare & Public Health/Hospital/Medical Clinic

2226 Abortion clinic

2227 SSI - Defense Industrial Base/Facility

2228 SSI - Transportation System

2229 SSI - Commercial Facilities

2230 SSI - Information Technology

2231 SSI - Banking and Finance

2232 SSI - Critical Manufacturing

2233 SSI - Emergency Services

2234 SSI - Waste

2301 Breach/Attempted Intrusion

2302 Misrepresentation

2303 Theft/Loss/Diversion

2304 Sabotage/Tampering/Vandalism

2305 Cyber Attack

2306 Espouses violent extremist views

2307 Aviation activity

2308 Eliciting information

2309 Recruiting

2310 Materials

2311 Acquisition of expertise

2312 Weapons discovery

2313 Finance

2314 TSC hit

2315 Sector-Specific Incident (SSI)

3001 T/C - Veh vs Non-collision

3002 T/C - Officer Involved T/C

3003 T/C - Veh vs Ped

3004 T/C - Veh vs Veh

3005 T/C - Veh vs Veh on other roadway

3006 T/C - Veh vs Parked Veh

3007 T/C - Veh vs Train

3008 T/C - Veh vs Bike

3009 T/C - Veh vs M/C

3010 T/C - Veh vs Animal

3011 T/C - Veh vs Fixed Object

3012 T/C - Veh vs Other Object

3013 T/C - M/C vs Veh

3014 T/C - M/C vs Fixed Object

3015 T/C - M/C vs Other

3016 T/C - Bike vs Veh

3017 T/C - Bike vs Train

3018 T/C - Bike vs Other

3019 T/C - Train vs Veh

3020 T/C - Train vs Train

3021 T/C - Train vs Bike

3022 T/C - Train vs Ped

3023 T/C - Train vs Fixed Object

3024 T/C - (A) Severe Injury

3025 T/C - (B) Visible Injury

3026 T/C - (C) Complaint of Injury

3027 T/C - (K) Fatal Injury

3028 T/C - (N) Non Injury

3029 T/C - Hit and Run Fel

3030 T/C - Hit and Run Misd

3032 T/C - Private Property - Yes

3033 T/C - Private Property - No

3034 T/C - City Property Involved - Yes

3035 T/C - City Property Involved - No

3036 T/C - At Intersection - Yes

3037 T/C - At Intersection - No

3038 T/C - DUI Felony

3039 T/C - DUI Misdemeanor

3040 T/C - Resulting from Street Racing/Speed Exhibition

3062 T/C - Bicyclist in Bicycle Lane

3101 T/C - PCF (A) In the Narrative

3102 T/C - PCF (B) Other Improper Driving

3103 T/C - PCF (C) Other Than Driver

3104 T/C - PCF (D) Unk

3201 T/C - Weather/Lighting/Roadway

3301 T/C - Traffic Control Devices

3401 T/C - Type of Collision

3501 T/C - Ped Actions

3601 T/C - Special Information and Other

3602 T/C - Unlicensed motorist

3603 T/C - Bicyclists colliding into opened vehicle door

3701 T/C - Movement Preceding Collision

3801 T/C - Sobriety

3901 T/C - Safety Equipment

4001 T/C - Central

4002 T/C - Rampart

4003 T/C - Southwest

4004 T/C - Hollenbeck

4005 T/C - Harbor

4006 T/C- Hollywood

4007 T/C - Wilshire

4008 T/C - West Los Angeles

4009 T/C - Van Nuys

4010 T/C - West Valley

4011 T/C - Northeast

4012 T/C - 77th

4013 T/C - Newton

4014 T/C - Pacific

4015 T/C - North Hollywood

4016 T/C - Foothill

4017 T/C - Devonshire

4018 T/C - Southeast

4019 T/C - Mission

4020 T/C - Olympic

4021 T/C - Topanga

4024 T/C - Central Traffic (CTD)

4025 T/C - South Traffic (STD)

4026 T/C - Valley Traffic (VTD)

4027 T/C - West Traffic (WTD)

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