Santa Barbara Ambulance Response for 2006: Performance under load

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Abstract

Hello

1 Introduction

Much research has been done on the effect of myocardial infarction survival due to ambulance response time. According to the American Heart Association, early access to advanced care is a crucial link in the Cardiac Chain of Survival.[3] A study in Ontario, Canada concluded that in order to improve survival rates after cardiac arrest, ambulance response times must be reduced and the frequency of bystander-initiated CPR increased[7]. A study performed in King County, Washington determined survival rate to decrease by 2.1% per minute without intervention by Advanced Cardiac Life Support (ACLS). Urban response time in a South-Western metropolitan county of population 620,000 was correlated with myocardial infarction survival rate, and it was found that a response time of under 5 minutes would have a beneficial impact on survival[2]. Similarly, there have been studies done on survival rates for trauma emergencies. A study on survival rates for abdominal gunshot wounds found response time and transport time to be correlated with survival rate.[5]. Another study found that the overall total EMS prehospital time interval was significantly lower for trauma survivors than non-survivors[4].

2 Materials and Methods

Santa Barbara County ambulance dispatch data for the year 2006 was provided by Santa Barbara's EMS agency for the UCLA Statistics Department's EMS study group. The data was exported from Santa Barbara's computer aided dispatch (CAD) system into a Microsoft Access database file that was then exported into an Excel spreadsheet. The Excel spreadsheet was then converted into an R dataset. All analysis of the data was done using the R Language and Environment for Statistical Computing[6].

The variables given in the data set included the incident time, geographical address, incident type, response code, response district, response district type, ambulance dispatch time, ambulance on scene time, hospital arrival time, and incident clear time. The addresses were geocoded by the EMS study group using Yahoo! Geocoder into longitude and latitude coordinates. The longitude latitude coordinates were then transformed into kilometer units using the universal mercator transformation.

Ambulance response times where calculated to be the time elapsed between ambulance dispatch and ambulance on scene arrival. Events for which ambulance response time could not be determined due to missing or nonsensical data were excluded. Events where the location could not be determined were excluded from analysis as well. Finally, since the focus of this study is on emergency calls, only Code 2 and Code 3 dispatched calls were considered. In all there were a total of 21944 emergency ambulance dispatch events for 2006 of which 15883 (72.4%) where Code 3 responses and 6061 (27.6%) where Code 2 responses.

As a measure of system load at the time of each call, a function denoted neighbors (η) was calculated for each call. Where $\{\zeta_i = (X_i, Y_i, T_i)\}_{i=1}^{N}$ represents the sequence of all calls in the data set sorted by time T and (X_i, Y_i) are coordinates of each call in kilometers east-west and kilometers north-south respectively,

$$\eta_i = \sum_{j=1}^{i-1} I\left(T_i - T_j \leq 1\text{hr}\right) I\left(\sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \leq 20\right) \tag{1}$$

is the total number of calls within the last hour within 20 kilometers of ζ_i. The parameters of one hour and 20 kilometers were chosen in order to maximize the correlation between the number of neighbors and the response time of a call. The choice for distance is meant to represent the area of an ambulance dispatch region; the choice for time interval is meant to represent the amount of time it takes for an ambulance to return to service after it has been dispatched to a previous call. Where M represents the total number of ambulances available for service in a particular area, and k represents the number of ambulances that are actively responding to incidents, $M - k$ is the number of ambulances in service that are available to respond to new calls. For regions where M is sufficiently high, one should not see much increase in response time as k increases. η acts as an analog to k, and likewise for areas where coverage is sufficient, one should not expect to see much increase in response time as η increases.

To see how variation of η is associated with variation in response time, the incidents were first blocked for response code and district type. Within each block, incident response times were sorted in ascending order. A moving average of both η and response time was calculated within each block and the relationship was seen graphically by plotting the moving averages against one another. For 2006, response time regulations effective January 2005 provided standards for the timeliness of an ambulance response given its response code and the district type of the area it is responding to. From these regulations it was determined whether or not each dispatch event was in compliance with the standard. Fisher's exact test using an one-sided null hypothesis is a useful tool for exactly determining if the proportion of violations is greater for incidents where $\eta > 0$ than incidents where $\eta = 0$. The relationship between the number of neighbors and the probability of a violation was determined using logistic regression using the logit link function.

The spatial call distribution was determined non-parametrically using kernel density estimation. The boundaries of Santa Barbara County[] were used as a bounding box for the call points. Due to geocoding precision inaccuracies, 24 call incidents lay outside of county boundaries. For the kernel density estimate, these points where excluded. The isotropic Gaussian kernel[] was used in conjunction with edge correction[] using the boundaries of Santa Barbara County. The conditional intensity for the number of incidents over the year within one squared kilometer was calculated at points in a 512x512 grid within a bounding box where Santa Barbara county was inscribed.

In order to look for evidence of spatial clustering of violation incidents that coincided with the presence of neighbors, a technique commonly used in seismology[8] was used. The inhomogeneous K-function[1] was calculated for incident locations where a violation coincided with one or more neighbors. To do this, the call intensity at each of these locations was interpolated from the kernel density estimate for call intensities. The estimated intensities where then corrected to account for the difference in the number of points by multiplying each estimated intensity by the number of incidents where a violation coincided with one or more neighbors and dividing by the expected number of points over all of Santa Barbara County given by the kernel density estimate. These intensities were then sufficient to calculate several edge corrected estimates for the inhomogeneous K-function. Since many of the points in the data set lie near the county borders, the choice of edge correction has a significant impact on the estimate for the inhomogeneous K-function.

To identify areas where η shows more of an effect on the proportion of violations, for each point where the kernel density estimate for call intensity was calculated, the difference in proportion between calls that were violations that had neighbors versus the proportion of calls that were violations without neighbors was calculated within 4 kilometers of each point wherever there where at least 10 incidents within 4 kilometers. These are regions that may benefit the most from increased ambulance units, or optimizing the deployment pattern of existing ambulances.

Incident inter arrival waiting times were calculated by finding the elapsed time between each incident. Using the inter arrival times, an exponential distribution was fitted using maximum likelihood parameter estimation. The exponential distribution for inter arrival waiting time described a time homogeneous Poisson process for call arrivals. The homogeneous in time model was improved by fitting a mixture Poisson process using the rate of arrivals for each one hour block of the day. The kernel density estimate for spatial call intensity and the two models for time dependent conditional intensity where then used to provide unbiased estimates for η at each call in the data set.

All multiple hypothesis testing was performed controlling family wise error rate at $\alpha = 0.05$ using Holm's stepwise p-value correction $\alpha_i = \frac{\alpha}{24-i+1}$.

3 Results

The goal of this paper is to explore how space-time specific system load impacted transport ambulance response performance in Santa Barbara County in 2006. As a measure of system load for a given place at a given time, we introduce "Neighbors" (η), where η represents the total number of Code 2 and Code 3 ambulance response events initiated within the previous hour within a radius of twenty kilometers. Figure 2 shows the distribution of η for all Code 2 and Code 3 events in 2006.

As measures of ambulance response performance, both response time and response time regulation compliance were used. Response time is measured as the time elapsed between ambulance dispatch and ambulance on scene arrival. The distribution of response times varies according to the response code and the response zone type (Figure 1). With this in mind, Santa Barbara County adapted response time regulations dependent upon population density and response code effective January 2005 governing response time standards and enforcement (Table 1). Overall, 95.1% of Code 2 and Code 3 ambulance responses had response times within the limits set by these regulations. Of the 861 events that were in violation of the regulations, 564 (65.5%) were Code 3 events and 297(34.5%) were Code 2 events. Overall, 3.55% of Code 3 calls had response times in violation whereas 4.90% of Code 2 calls had response times in violation.

For calls where $\eta = 0$, the proportion of response time violations was 2.96%, whereas for $\eta > 0$, the proportion of violations was 4.56%. The increase in probability of violation associated with having neighbors is statistically significant (Fisher's exact test; p<0.001). As η increases, both the response time and the probability of a response time violation were seen to increase. By fitting a logistic regression model to the relationship between violation and η, it is seen that on average, for each additional neighbor, the log odds ratio ($\log \frac{p}{1-p}$) of the probability of violation increased by 19.1% ($p < 0.001$). The increase in response time associated with increasing η can be visualized with a moving average plot (Figure 3). The difference in probability of violation associated with changing η was seen to vary across response codes and district types. The increase in proportion of violations was most pronounced in Code 3 semi-rural calls (Figure **??**).

Overall, the inter arrival times between calls follows approximately an exponential distribution with rate of 2.51 calls per hour. The call arrivals can therefore be modeled as a homogeneous Poisson process. The rate of call arrivals does however seem to vary according to the time of day (Figure 4). Unremarkably, the distribution of η varies according to the time of day. Furthermore, the proportion of calls where $\eta > 0$ varies according to the time of day as well. A multiple comparison test controlling family wise error rate at an $\alpha = 0.05$ level shows that the hours 10:00:00AM-6:59:59PM have a statistically significant higher proportion of calls that have neighbors (One-sided Fisher's exact test; Holm stepwise correction). The difference in proportion of calls that were violations for $\eta = 0$ and $\eta > 0$ varies according to the hour of day as well (Figure 5). (TODO: Significance of difference between proportions by hour to see which hours have a significantly higher difference than average. Then those hours are the times of day when the neighbor effect is the greatest)

The spatial distribution for ambulance response events shows a few areas of high concentration, and vast areas of low concentration. Kernel density estimation using a an edge corrected isotropic Gaussian kernel provides an estimate of the spatial conditional call intensity (Figure 6). Using the estimate for the spatial conditional intensity, we can calculate the in-homogeneous K-function for any subset of points. The in-homogeneous K-function allows us to assess whether the points are more or less clustered than expected under the null hypothesis that the points are drawn randomly without bias with the estimated conditional intensity. The in-homogeneous K-function (Figure 7) for calls where a violation coincided with the presence of neighbors (Figure 8) was calculated. It provides evidence that there are areas where violations are more likely to coincide with neighbors than expected under the null hypothesis. This may not be surprising since the relationship between system load and response time violation was determined to be in-homogeneous in time - one may suspect that it is inhomogeneous in space as well.

Since it has been established that there is spatial clustering in the points where calls with neighbors were violations, it is useful to identify areas where this clustering is occurring. Locally, the difference in proportion of violations between $\eta = 0$ and $\eta > 0$ ambulance responses was calculated. This was done by calculating the difference for a radius of 4 kilometers about each location where there was a minimum of 10 calls (TODO: Find a value for n where any difference over some threshold difference will be statistically significant at some alpha level and recalculate using that n and draw contours for differenences above the threshold) within 4 kilometers. Contours were drawn around regions where the difference in proportion of violations was 5% or greater for Code 3 calls, and 3% or greater for Code 2 calls (Figure 10). The regions within these contours have a statistically significant greater proportion of violations for calls where $\eta > 0$ than calls where $\eta = 0$. These regions represent areas where ambulance response time is more sensitive to system load than on average.

A scatterplot of calls versus the number of neighbors (Figure 9) provides a helpful way to gauge the levels of system load throughout Santa Barbara county. Since we have an estimate for the conditional intensity of call arrivals in space given by the kernel density estimate, we can easily obtain estimates for the number of neighbors expected. Where $\lambda(t)$ is the conditional intensity in time, and $\lambda(x, y)$ is the conditional intensity in space, for any given region A, and some time interval $[t_0, t_1)$, the expected number of points can be calculated as

$$E\{N_A[t_0, t_1)\} = \frac{\int_{t_0}^{t_1} \int_A \lambda(x, y)\lambda(t) dA' dt}{\int_{SB} \lambda(x, y) dx dy} \tag{2}$$

Using this, an unbiased estimate for η at some location (χ, ψ) and time τ can be written as $\hat{\eta} = E\{N_{B_{20}(\chi,\psi)}[\tau - 60\text{min}, \tau)\}$ where $B_{20}(\chi, \psi)$ represents a circle of radius 20 kilometers centered around (χ, ψ). A time homogeneous model, and a model using hour by hour conditional intensities were used as estimates for $\lambda(t)$. The homogeneous model had a mean squared error of 1.35 whereas the inhomogeneous model had a mean squared error of 1.14. The residuals for either model are not homogeneous in time (Figure 11), but the inhomogeneous time intensity model shows marked improvement. (TODO: alternative biased estimate for number of neighbors minimizing some risk function)

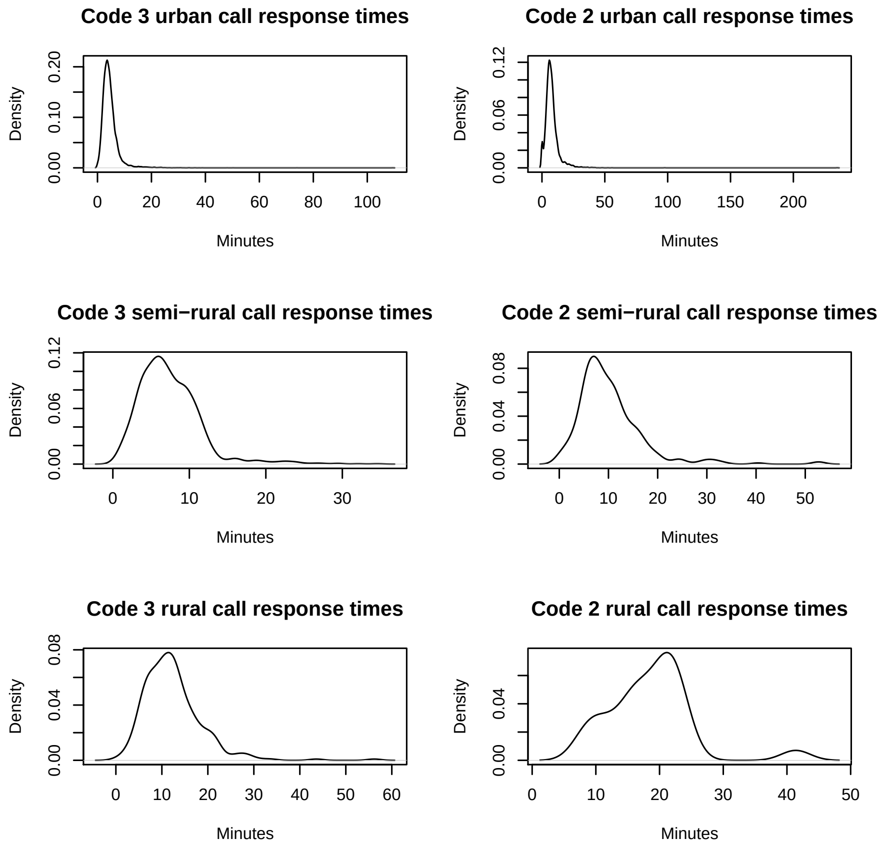

Figure 1: Distribution of Response Times

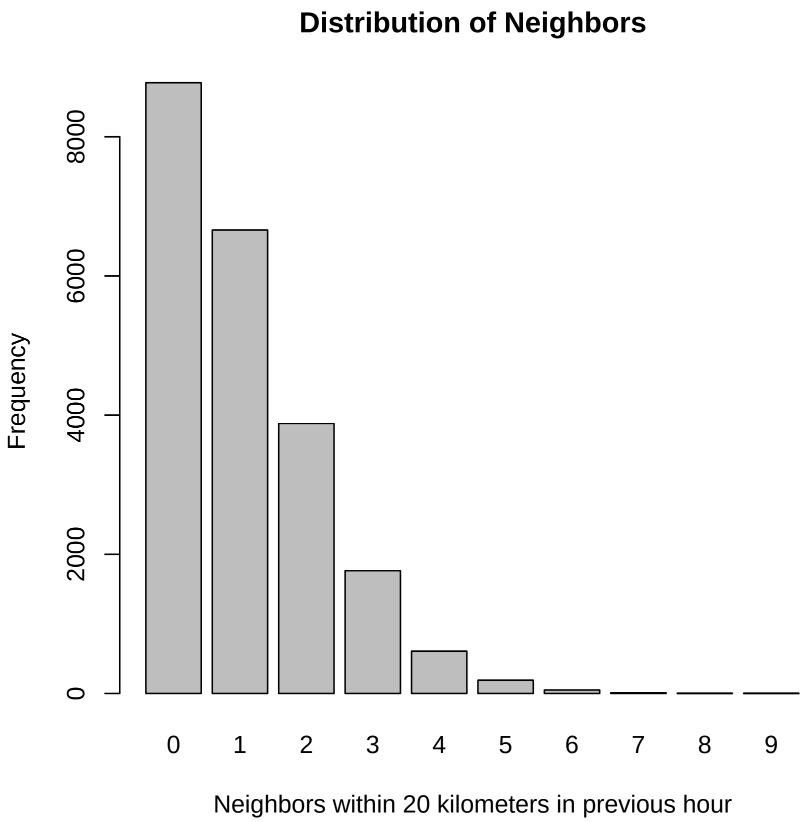

Figure 2: Distribution of Neighbors within 20 kilometers within the previous hour.

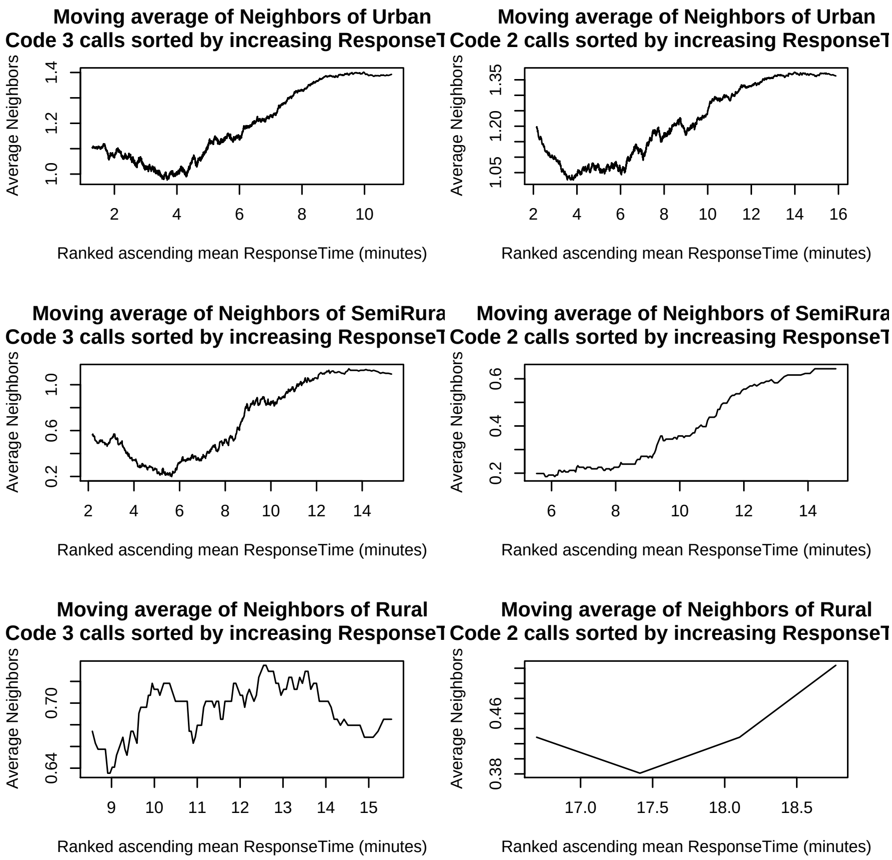

Figure 3: Moving average for η sorted by ascending Response Time.

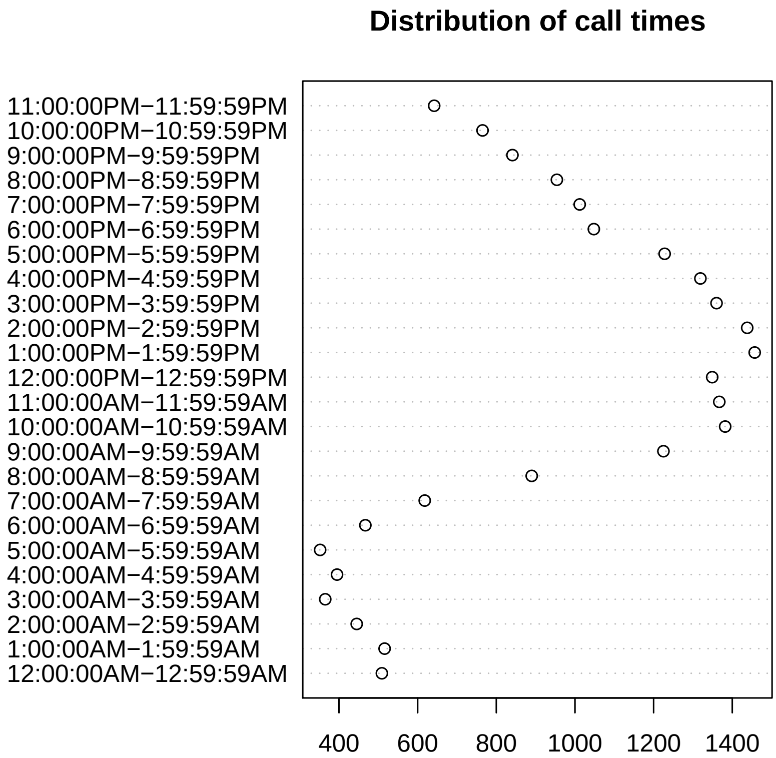

Figure 4: Total Code 2 and Code 3 dispatch events for 2006 by hour of day of incidence.

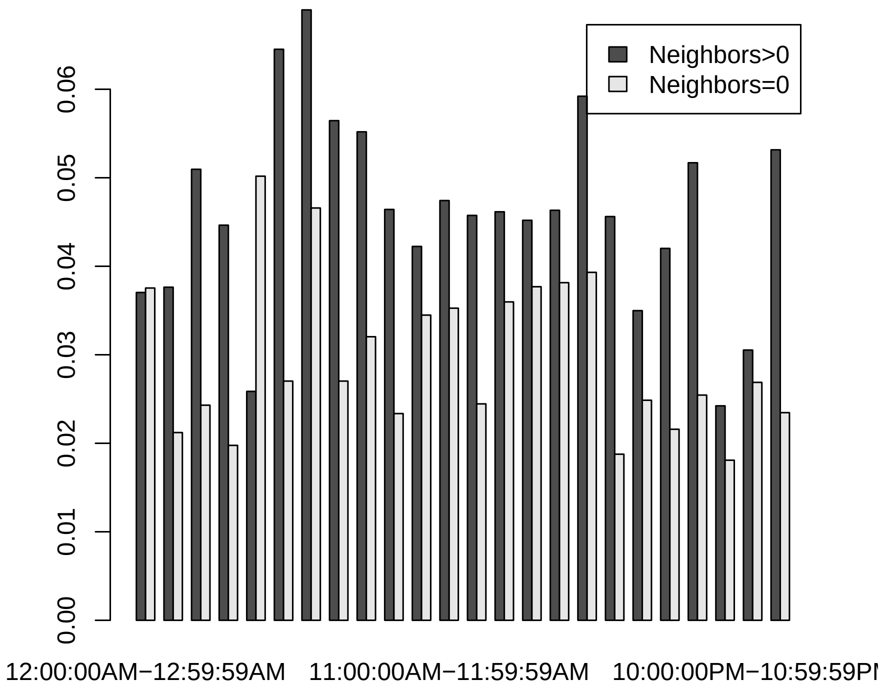

Figure 5: Proportion of call violations by hour of day versus the existence of neighboring calls

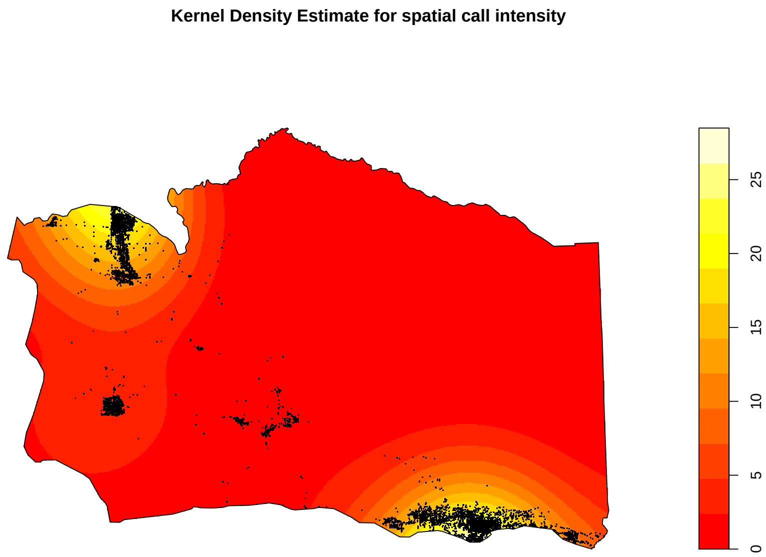

Figure 6: Kernel density estimate using isotropic Gaussian kernel for the number of calls per squared kilometer over 2006.

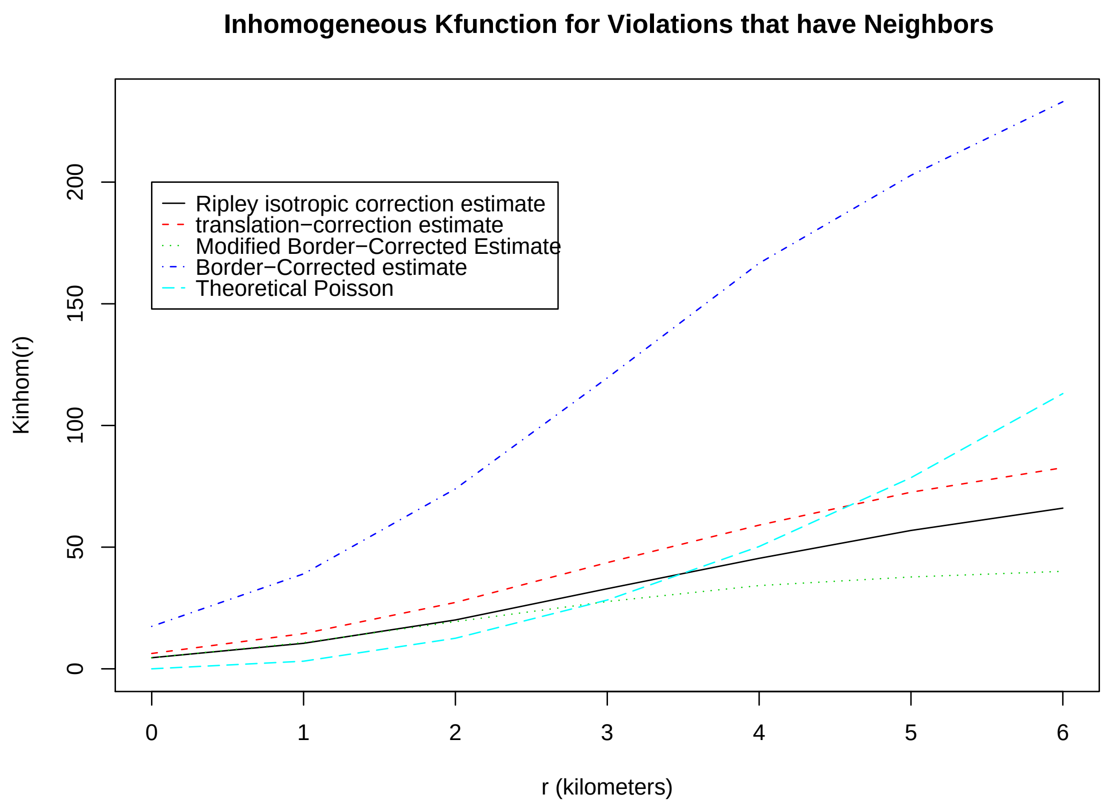

Figure 7: Inhomogeneous K-function for calls where the presence of neighbors coincided with a violation.

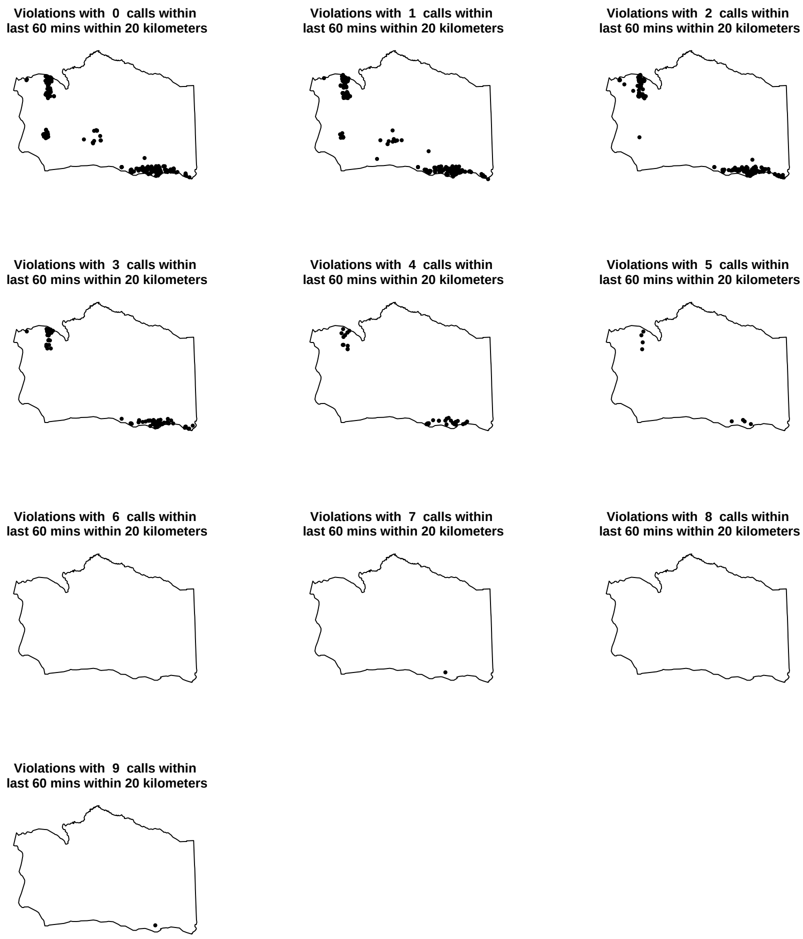

Figure 8: Map of locations where violations have coincided with the presence of neighbors.

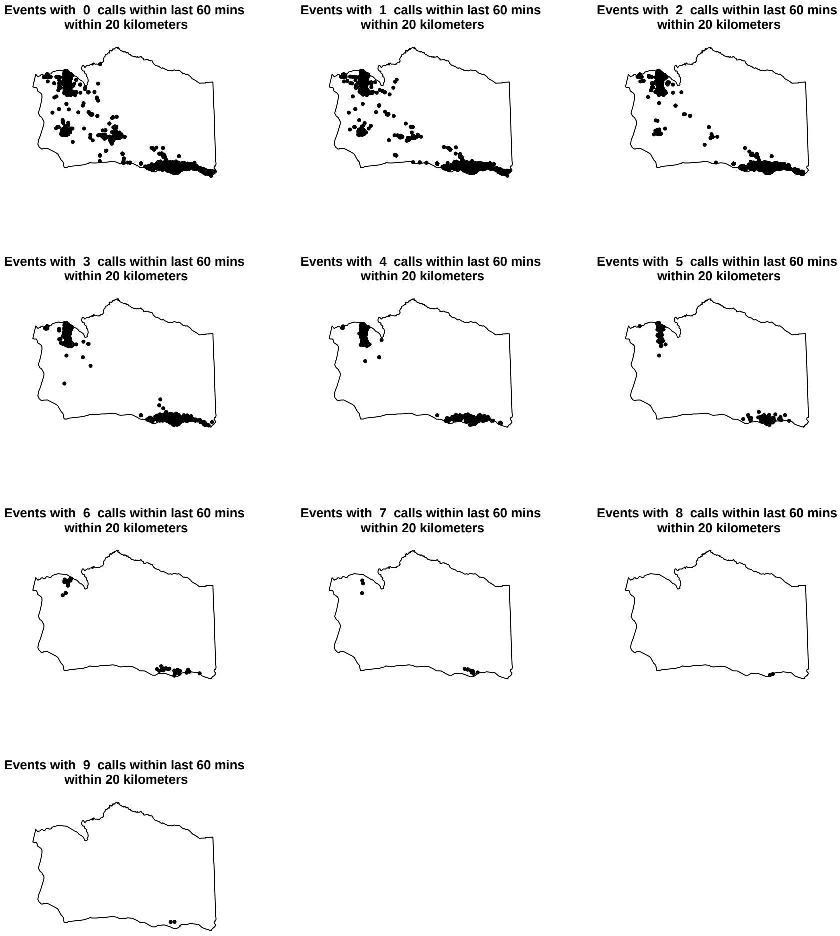

Figure 9: Map of where calls with neighbors have occurred.

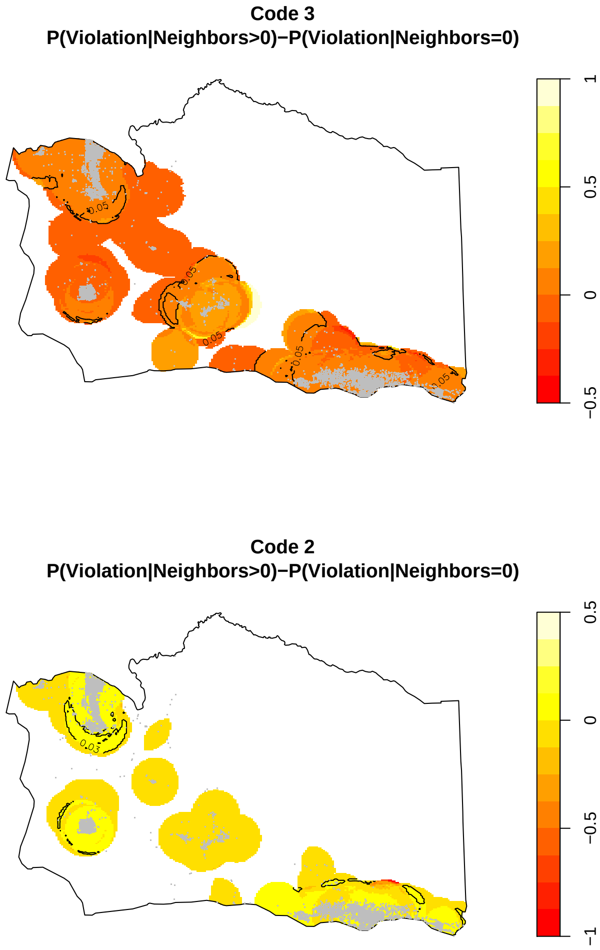

Figure 10: Localized increase in probability of violation for calls with neighbors versus calls without neighbors

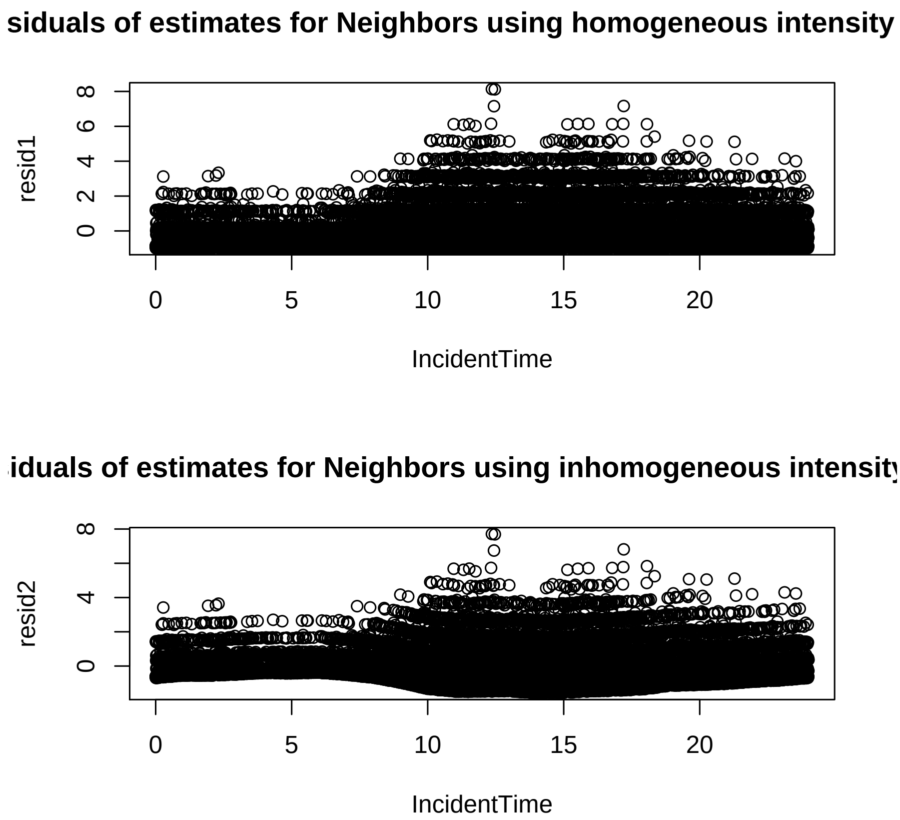

Figure 11: Residuals for predicted neighbors by time of day

	Response Code	Population Density	ALS First Responder	ALS Ambulance
1	Code 3	Urban	7:59 min or less	9:59 minutes of less
2	Code 3	Semi-Rural	14:59 minutes or less	16:59 minutes or less
3	Code 3	Rural	29:59 minutes or less	32:59 minutes or less
4	Code 2	Urban	14:59 min or less	16:59 minutes of less
5	Code 2	Semi-Rural	24:59 minutes or less	26:59 minutes or less
6	Code 2	Rural	39:59 minutes or less	42:59 minutes or less

Table 1: Santa Barbara County ambulance response time regulations effective January 2005.

4 Discussion

5 Limitations

6 Conclusions

7 Figures

References

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