2016-03

Spatiotemporal modeling of community risk

Tuggle, Todd T.

Monterey, California: Naval Postgraduate School

https://hdl.handle.net/10945/48484

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

SPATIOTEMPORAL MODELING OF COMMUNITY RISK

by

Todd T. Tuggle

March 2016

Thesis Advisor:	Lauren Wollman
Co-Advisor:	Rodrigo Nieto-Gomez

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.			
1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** March 2016	**3. REPORT TYPE AND DATES COVERED** Master's thesis	
4. TITLE AND SUBTITLE SPATIOTEMPORAL MODELING OF COMMUNITY RISK			**5. FUNDING NUMBERS**
6. AUTHOR(S) Todd T. Tuggle			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number ____N/A____.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			**12b. DISTRIBUTION CODE**

13. ABSTRACT (maximum 200 words)

Every day throughout the country, fire departments respond to a variety of emergencies in their communities. Steadily over the last decade, departments have mitigated these threats in an atmosphere of decreasing budgets, declining fire volume, and a burgeoning call volume. Thus, fire service leaders require data and analysis to justify the dollars spent to mitigate the risks within communities. Community risk is dynamic in that it fluctuates over geography and time; spatiotemporal modeling is one proven method for illustrating such dynamic modulations. This thesis produces a spatiotemporal model of fire department call volume to depict fluctuations in community risk in the Fresno (CA) Fire Department's area of operations. This study led to several findings. First, using historical records for spatiotemporal modeling of community risk could help leaders visualize the dynamic nature of risk. Second, visualizing community risk with spatiotemporal modeling could provide the basis for resource deployment models attuned to specific risks. Finally, investigating additional data sets in conjunction with such methodology could uncover the causal factors of risk dynamics from which leaders design proactive preventative measures.

14. SUBJECT TERMS GIS, geospatial information systems, fire service, fire department, community risk, spatiotemporal, spatial, temporal, quantitative analysis, deployment model			**15. NUMBER OF PAGES** 115
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

SPATIOTEMPORAL MODELING OF COMMUNITY RISK

Todd T. Tuggle
Battalion Chief, Fresno Fire Department, California
B.S., California Polytechnic State University San Luis Obispo, 1996

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF ARTS IN SECURITY STUDIES
(HOMELAND SECURITY AND DEFENSE)

from the

NAVAL POSTGRADUATE SCHOOL
March 2016

Approved by: Dr. Lauren Wollman
Thesis Advisor

Dr. Rodrigo Nieto-Gomez
Co-Advisor

Dr. Erik Dahl
Associate Chair of Instruction
Department of National Security Affairs

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Every day throughout the country, fire departments respond to a variety of emergencies in their communities. Steadily over the last decade, departments have mitigated these threats in an atmosphere of decreasing budgets, declining fire volume, and a burgeoning call volume. Thus, fire service leaders require data and analysis to justify the dollars spent to mitigate the risks within communities. Community risk is dynamic in that it fluctuates over geography and time; spatiotemporal modeling is one proven method for illustrating such dynamic modulations. This thesis produces a spatiotemporal model of fire department call volume to depict fluctuations in community risk in the Fresno (CA) Fire Department's area of operations. This study led to several findings. First, using historical records for spatiotemporal modeling of community risk could help leaders visualize the dynamic nature of risk. Second, visualizing community risk with spatiotemporal modeling could provide the basis for resource deployment models attuned to specific risks. Finally, investigating additional data sets in conjunction with such methodology could uncover the causal factors of risk dynamics from which leaders design proactive preventative measures.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

CAD	Computer Aided Dispatch
CPSE	Center for Public Safety Excellence
CUNY	City University of New York
EMS	Emergency Medical Services
ESRI	Environment Systems Research Institute
FFD	Fresno Fire Department
FSEC	Fire Service Emergency Cover
GIS	Geospatial Information Systems
GPS	Global Positioning System
ICMA	International City/ County Management Association
ISO	Insurance Services Office
JPEG	Joint Photographic Experts Group
KDE	Kernel Density Estimation
NFIRS	National Fire Incident Reporting System
NFPA	National Fire Protection Association
RMS	Records Management System
TOT	Time on Task
USFA	United States Fire Administration

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Fire stations are fixtures in their communities and respond to a variety of emergencies every day. In the context of the recent recession, many municipal leaders have called into question firefighter quotas, citing reduced budgets, a decrease in the number of fire incidents, and an increase in the number of medical calls. As a result, fire departments are struggling to justify their existence against the risks within the community.

It is from the depiction of call volume that fire service and municipal leaders can comprehend more thoroughly the dynamic nature of risk within the community. Spatiotemporal modeling maps community risk by using historical data from fire department databases and depicting it with heat maps. These heat maps are produced for increments of time, such as hour of the day, and shown in sequence to depict how community risk changes over time and space.

Spatiotemporal modeling provides a unique perspective of data fluctuations. The literature for fire service data models fire incidents and provides for basic inquiries into the statistical underpinnings for incident distribution. However, fire departments increasingly respond to more than just fires, and quantitative assessments of entire call volume are necessary. This thesis offers spatiotemporal modeling as a starting point for quantitative analysis of all risks represented within the community.

To model community risk with spatiotemporal tools, this thesis used geospatial information systems software, ArcMap 10.2 from ESRI, for heat maps of individual point data. For the purposes of this thesis, a sample dataset of more than 40,000 entries was used from Fresno (CA) Fire Department. The data were broken into three temporal partitions: by 24 hours, 12 months, and seven days. The heat maps for each time partition were analyzed sequentially to create a visualization of fluctuations over the different partitions of time. Analysis was conducted by hour of the day, day of the week, and month of the year.

This thesis developed models for fluctuations in the data over time. The spatiotemporal changes fell in line with the hypotheses in some cases. Call distribution throughout the day, for instance, was expected to follow a circadian rhythm, which occurred. However, the models showed other hypotheses were incorrect. It was expected that call volume would follow seasonal variations; the winter would see severe spikes because of cold and flu season, while the summer would see spikes in call volume from the effects of asthma and summer heat. Surprisingly, the monthly trends of EMS call volume depicted a stable call volume across the months with no apparent seasonal modulations. By sheer numbers, call volume by the day of the week experiences daily fluctuations, with Monday and Wednesday as the busiest days. The spatial distribution of that call volume, however, showed little fluctuation. The examples of analysis in this thesis provide valuable quantitative and objective information for fire service leaders.

Spatiotemporal modeling is a dynamic method for visualizing a dynamic problem—assessing the static deployments of the fire service. Implementing spatiotemporal modeling does not require much in the way of change, and the tools and methods used in this thesis could be easily reproduced. Fire departments need to assess risk within the community objectively and quantitatively as well as the deployment plans meant to mitigate that risk. In many cases, spatiotemporal modeling justifies the current deployment plans. Risk across days of the week and months of the year were remarkably static, closely matching the current static deployment plans. However, call volume fluctuated greatly by hour of the day, suggesting that a dynamic deployment during the busiest portions of the day may be the most cost-efficient use of resources.

Spatiotemporal modeling is just the beginning of quantitative assessment of community risk. Accessing the data for spatiotemporal modeling and its causal factors opens the door to a host of opportunities for future research. The three opportunities outlined in the thesis are as follows. First, the entire spectrum of call volume should be modeled. Fire-service call volume continues to grow while fire calls are dropping; community risk is not solely about fires anymore. Second, future research should focus on the causal factors for the observed spatial and temporal trends in the data. To develop proactive preventative efforts and reactive deployment plans, fire service leaders need to understand what is causing the patterns in the first place. Third, future research should look at time studies by incident type. Though fire call volume was down, the time committed to fires remained at approximately 40 percent of total time committed to incidents in the dataset from this thesis. Time commitment studies could provide another layer of understanding to spatiotemporal modeling when addressing deployment models.

The fire service faces many important challenges as communities continue to recover from the Great Recession, fire call volume continues its downward trend, and the demands of non-fire calls continue to rise. The response to these challenges must include increased quantitative studies and spatiotemporal modeling, which can support analytical investigation. Spatiotemporal modeling provides a unique view into community risk changes relating to public safety. The three-dimensional view can help leaders visualize the dynamic nature of risk and develop measures to address it.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

I would like to thank my wife, Jules: You were there in the beginning to inspire me in pursuit of higher education; you were there in the middle when the classes were brutal; and more than anything, you were there in the end to talk me off the ledge when I was on the verge of quitting. At the end of this journey, I say wholeheartedly, thank you for not giving up on me or us.

To my kids, Theo, Claire, Max, and Quinn: I appreciate your patience, which allowed me to see this process through. When Dad was reading peculiar books about the psychology of terrorists or discussing statistics of geospatial modeling, you put on your game faces and paid attention. I love you, and I thank you.

I also would like to express my gratitude to my advisors, Lauren Wollman and Rodrigo Nieto-Gomez, who gutted it out over the duration of my thesis work. In some ways, I feel awkward calling it "my" thesis when I received so much help.

In addition, I want to acknowledge Noel Yucuis. As a writing coach, you refined my erratic writing style, helping me hone the structure and pare it down to a manageable size.

To Glen Holder, Cherie Penn, Max Geron, Monica Mapel, Keith Johnson, Matt Wenthe, and Tom Healy: Thanks for providing a great network of peers from which to learn and grow. I am impressed by not only the CHDS instruction but also by the network of inspirational professionals the program attracts.

Finally, to all the members of the Center for Homeland Defense and Security staff: you run a program that is the bar by which professional, advanced education should be measured.

In coming full circle, I again want to express my gratitude to my wife: thank you for staying side by side through this journey. I see many flower bouquets and vacations in your future

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

Fire stations are fixtures of stability, known for their roles responding to community emergencies and preventing injury or loss of life. While all communities need emergency assistance, how do communities decide where to build their firehouses? This project seeks to assess community risk by mapping geographic and temporal distribution of fire-service call volume.

A. PROBLEM STATEMENT

Several organizations representing fire service interests in the United States, such as the National Fire Protection Association (NFPA), the Center for Public Safety Excellence (CPSE), and the Insurance Services Office (ISO), offer specific guidelines that many local governments use for deploying fire service resources to mitigate risks. The NFPA, CPSE, and ISO focus on what Charles Jennings of City University of New York calls "conflagration avoidance" for fire service deployment—an organic distribution of fire trucks throughout an area designed "to develop and deliver high volumes of water."[1] The ISO focuses solely on responses to fires in deploying fire department assets. And while fires still occur and take American lives, many departments have seen their responses to fires drop off significantly, while their overall call volume has steadily increased. In light of this change in call types, local governments are looking for guidance on deployment models.

This thesis focuses on understanding the risk within our communities to which fire-service resources respond. Obviously, finances cannot be ignored when deploying resources. However, as noted at one popular fire service website, no one wants to play "the 'buildings will burn and people will die' game."[2] Old-school political tactics do not work under today's severe economic

[1] Charles Jennings, *The Promise and Pitfalls of Fire Service Deployment Analysis Methods* (Alexandria, VA: Institution of Fire Engineers, 1999).

[2] "Firefighter Staffing," FirefighterCloseCalls.com, accessed February 1, 2016, http://firefighterclosecalls.com/firefighter-staffing/.

conditions. The cost of doing business continues to grow for fire departments, and recent financial calamities have forced local governments to make monstrous cuts.[3] Only objective facts and analysis can justify the costs of the contemporary fire service.

The profile of fire department call volume continues to shift significantly, with a heavy pivot toward emergency medicine and specialized rescue skills. This author suggests that guidelines for fire department deployment should include risk assessments based on past call volume. In this work, risk in our communities is defined as the cumulative distribution of emergency events that have already occurred. Jennings, the aforementioned City University of New York associate professor and director of its Center for Emergency Response Studies, refers to this type of risk as “actualized risk.”[4]

The following chapters introduce a visualization of risk across geography and time, referred to as spatiotemporal risk modeling, which could augment fire service guidelines when determining deployment of fire resources. Furthermore, the assessment of resource allocation to risk models could provide a more financially accessible deployment of risk protection by fire departments.

B. LITERATURE REVIEW

The literature review provides background and relevant research of spatiotemporal modeling. The research focuses on quantitative analysis of fire-service response data, and in particular, the connection between objective research and deployment models. Research in the fields of geographic information systems and spatial statistics provide context to the discussion of spatiotemporal modeling. Little research covers spatiotemporal modeling of fire service data specifically; however, two researchers, one from Canada and the

[3] Jonathan Walters, “Firefighters Feel the Squeeze of Shrinking Budgets,” Governing, January 2011, http://www.governing.com/topics/public-workforce/firefighters-feel-squeeze-shrinking-budgets.html.

[4] Charles R. Jennings, “Evaluating and Managing Local Risks,” in *Managing Fire and Emergency Services*, 1st edition, ed. Adam K. Thiel and Charles R. Jennings (Washington, DC: International City/County Management Association, 2012), 73.

other from Turkey, have explored spatiotemporal analysis of fires.[5] These articles provide insight into spatiotemporal modeling methods, as well as causal factor analysis. This work includes quantitative non-fire research to elucidate how all calls for service, not those solely for fires, can have a significant effect on policy-maker decisions concerning fire apparatus allocation.

The literature review comprises three parts. The first section identifies and defines relevant terms. The second section addresses methods and challenges of spatiotemporal modeling, and inquiries in which researchers used spatiotemporal modeling for visualizing fire distribution. The third section recognizes that fire departments respond to more than incidents of fire and, as a result, analysis of those service calls is needed. In addition, case studies reference examples of how quantitative analysis can affect policy decisions driving the need to incorporate all calls for service into spatiotemporal modeling.[6]

1. Terminology

Spatiotemporal modeling, also referred to as geotemporal modeling, depicts the relationship between geographic distribution of spatial data and its temporal fluctuations.[7] Spatial data are represented by the two-dimensional positioning of point data as defined by *x, y* coordinates. Temporal data are defined by time of day, day of the week, or month of the year and are represented as two-dimensional positions on a timeline. Spatiotemporal modeling attempts to combine the visualizations of two-dimensional *x, y* coordinates and

[5] Ali Asgary, Alireza Ghaffari, and Jason Levy, "Spatial and Temporal Analyses of Structural Fire Incidents and Their Causes: A Case of Toronto, Canada," *Fire Safety Journal* 45, no. 1 (January 2010); Elvan Ceyhan, Kivanc Ertugay, and Sebnem Duzgun, "Exploratory and Inferential Methods for Spatio-Temporal Analysis of Residential Fire Clustering in Urban Areas," *Fire Safety Journal* 58 (May 2013): 226–239.

[6] Office of the Deputy Prime Minister, *Using FSEC to Develop an Integrated Risk Management Plan* (London: Office of the Deputy Prime Minister, 2003); Alan M. Craig, Richard P. Verbeek, and Brian Schwartz, "Evidence-based Optimization of Urban Firefighter First Response to Emergency Medical Services 9–1-1 Incidents," *Prehospital Emergency Care* 14 (2010).

[7] B. M. Tomaszewski, "Developing Geo-Temporal Context from Implicit Sources with Geovisual Analytics," presented at the ICA Commission on Visualization and Virtual Environments Annual Meeting, Helsinki, Finland, August 2, 2007.

two-dimensional time coordinates into an understandable two-dimensional image.[8]

According to authors Asgary, Ghaffari and Levy in their study of Toronto fire incidents, when developing a spatiotemporal model, analysts first need a spatial visualization of the point data.[9] Researchers typically display data on two-dimensional maps using point data to form what are collectively known as clusters, hot spot maps, or heat maps. These maps provide users a broad overview of relative point density across a geographic area. All of the map types have the ability to extrapolate, or interpolate, data density in areas where no data exist. The distinction between a hot spot, cluster, or heat map lies in how the thresholds for determining density levels are determined. Hot spot maps usually have defining threshold before the density is displayed on a map.[10] Cluster maps create a threshold of the spatial distance between points before they are mapped as cluster.[11] On many occasions, all three styles of maps will look similar to the untrained eye. For the purposes of this thesis, heat map is the preferred generic term for a map illustrating point density. The specific methods for converting point data into a heat map include statistical processes wherein densities are calculated across a denoted area and then color-coded based on predetermined criteria. Some methods have statistical significance, while researchers can arbitrarily choose other methods based on the presentation of the map. Figure 1 is a depiction of a heat map.

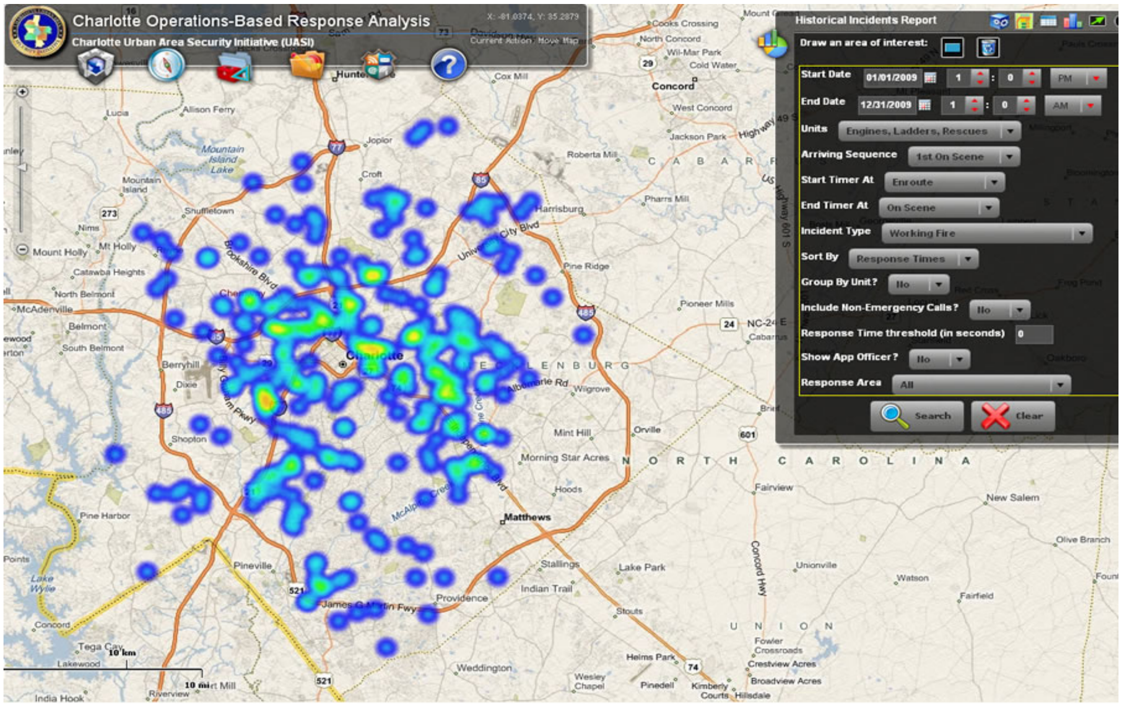
[8] May Yuan, “Temporal GIS and Spatio-Temporal Modeling,” University of Oklahoma, April 18, 2007, Abstract, http://geosensor.net/temp/yuan1996.pdf.

[9] Asgary, Ghaffari, and Levy, “Spatial and Temporal Analyses.”

[10] Lauren Rosenshein, “Extending Your Map with Spatial Analysis,” Environmental Systems Resource Institute, accessed February 8, 2016, http://resources.arcgis.com/en/communities/analysis/017z00000015000000.htm.

[11] “Space-Time Cluster Analysis,” Environmental Systems Research Institute, accessed February 9, 2014, http://resources.arcgis.com/en/help/main/10.1/index.html#//005p00000056000000.

Figure 1. Call Volume Heat Map



This Charlotte (NC) Fire Department heat map illustrates the area call volume. Source: "Charlotte Fire Department Links Live Data, Multiple Systems," ArcNews, Summer 2012, http://www.esri.com/news/arcnews/summer12articles/charlotte-fire-department-links-live-data-multiple-systems.html.

Many methods exist for visualizing spatial information. In their research on the Toronto fire department, Asgary, Ghaffari and Levy found that kernel density estimation, quadrant count and nearest neighbor distance are the "most common and well-established methods."[12] Kernel density estimation (KDE) offers simplicity, functionality within mapping software, and the ability to employ an additional variable for deeper analysis. KDE breaks up spatial data into geographic spaces, called neighborhoods, defined by the user. These neighborhoods are analyzed for the point data density within them and given an average value.[13] Then, the areas within each neighborhood are compared to the adjacent neighborhoods. Next, the KDE process smooths the transition between

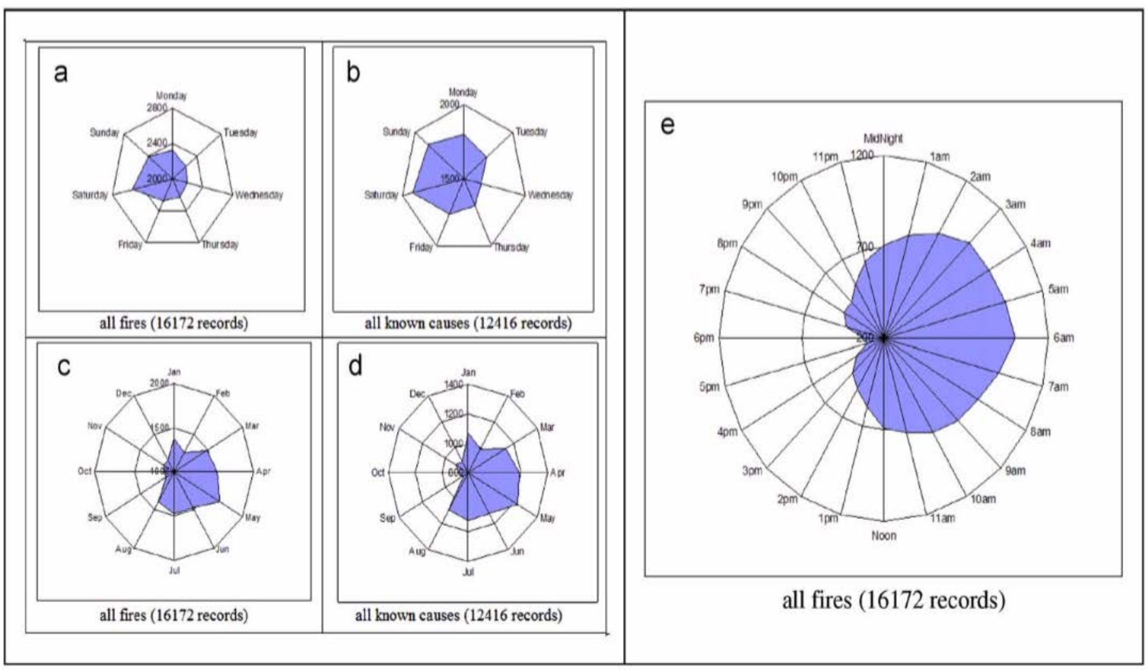
[12] Asgary, Ghaffari, and Levy, "Spatial and Temporal Analyses," 46.

[13] "How Kernel Density Works," Environmental Systems Research Institute, accessed March 21, 2016, http://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/how-kernel-density-works.htm.

the adjoining neighborhoods with different average densities.[14] Resolution of the visualization is a function of the size of the neighborhood: the smaller the neighborhood, the higher the resolution of the density visualization. KDE provides an accurate and flexible approach to spatial density visualization

Temporal visualization of data provides users an image event distribution over time. While researching fire incidents in Toronto, Canada, Asgary, Ghaffari, and Levy used a circular plot visualization tool to show time of day distribution of various fire types.[15] The circular plot conforms to the appearance of a clock and provides the reader an intuitive display. Figure 2 depicts a circular temporal plot of structures by the hour of day.

Figure 2. Fire Incident Circular Temporal Plot



Source: Ali Asgary, Alireza Ghaffari, and Jason Levy, "Spatial and Temporal Analyses of Structural Fire Incidents and Their Causes: A Case of Toronto, Canada," *Fire Safety Journal* 45, no. 1 (January 2010): 45.

[14] Asgary, Ghaffari, and Levy, "Spatial and Temporal Analyses," 47.

[15] Ibid.

As with the spatial display, however, temporal visualization gives only a partial story about data change over time. Spatial and temporal visualizations provide important data but not a complete picture. In order to achieve spatiotemporal visualization, spatial distribution must be combined in a cogent fashion with its time components. The literature speaks to several methods of depicting spatial distribution over time, but none of which is without challenges. Shekhar et al., in their non-fire-specific study, and Ceyhan, Ertugay, and Duzgun, in their fire-specific work, describe a temporal snapshot as the predominant method for depicting spatial and temporal distributions, also known as spatiotemporal modeling.[16]

Shekhar et al. observe that in a temporal snapshot model, the spatial layers possess a common theme and time stamp for each layer.[17] The snap-shots of spatial data for each time segment are pieced together using an animation process to show the change from one time block to the next. The user sees a stop action view of spatial distribution change over the course of a defined period of time. It is this view of spatial distribution over time that provides the analyst with an intuitive visualization of fire department responses.

These terms provide a basic lexicon for the review of various studies about spatiotemporal modeling. The following section addresses specific components in more detail in an attempt to elaborate on spatiotemporal modeling as a tool for visualizing community risk for fire department leaders.

2. Spatiotemporal Modeling

Various researchers are included in this literature review for their contributions to spatiotemporal modeling as a non-discipline-specific study. These researchers describe varying methods for visualizing spatial and temporal data in combination. Other research addresses the spatiotemporal distribution of

[16] Ceyhan, Ertugay, and Duzgun, “Exploratory and Inferential Methods,” 227.

[17] Shashi Shekhar et al., “Spatiotemporal Data Mining: A Computational Perspective,” *ISPSR International Journal of Geo-Information* 4, no. 4 (2015): 2310, doi: 10.3390;ijgi4042306.

fires specifically for studies of the fire service. Missing from the literature is a composite view assessing the range of fire department calls for service.

Fire service data come in the form of spatial data with an intrinsic time stamp. Each call for service possesses at least an *x, y* coordinate and time. Visualizing the spatial components of these data takes on many forms, but KDE provides the optimal combination of flexibility, accuracy, and simplicity. The method offers researchers and policy makers a view of density estimates. The KDE process takes an average density across the neighborhood defined by the user and defines the resolution of the map. The important part of density mapping as a spatial visualization tool is analyzing the patterns within the data.

Shekhar et al. provide a compendium of spatial, temporal, and spatiotemporal visualization tools.[18] Among the spatiotemporal tools cited, is the temporal snapshot. The resolution of spatiotemporal visualization through a temporal snapshot is a direct function of the size of the time increment. As users move from one snapshot to the next, they see abrupt spatial distribution change for each snapshot over time.[19]

As Yuan points out in “Temporal GIS and Spatio-Temporal Modeling,” snapshots can display only sudden changes over time.[20] Yuan discusses temporal snapshots and captures the difficulty of spatial temporal relationships. Because spatial and temporal distributions are two-dimensional in nature, combining them requires a three-dimensional display to show the relationship.[21] According to Shekhar et al. in an article summarizing spatiotemporal methodology, the snapshot model allows users to see point trajectories and data distribution over consecutive moments in time.[22] However, spatial and temporal visualizations each offer mechanisms for smoothing the transitions between point

[18] Shekhar et al., “Spatiotemporal Data Mining,” 2310.

[19] Ibid.

[20] Yuan, “Temporal GIS.”

[21] “Space-Time Cluster Analysis,” Environmental Systems Research Institute.

[22] Shekhar et al., “Spatiotemporal Data Mining,” 2310.

data, depicting spatial and temporal representations together proves difficult to smooth. This shortcoming forces analysts to use snapshots in time sequences to visualize the progression of change. Yuan states that methods like temporal snapshots represent only “sudden changes upon an independent, discrete, and linear time structure,” adding that none are “able to portray the concepts about transition, process, or motion.”[23]

Despite challenges with spatiotemporal modeling, methods for displaying spatial temporal data can still provide keen insight. Asgary, Ghaffari, and Levy provide ample evidence that spatiotemporal modeling of fires in Toronto can help “develop more meaningful and relevant policy decisions.”[24] This thesis seeks to incorporate the researched methods to visualize not only fire risk but all community risk fire departments face.

In the analysis portion of “Spatial and Temporal Analyses of Structural Fire Incidents and Their Causes,” Asgary, Ghaffari, and Levy say the most dramatic instance of change in incident density occurs in the spring, at night, and on the weekends.[25] Their possible explanations for the patterns need confirmation, but the visualization shows the pattern occurring consistently. They also suggest further research into causal factors for the patterns, for instance looking into an “ecological approach” to the spatiotemporal distribution of fire origin. Visualizations of fires provide valuable information to policy makers when determining resource allocation “and thus enhance fire safety and response in communities.”[26]

In “Exploratory and Inferential Methods for Spatio-temporal Analysis of Residential Fire Clustering in Urban Areas,” Ceyhan, Ertugay, and Duzgun provide a spatiotemporal study of residential fire location over a four-year span in a district of Ankara, Turkey. The location, time, and date of residential structure

---

[23] Yuan, “Temporal GIS.”

[24] Asgary, Ghaffari, and Levy, “Spatial and Temporal Analyses.”

[25] Ibid.

[26] Ibid.

fires was plotted with the express purpose “to inform policy makers from both a reactive, resource allocation perspective and a more proactive perspective.”[27]

The researchers used kernel estimation in plotting the spatial density and intensity of their point data. They developed a spatial visualization of fire distribution against a random sampling of non-affected buildings, effectively creating a control group. In their analysis of the data the team describes spatial distribution of fires as adhering to one of three patterns: “complete spatial randomness (CSR), clustering, or regularity.”[28] Ceyhan, Ertugay, and Duzgun also break down spatial correlation into first- and second-order effects. First-order effects are density and intensity. Second-order effects look closer at the corresponding patterns within adjoining datasets for causal factors. In their study, the team examined structure fire distribution and compared it to a control group of residences not affected by fire. Specific patterns were identified in location and times that fires occurred (first-order effects). In short, the distribution was not random, though causal agents (second-order effects) were not identified with certainty. The density of fires showed clustering around certain residential neighborhoods, while the intensity calculations showed that the clustering was not random in nature.[29] Spatiotemporal modeling provided the researchers with a visualization of fire activity throughout their districts with which they could make policy decisions.

Spatiotemporal visualization provides valuable information to policy makers and fire service administrators in understanding the dynamics of local fire problems. As analysis improves and becomes ubiquitous, the value will only increase. However, spatiotemporal visualization has been applied mostly to fire incidents, and fires consistently make up less and less of the overall call volume. To understand the trends in other call types, fire departments should use spatiotemporal visualization. The following section elaborates on two data

[27] Ceyhan, Ertugay, and Duzgun, “Exploratory and Inferential Methods.”

[28] Ibid., 227.

[29] Ibid., 232.

sources that show how data analysis affects policy decisions, justifying incorporation of all call types into spatiotemporal analysis.

3. Case Studies

The practices gleaned from the following case studies could provide policy makers information for more effective deployment of resources. The studies examine the breadth of call volume to which fire resources respond. In "Evidence-based Optimization of Urban Firefighter First Response to Emergency Medical Service 9-1-1 Incidents," Craig, Verbeek, and Schwartz analyzed the outcomes of approximately 200,000 medical responses by the Toronto fire department.[30] They found significant justification in their study to radically change the way fire apparatuses respond to medical calls. In the second study, *Using FSEC to Develop an Integrated Risk Management Plan*, the Office of the Deputy Prime Minister addressed risk modeling in the United Kingdom. This kind of risk modeling provides policy makers significant information when they seek to establish deployment plans, prevention efforts, and budget allocations.

The first case study of Toronto Fire Services' medical responses provides valuable insight into how statistical analysis can provide a detailed picture of community risk. In the study, Craig, Verbeek, and Schwartz sought to optimize fire responses by surveying historical data. They examined Toronto fire department responses to medical calls over the course of 16 months. Analysts compared categories of dispatched calls to the interventions conducted by firefighters in an attempt to create a predictive model that, according to the study's authors, "maximizes the opportunities for [firefighter first responders] interventions while minimizing unwarranted responses."[31] The results showed that fire engine responses to medical calls could be reduced by 90 percent, depending on how the researchers reconfigured the response criteria. The results varied based on response criteria modifications, but as the study

[30] Craig, Verbeek, and Schwartz, "Evidence-based Optimization," 110.

[31] Ibid.

mentions, in many jurisdictions, fire departments “respond to a large proportion of their total EMS call volume without an objective, comprehensive mechanism for evaluating any of these factors.”[32] In the case of Toronto fire department, objective statistical evaluation shows that changes can be made to more efficiently utilize resources. As a result, fire engines were available for more responses when a fire engine was truly needed, such as fires, rescues, and other specialized calls.

The United Kingdom has worked for the last three decades honing risk assessment strategies, starting with those of the Fire Service Emergency Cover (FSEC). The FSEC quantifies community risk by mapping roads, bridges, waterways, building types, and demographics.[33] The latest working editions of the FSEC possess detailed risk-assessment modeling that seeks to incorporate risk levels of individual buildings cross-referenced to historical data.

The FSEC provides policy makers important details about risk by examining all call types. In the UK, the fire service does not play as significant a role in the emergency medical system as does its American counterpart, but it does play a large role in other areas, such as motor vehicle accidents, rescue, and hazardous materials responses. The FSEC analysis incorporates all hazards that fire apparatuses respond to when fire service leaders determine deployments and budgets.[34] In the 2010 *Update of Response Time Loss Relationships for the Fire Service Emergency Cover Toolkit*, the FSEC toolkit was updated to reflect fatality and damage rates from all incidents that UK Fire Rescue Services attended.[35] These fatality rates and damage rates were correlated to response times such that policy makers could grasp an accurate

---

[32] Ibid., 113.

[33] Office of the Deputy Prime Minister, *Using FSEC*.

[34] John Wicks, *Fire Service Emergency Cover: Presentation Strategy Toolbox* (Research Report No. 4/2003) (London: Office of the Deputy Prime Minister, 2003).

[35] Martin Stone, *Update of Response Time Loss Relationships for the Fire Service Emergency Cover Toolkit* (Fire Research Report 3/2010) (Reading, United Kingdom: Greenstreet Berman, 2010), 10.

view of how station location and apparatus availability directly affected damage to structures and survivability of citizens.[36] This all-hazards and quantitative approach delivers significant evidence for deciding resource type and location.

However, what the FSEC lacks is an intrinsic spatiotemporal modeling tool. FSEC quantifies risk and shows its location throughout jurisdictions but stops short of explicitly visualizing risk dynamics over time and space. Despite a lack of spatiotemporal capability, the FSEC shows that risk modeling can have a significant impact by providing information to policy makers as they develop strategic plans for fire resources. Quantitative analysis of risk modeling of all call types in the UK has shown already that it can have important impacts on resource allocation, budgets, and prevention efforts.[37] Additional analysis at a spatiotemporal level can enhance the existing the methodology.

4. Conclusion

Spatiotemporal modeling provides a valuable tool for researchers as they seek to understand changes in geographic distribution of incidents over time. Spatial analysis and temporal analysis have been studied as unique entities; it is the combination of the two in the form of spatiotemporal modeling that is a relatively new field, especially for the fire service. Where the fire service has incorporated spatiotemporal modeling, researchers have found that patterns emerge in distribution of fires across spans of days, months, or years. Toronto Fire Services and the United Kingdom Fire Service Office of the Deputy Prime Minister, Fire Health and Safety Directorate have both shown that analysis of all fire department calls for service can yield significant results in terms of honing deployment plans. The remainder of this work examines the incorporation of

---

36 Stone, *Response Time Loss Relationships*, 10.

37 The IRMP discusses the themes of the FSEC as an impetus to key objectives in its plan. The IRMP drives budget provisions for the Fire Rescue Service. See Northern Ireland Fire and Rescue Service, *Integrated Risk Management Plan 2012–2015* (Lisburn, Northern Ireland: Northern Ireland Fire and Rescue Service, 2012).

spatiotemporal analysis into modeling all call types to understand risk within communities.

C. RESEARCH DESIGN

This thesis visualizes how fire department requests for service fluctuate both geographically and temporally through a means of spatiotemporal modeling. By categorizing and mapping different call types, different patterns of change emerge across time and space. Spatiotemporal modeling best illustrates this concept because it encapsulates geographic and temporal change in the same visualization.

Spatiotemporal modeling requires a time-stamped, geographic data source. Computer-aided dispatch (CAD) and records management system (RMS) data provide such sources for modeling spatiotemporal distribution. Most jurisdictions direct fire service equipment to emergencies with (CAD) systems that store and track time-stamped locations of incidents and apparatuses. Data from a records management system (RMS) offer complete accounts of events by fire service personnel including geographic locations and time stamps.

Jennings, the aforementioned City University of New York associate professor, states that "actualized risk is determined by examining the history of fires in the community."[38] CAD and RMS systems provide a history of all incidents, not just fires. Thus, CAD and RMS provide the raw data for all actualized risk. Spatiotemporal modeling consumes the raw historical data and allows the user to visualize actualized risk and its spatiotemporal distribution across the community.

To model distribution of historical activity, the author accessed CAD and RMS data to create homogenous groupings of incidents. These RMS incidents are grouped with two criteria. The first criterion is the type of apparatus that responds. For instance, emergency medical calls are grouped together because

[38] Jennings "Evaluating and Managing Risks," 73.

they typically require only a single fire apparatus to respond. Structure fires are grouped together because they require a much larger response. Similar call types provide the second criterion for groups. Vegetation fires, for example, are a separate group because they tend to follow predictable seasonal patterns.

The homogenous groups of incidents were further organized into specific time increments: month of the year, day of the week, and time of day. After the data were categorized into homogenous groups and segregated by time increments, they were plugged into the kernel density estimation spatial analyst tool in ESRI ArcMap 10.2. The KDE tool creates a heat map of the incident density for the time increments of each group. For example, seven KDE images were created of emergency medical calls, each one representing incident density for a day of the week. In order to help depict spatial distribution changes from one time increment to the next, slides of the density images were produced.

Most current deployment models involve a static distribution of fire resources spread across the community. Spatiotemporal modeling shows that actualized risk is dynamic and relatively patterned. Though actualized risk fluctuations do not coincide with current deployment plans, spatiotemporal modeling can still provide input to policy makers for future deployment models. Subsequent chapters of this thesis explore strategies for integrating a spatiotemporal model into deployment plans based on actualized community risk.

D. THESIS ORGANIZATION

The next chapter makes the connection between historical data, actualized risk, and spatiotemporal modeling of community risk. Then, Chapter III outlines the research plan, which involves accumulating, categorizing, partitioning, and processing large amounts of data with spatiotemporal mapping software. Chapter IV indicates how a fire department can implement spatiotemporal risk modeling. This method conflicts with existing static fire-service deployment plans, so this chapter addresses the challenges facing dynamic deployments. The final chapter identifies areas of future research.

THIS PAGE INTENTIONALLY LEFT BLANK

II. METHODS

A. METHODOLOGICAL APPROACH

The data for this thesis come from two primary sources, computer aided dispatch (CAD) and records management system (RMS) systems. Fire service dispatchers use CAD to locate emergencies and identify apparatuses available to respond. Dispatchers define the nature of emergencies based on the information shared with them by callers who witness the incidents. CAD systems log the geographic location of an incident, apply a time stamp, capture the nature of emergency, and transfer it to units responding to the incident. The CAD data provide the initial source for RMS data. At the completion of an incident, CAD data are uploaded to an RMS system, at which point fire department personnel complete a report summary of the incident.

In many fire-dispatching centers across the country, CAD platforms and RMSs are separate databases, and in many cases, they do not share information. In other systems, the CAD platform feeds the RMS, so incident reports reflect all the data points gathered by CAD in addition to information the report writer uses to supplement the report. For the purposes of this thesis, the data are an amalgamation of both CAD and RMS data sets.

CAD and RMS data represent a historical picture of fire service activity. Each call for service represents an event when risk is actualized. For example, planners can discuss the possibility, or potential, that a building will catch fire or a train will derail. However, until the event occurs, the risk is hypothetical. When a building catches fire or a train derails, the event goes from a potential risk to one that is actualized, as coined by Jennings.[39] CAD and RMS data capture actualized risk, whether fire, flood, heart attack, or train derailment. The history of events in a community represents actualized community risk. Furthermore, as policymakers look retrospectively at actualized risk, patterns begin to emerge

[39] Jennings, “Evaluating and Managing Risks,” 73.

that can help planners make presumptions about future, or potential, risk. Spatiotemporal modeling of CAD and RMS data visualizes actualized community risk in hopes of illuminating potential risk.

To utilize CAD and RMS data for spatiotemporal modeling, several steps must occur. The first step is to categorize the data into meaningful groups. In order to visualize spatiotemporal patterns, the incidents must be similar in nature. Each incident type requires a complement in the form of equipment. For many agencies, vegetation fires require a specific apparatus that has the ability to fight fire off the road. Vegetation fires also have a specific seasonal variation; consequently, access to or staffing of specialized off-road equipment is not relevant to the distribution of rescue calls, which use different specialized equipment.

The second step in utilizing CAD and RMS data involves partitioning the incidents into pertinent time increments. The author segregated the incident categories into three time increments: month of the year, day of the week, and hour of day. The time increments correspond to the method by which the CAD and RMS data is stored.

Prior to loading the data into ArcMap 10.2, KDE spatial analyst tool, dozens of separate data sets comprised each time increment for each of the call type categories. In the data for this thesis, the emergency medical calls composed the largest data by volume. Based on the size of the data, the author chose to use emergency medical calls as the sample data set and created KDE raster images for each time increment. The result was 12-months-of-the-year, seven-days-of-the-week, and 24-hours-of-the-day raster images of emergency medical call distributions.

When the heat maps of the incident data were finished, the necessary components were in place for a temporal snapshot to show the data trajectories over chosen periods of time. For each of the three time increments, a slide presentation was built of the individual raster images, to illustrate for the analyst changes in spatial distribution.

B. DATA SOURCES

All data, covering a span of 27 months, from January 1, 2012, to March 30, 2014, came from Fresno (CA) Fire Department's geographic information systems database. The total call volume during that time comprised 82,591 incidents; however, 676 calls were not analyzed due to the infrequency of the call type. The total number of calls not analyzed represents less than 0.8 percent of call volume.

Fresno Fire contracts with the Fresno County Emergency Medical Services Communications Center, which dispatches for several fire agencies and the local ambulance company. The communications center uses a TriTech computer-aided dispatch system to log call information, direct apparatuses, and capture the following information among the data fields for each incident: call type, geographic location, and time stamps. At the conclusion of the incident, the CAD platform pushes the incident data to a server at Fresno Fire Department, where the data is uploaded in the Tiburon records management system (RMS). The RMS platform absorbs the CAD data and initiates an incident report. The responding fire officer logs into the RMS server to complete the incident report by filling in an incident summary and other required fields not uploaded by CAD. The RMS feeds the data to a geographic information system (GIS) database housed by Fresno Fire in which each individual incident is represented by an individual geographic data point.

1. Data Processing

The 81,915 incidents required sorting into useful partitions. ArcMap 10.2 was used to query the data into the partitions. Table 1 illustrates the breakdown of the incident data by type.

Table 1. Data Partitions Using NFIRS Codes

Description	NFIRS[40] Codes	Call Qty	Raster Map Scale
Structure Fires	11-123	2,019	
Mobile Property Fires	130-138	796	
Vegetation Fires	140-143, 170–173	866	
Outside NonVeg Fires	150-163	1,834	
Medical/ EMS	300-321	40,553	0-200/SqMi
Motor Vehicle Accidents	322-324	5,367	
Hazardous Materials/Rescue	340-499	2,009	
Utility Standby	200-251, 444	428	
Service/ Good Intent	500-699	8,214	
Canceled Calls	611	13,341	
Alarms	700-799	6,488	
Total analyzed call volume		**81,915**	

Each partition was further grouped into following time increments:

- The incident data set were sorted by hour of the day, starting with midnight (0000 hours), ending with 11:59 P.M. (2359 hours) yielding 24 groups of call data.
- The incident data set were sorted by day of the week, starting with Monday and ending with Sunday, yielding seven separate groups of call data.

[40] National Fire Incident Recording System (NFIRS) publishes standardized three-digit codes representing the array of different call types experienced by fire departments. NFIRS codes are published by the United States Fire Authority (USFA) as a way of standardizing call categorization across the country. Fresno Fire Department complies with NFIRS guidelines, and the data reflects those categories.

- The incident data were sorted by month of the year, starting with January, ending with December, yielding twelve separate groups of data.

2. Spatiotemporal Modeling Method

A heat map was created for each partition of incidents that included all incidents. A second set of heat maps was created using each time increment group within the incident partitions utilizing the ArcMap kernel density function in the Spatial Analyst toolbox using the following settings (all base units were in feet):

1. The population field was set to none.
2. The output cell size to 400.
3. The search radius to 2640.
4. The area units to square miles.

Once the heat maps were created for each time increment group within the incident partitions, the collection of heat maps were then exported as JPEG image files. The groups of JPEG images were then compiled into a single image for display in Findings and Analysis chapter.

The heat map created for each partition with all incidents became the base map for an additional method of visualizing spatiotemporal distribution. A composite heat map showed all emergency medical calls that occurred in the data set. Then, for each station, a circular plot was created showing the temporal distribution of emergency medical calls in that station. Each of these circular plots was added to the map, giving the analyst an idea of spatial density through heat map and the temporal distribution via the circular plot. See Figure 13 in Chapter III for this product.

THIS PAGE INTENTIONALLY LEFT BLANK

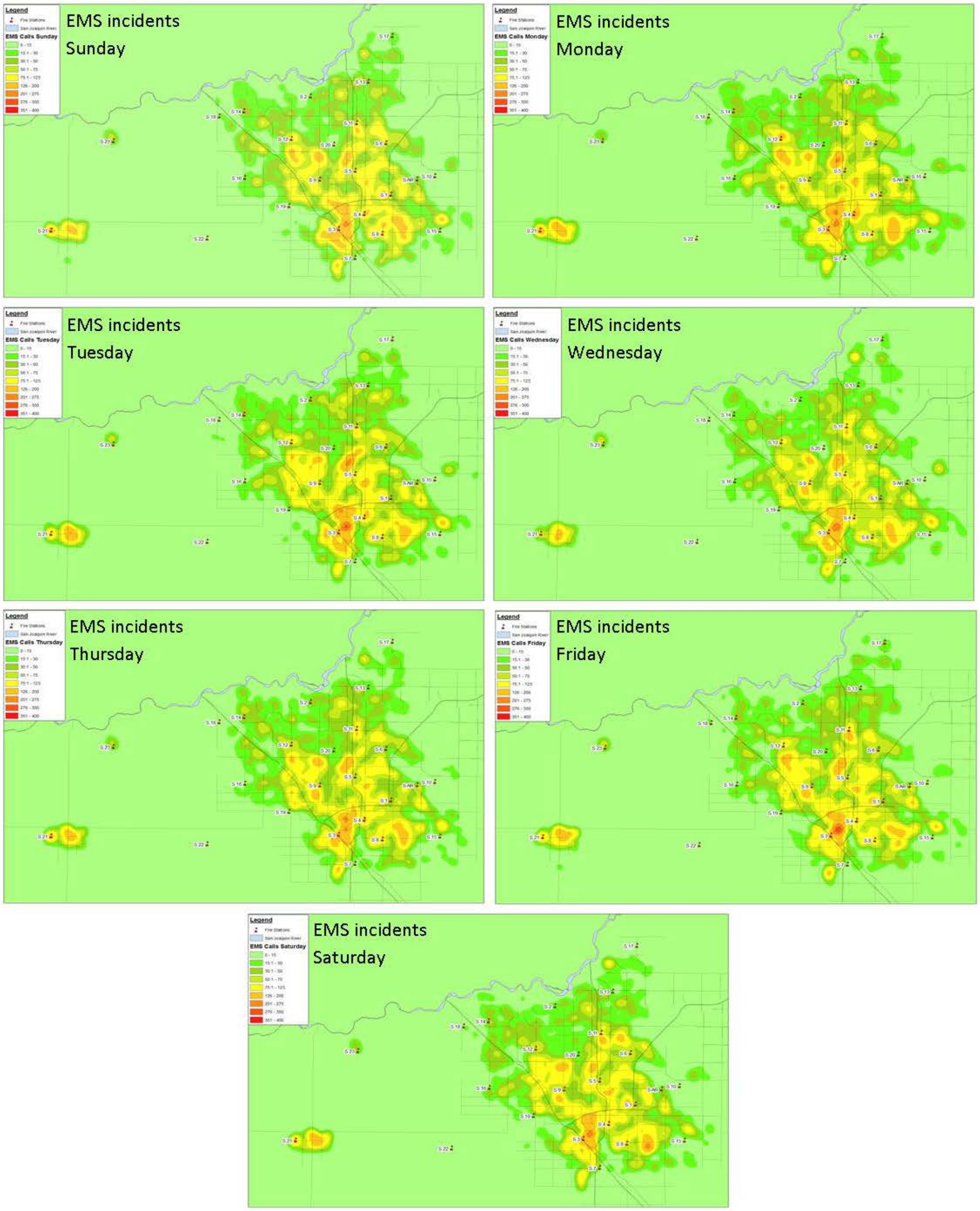
III. FINDINGS AND ANALYSIS

This chapter comprises four types of heat maps for Fresno, California, each of which partition emergency medical calls into different time increments. The first set of heat maps depicts EMS call volume by day of the week, resulting in seven hot spot maps. The second set of maps categorizes EMS calls by hour of the day. Twenty-four heat maps were created, one for each hour of the day. Additionally, a composite heat map of all emergency medical service calls over the period studied, January 2012 to April 2014, was generated along with circular plots of the hourly distribution of calls for each station. The third set of maps partitions emergency medical service calls by month of the year, so 12 hot spot maps were created. Each set of findings are followed by analysis.

A. CALL DENSITY BY DAY OF THE WEEK

In order to visualize spatiotemporal patterns across days of the week, seven heat maps were produced to display the density of calls that occurred on each day, starting with Sunday and ending with Saturday. The maps depict the entire coverage area and include fire station locations along with main roads plotted for reference. There were nine classifications of call density represented on the heat map (see Figure 3), with a range from 0 to 15 incidents per square mile, indicated in pale green; to 400 incidents per square mile, indicated in red.

Figure 3. Call Density by Day of Week



1. Daily Distribution Summary Analysis

The most notable feature of the daily distribution of calls was the remarkable consistency from one day to the next. There were some fluctuations in specific areas, but no identifiable patterns across the entire jurisdiction. Three areas showed localized fluctuations worthy of mention: the downtown area between Station 3 and Station 4, a small area east of station 10, and a hot spot on the north end between Stations 13 and 17. The continuity across the days and its possible ramifications will be discussed toward the end of this section.

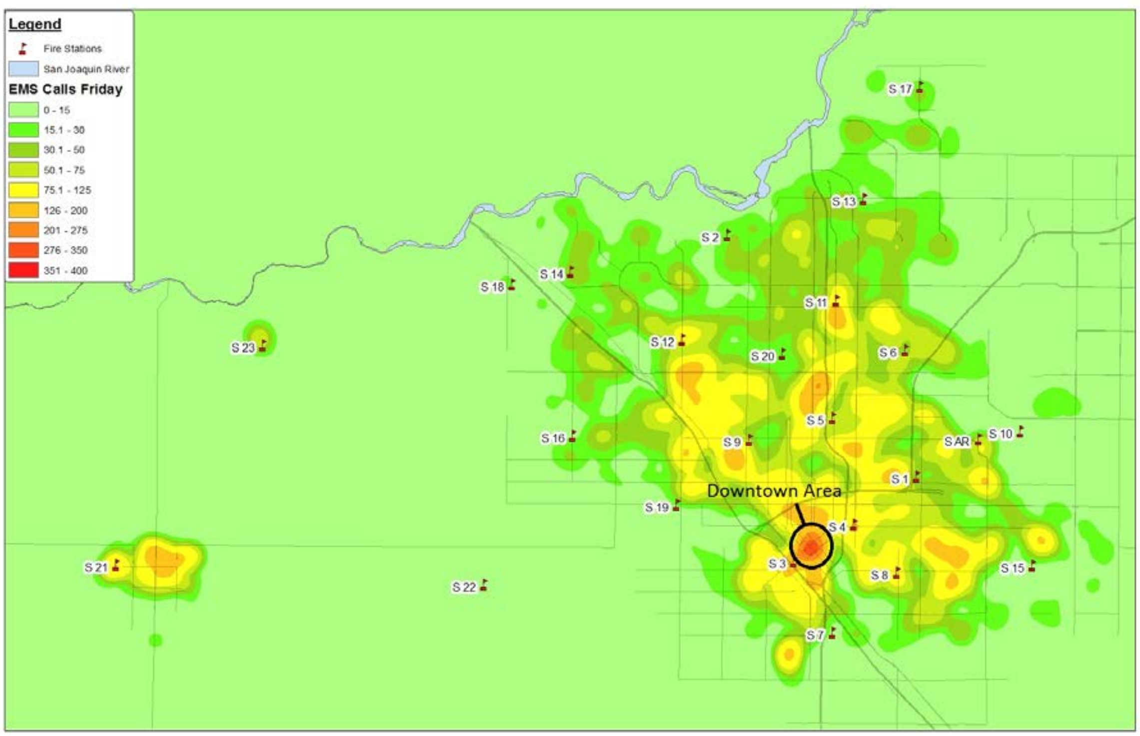
2. The Downtown Core

The downtown area of Fresno is situated between Fire Stations 3 and 4 and represents the commercial and governmental hub, with little residential occupancy. Most of downtown's daytime population is made up of business commuters who reside elsewhere Traffic patterns look like many downtown areas: heavy flows into downtown in the morning followed by ebbs in the evening hours. The expected daily distribution was a dense call volume from Monday through Friday followed by a significant lull in activity on Saturday and Sunday. Throughout the week, the call density was fairly consistent each day, between 100 and 150 calls per square mile. On the heat map for Tuesday, a small area appears in the middle of downtown showing a spike of 250 calls per square mile, but generally, the call volume stays constant everywhere else. Call volume on Friday, however, increases significantly. Friday shows a hot spot in the same area as Tuesday but nearly three times larger, indicating a significant increase in the call volume for that day. Another notable feature of this uptick in activity is that the surrounding area does not experience any noticeable change in call volume.

Downtown is generally described as a triangular area bounded by Highway 99, which runs at a diagonal to the west, Highway 180 to the north, and Highway 41 to the east. See Figure 4 for the location of downtown and call densities.

On the heat maps, the area between Stations 3 and 4 has a consistent call density of 126 to 200 for each day of the week, with upticks of more than 200 calls per square mile in isolated areas every day. On Friday, the density climbs to over 275 calls per square mile across several blocks. This trend on Fridays represents nearly a 35 percent increase in call volume over the rest of the week. This small geographic area has the greatest call density of any area in the Fresno Fire Department's coverage area yet has the fewest full-time residents by density. It is reasonable to expect that commercial centers would have the heaviest call volume during the weekdays and attenuate into the weekend. Downtown follows a pattern other than the expectation, which creates an opportunity for investigation into causal factors.

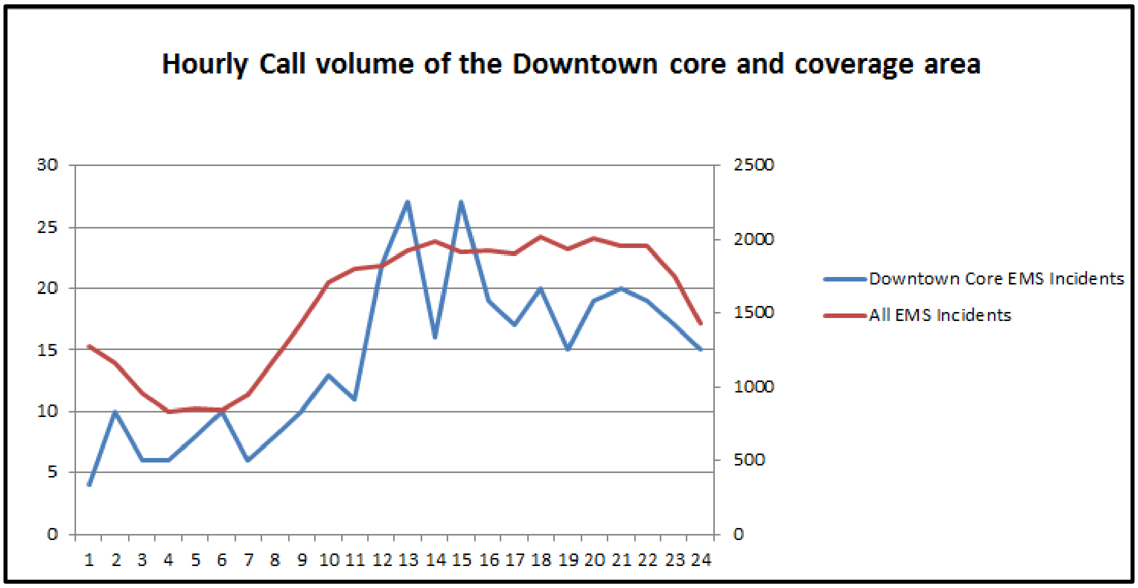
Figure 4. Downtown Core



An explanation for the observed density was elusive. For clarification, actual call volume in the area was investigated. The average call volume per day in the center of downtown was just over 90 incidents per day, with a standard deviation of 14 calls per day. The call volume on Tuesday was 102 calls, about one standard deviation above average, while the volume on Friday was almost two standard deviations greater than the average at 117 calls. The question remains as to why there is such an increase on Tuesday and Friday. An increase on a Tuesday seems in line with the original theory that weekdays should be busier than weekends due to the commercial nature of most downtown occupancies, but the uptick on Friday seems contrary.

A possible explanation for the Friday uptick may come from increased restaurant and bar activity at the end of the workweek. The city of Fresno built a stadium downtown near the middle of the hot spot, and the related activities may be connected to Friday's increase in call volume. Because stadium games are usually scheduled on weekend nights such as Fridays, they may keep local workers downtown to attend events. The additional traffic and activity may very well drive the higher call density in the area. Further analysis of the daily call volume vis-à-vis hourly analysis could illuminate when Friday is busier. However, the hourly pattern of calls on Friday does not directly correspond to evening events. Friday shows heavy surges in call from 12:00 P.M. to 3:00 P.M. then tapers off to a pattern similar to what the rest of the city observes. See Figure 5 for a comparison of the citywide and downtown area patterns for Fridays. These data fail to provide analysts with a conclusive answer to the observed call density on Friday and beg for further investigation into causal factors.

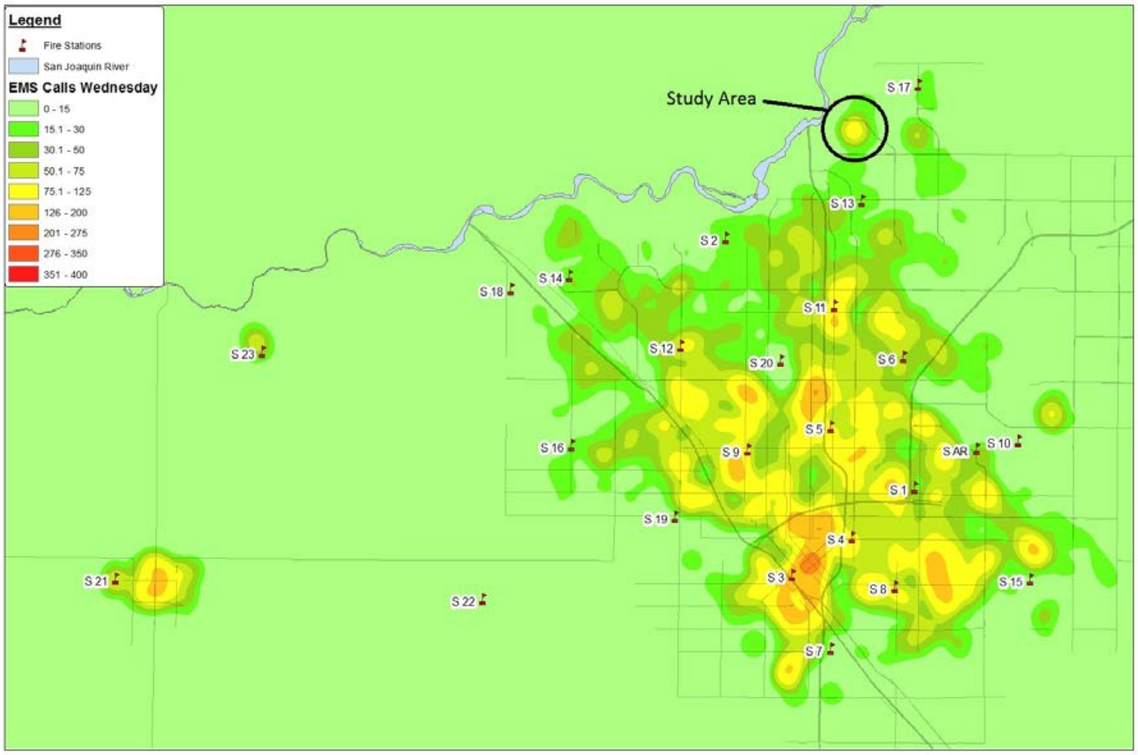
Figure 5. Downtown Fresno Core Call Volume on Fridays



3. Fort Washington Area

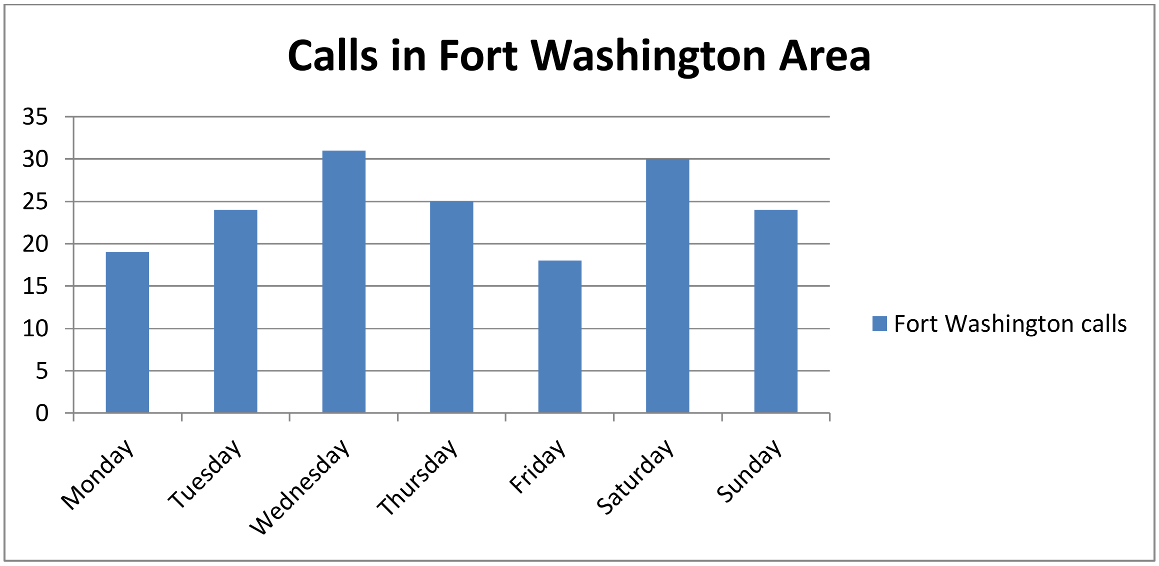
The Fort Washington area of Fresno is roughly bounded by Woodward Park along the west, Champlain Avenue to the east, and Shepherd Avenue to the south. The residential area is home to custom properties and one of the most exclusive golf courses in the city, the Fort Washington Country Club. This area falls between two fire stations, 13 and 17, and is one of the city's districts with the lightest overall call volume. The demographic of the area is mostly upper middle class to upper-class households. Most occupancies are single-family residential developments with a sprinkling of condominiums and an assisted-living center, the Fairwinds, which houses a significant convalescent population. See Figure 6 for location of the Fort Washington area in the northern part of Fresno.

Figure 6. Fort Washington Area



As shown in Figure 6, the area between stations 13 and 17 experiences an approximate 27 percent increase in call volume on Wednesday and Saturday (30 and 31 calls, respectively) relative to the average for the area on Sunday, Tuesday, and Thursday (24 calls per day). On Monday and Friday (19 and 18 calls, respectively), the volume drops by approximately 23 percent. A bar graph is especially useful for illustrating the variation between days of the week. As shown in Figure 7, the call volume exhibits fluctuations that peak on Wednesday and Saturday. By comparing the daily data with monthly data over 27 months, the number of calls per particular day was remarkably similar. It appears that the pattern observed over the days of the week extends throughout the year, indicating that the pattern does not have a seasonal or monthly variation.

Figure 7. Fort Washington Weekly Call Volume



A demographic analysis and comparative analysis of this area using an additional EMS dataset may lead to some fruitful conclusions. The second emergency medical call dataset includes calls for service by the area ambulance company. The ambulance data includes the call outcome and details of the treatments ambulance personnel provided by the patients at the scene and en route to the hospital. Analyzing the fire department data against the ambulance data and reviewing patient outcomes could provide insight into the patterns observed. Cross-referencing the fire department data with ambulance company EMS data could provide the kind of detail necessary to derive proactive measures to the population. If patients experience short hospital visits corresponding with the three-day cycle observed in the fire department data, it is possible that outreach to those patients in their homes may provide better care for them.

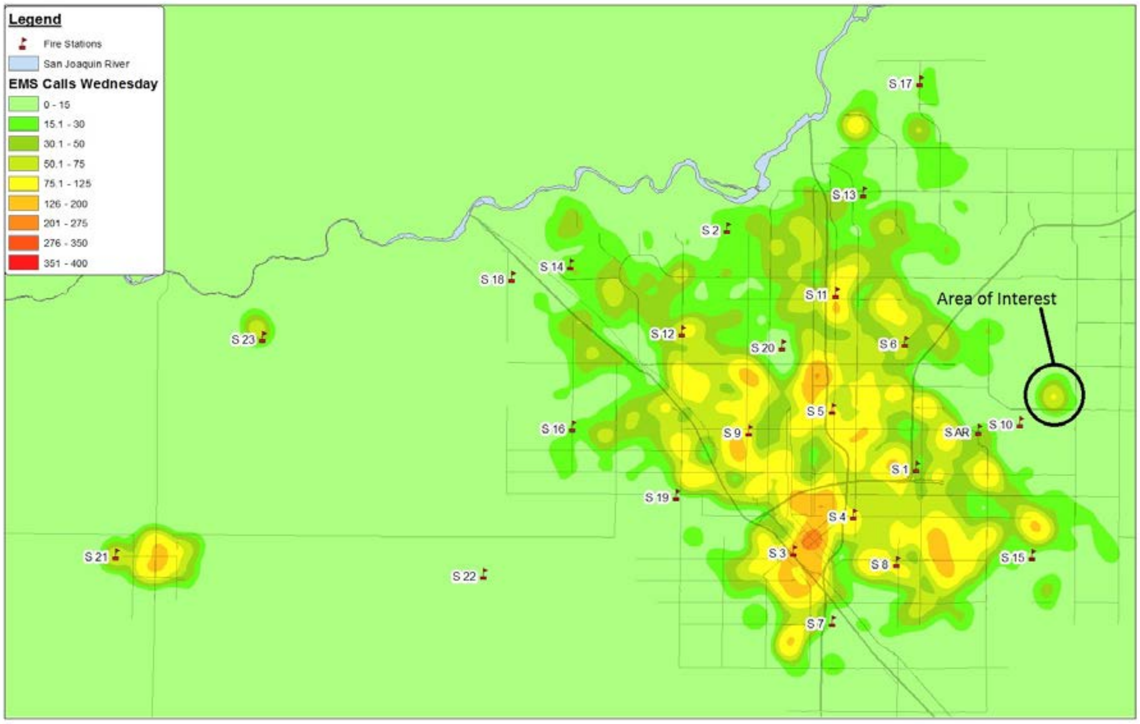
Several fire departments in the United States, including the Los Angeles Fire Department (LAFD), are reaching out to patients in attempts to extend hospital care. LAFD is a transporting paramedic-level fire department that has begun a pilot program that assigns a nurse practitioner to paramedic ambulances. Ambulances can now extend the level of pre-hospital care to its citizens in lieu of tying up firefighters for non-emergency calls.[41] Fresno Fire could work collaboratively with local care facilities and the ambulance company to investigate proactive measures. Proactive measures could reduce the committed time for fire engines when a smaller piece of equipment with fewer personnel would suffice for the nature of the call.

4. Airport Industrial Area

Fire Station 10 resides on the east side of Fresno, adjacent to the Fresno Yosemite International Airport. The station responds to about 1,000 calls for service a year and houses a single apparatus. The district is largely industrial with some older single-family residences. The bulk of the residences immediately east of the station do not experience a large quantity of calls, especially relative to the downtown core, but an abrupt daily call pattern. Over the 27 months in the dataset, the total call volume reached 152, which, when compared to the 633 in the downtown core for the same time period, seems quite insignificant. However, the incident pattern was so apparent that the causal factors deserve analysis. See Figure 8 for a geographic reference of Station 10 and the unusual hotspot in the airport industrial area.

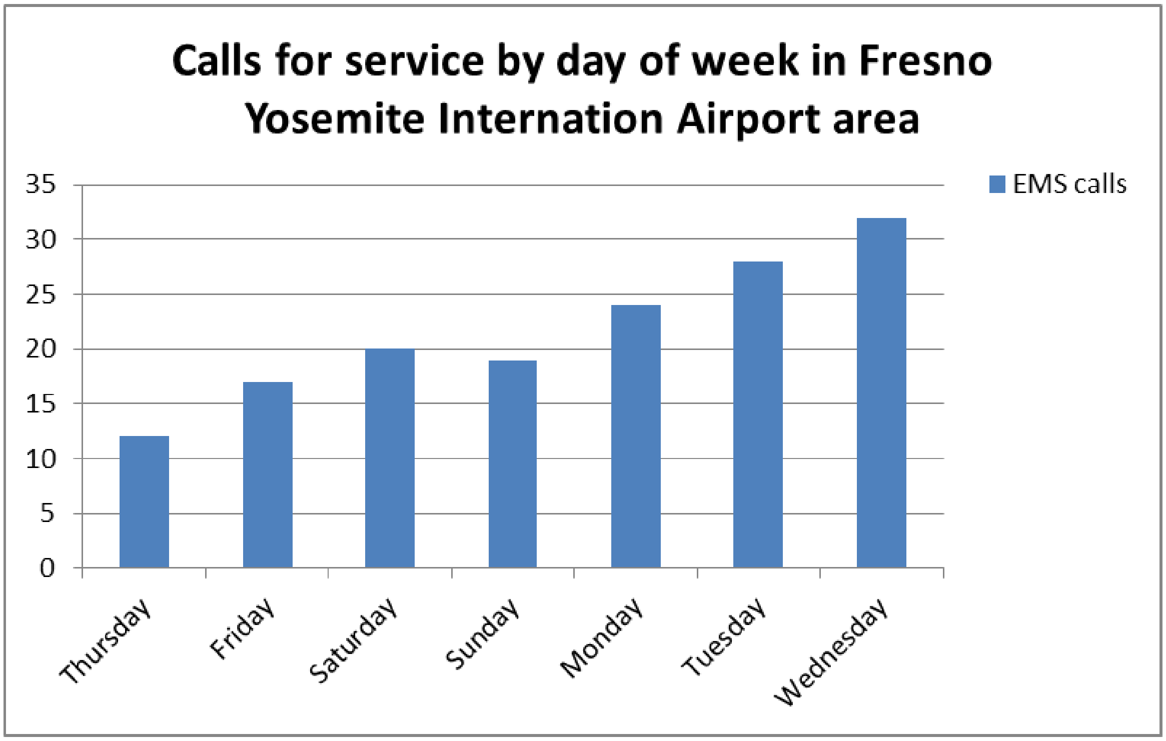
41 “Let Paramedics and Nurse Practitioners Handle Some 911 Calls,” *Los Angeles Times,* April 8 2015, 2015, sec. Opinion/Editorial.

Figure 8.   Airport Industrial Area



The call distribution across all days of the week follows a distinct incremental increase starting on Thursday and peaks on Wednesday. On Thursday, the call volume is at its lowest, 12 calls. Call volume steadily increases, with a slight dip on Sunday, peaking on Wednesday at 32. From Wednesday to Thursday, the call volume drops by 60 percent, which equals more than three standard deviations. See Figure 9 for the daily distribution of calls in the area.

Figure 9. Call Volume for Airport Industrial Area



The pattern—a steady increase to Wednesday followed by the precipitous drop before the cycle starts again—is peculiar. This area is less than half of a square mile composed of mixed residential and commercial occupancies that produced 152 calls for service. It seems highly improbable that the calls for service would randomly follow a pattern like the one observed, especially since it stands in such contrast to the broader trends across the city as a whole. The pattern is most likely not random, so there must be an underlying causal factor for steady buildup of calls to Wednesday. Nowhere else in the coverage area is the pattern so clear and so precipitous from one day to the next. An analyst might ask, what happens on Wednesdays to drive such a pattern?

Deriving the causal factors for this pattern could provide fruitful data for preventative efforts. Furthermore, the causal factors in this neighborhood could drive intervention efforts elsewhere in the community. Future research may also address other call types in this area to see whether this is a general trend or one specific to EMS-related calls. Analysts may find that activity in this neighborhood ebbs and flows according to days of the week, driving calls for all services, not just medically related ones.

The area in question is home to a dense industrial and commercial district. Some of these businesses use chemicals, which may have downwind effects on the community. One way to investigate this hypothesis could be to look at all calls for service. If all calls for service follow a similar pattern as the EMS calls, an analyst could surmise that the patterns stem from something other than the industrial activity. However, if analysts find that only EMS calls follow this pattern, the nucleus of a causal factor may emerge. In this case, an investigation into the ambulance data would be warranted to see if the patient outcome data (similar to that used in the Fort Washington study) could reveal specific nature of the calls. If the patient outcome and call natures matched those indicative of downwind exposure to toxins, a greater health study could begin.

5. Conclusion

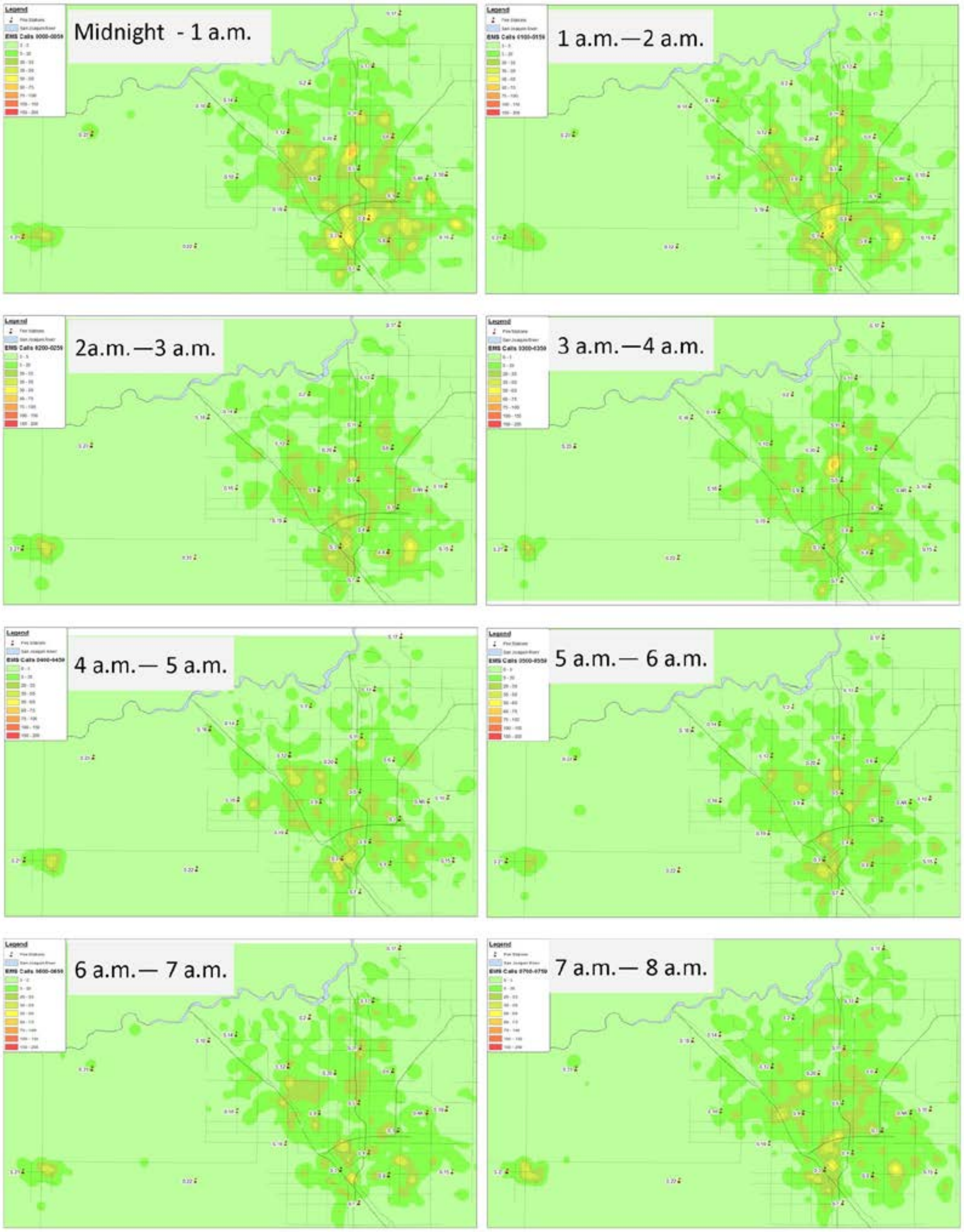
Aside from the aforementioned localized geographic patterns, an overarching theme appeared: a remarkable continuity spanning the days of the week. Even though each day had its distinctive distribution of call density, there were few global patterns that emerged from the data. It was difficult to observe patterns that encompassed the entire coverage area. It appeared that density shifted slightly or intensified but not by any substantial amount. When the raw numbers for each day of the week were plotted in a bar graph, the difference between the busiest day and the slowest day was approximately 400 incidents, or about eight percent of the maximum daily volume.

Spatiotemporal distribution of call density was consistent during the week, necessitating little change to resource allocation for emergency medical incidents. With little variation across the days of the week, it seems unnecessary to push for any type of redeployment of resources based on the busiest day of the week. It appears that the current static resource deployment matches the risk associated with emergency medical service calls.

B. CALL DENSITY BY HOUR OF THE DAY

Call density by hour of the day breaks total EMS calls into 24 separate heat maps (staring with Figure 10), each representing the call density for an hour of the day. The maps run midnight to midnight 11:59 P.M., each map representing one hour's worth of calls. The last map is a composite map comprising two parts—a heat map and circular temporal plots for each fire station. The circular plots depict the calls in each station's area throughout the 24-hour day. Though the composite map does not provide the resolution of individual hourly heat maps, it does provide an alternate visual tool for spatial and temporal distribution of EMS calls. The hourly map sets use density ranges from 0–15 calls per square mile, represented by pale green, and up to 150–200 calls per square mile, indicated in red. The composite map uses a wider value range, 0–30 calls per square mile up to 2,500 calls per square mile, with the same color schematics.

Figure 10. Call Density by Hour of Day, Midnight to 8:00 A.M.



.

Figure 11. Call Density by Hour of Day, 9:00 A.M. to 4:00 P.M.

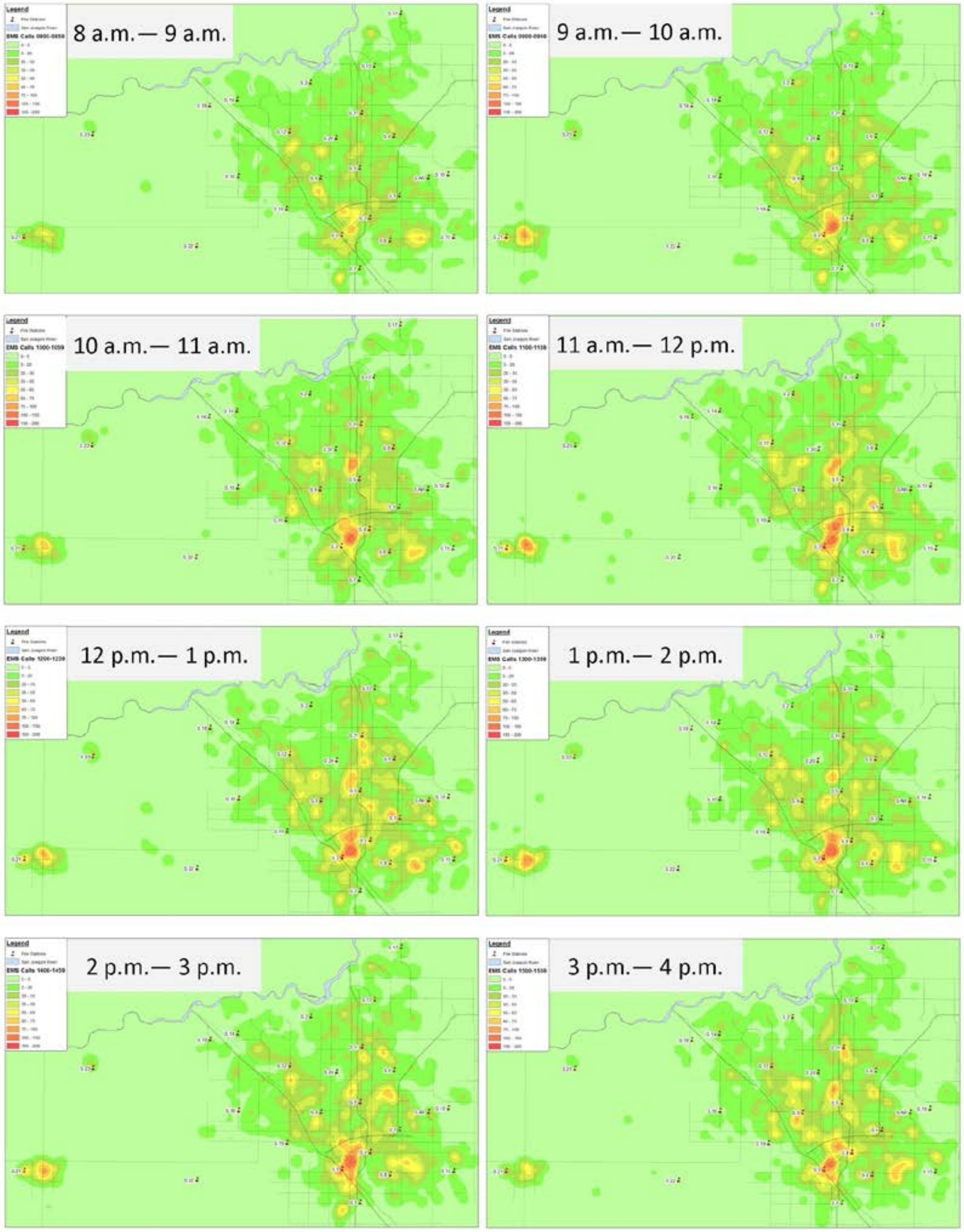


Figure 12. Call Density by Hour of Day, 5:00 P.M. to Midnight

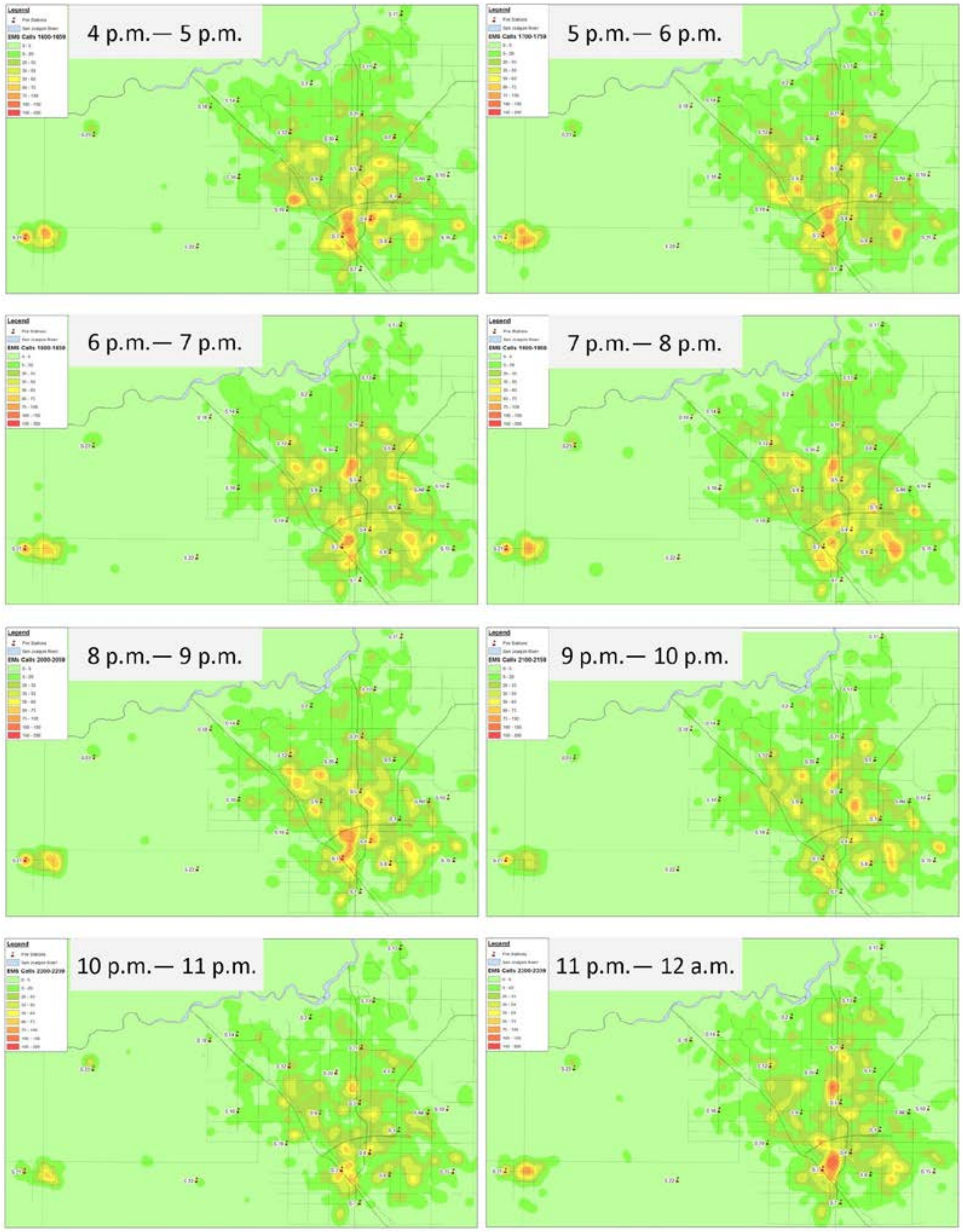
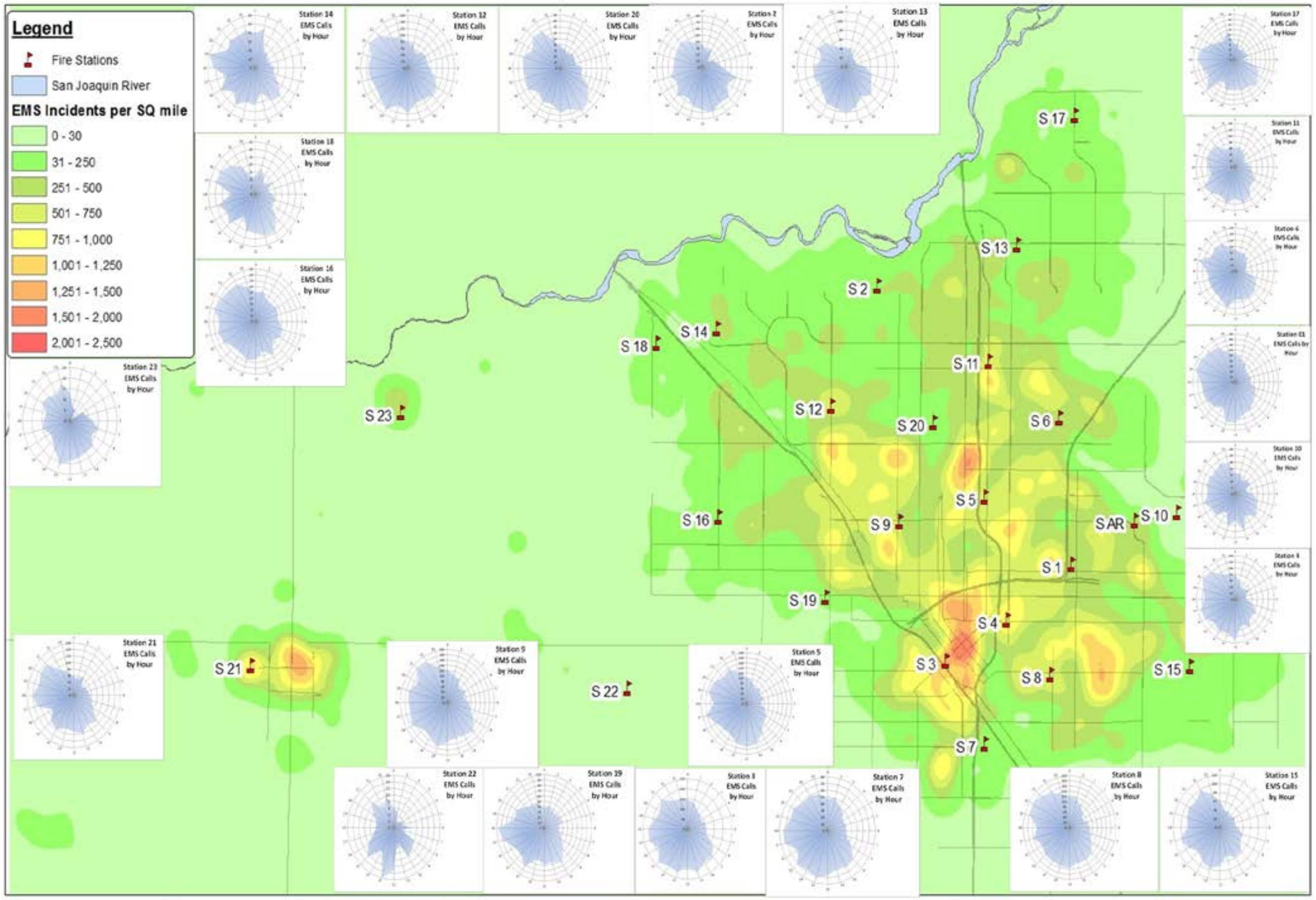


Figure 13. Composite Map of Call Density with Circular Temporal Plots by Hour

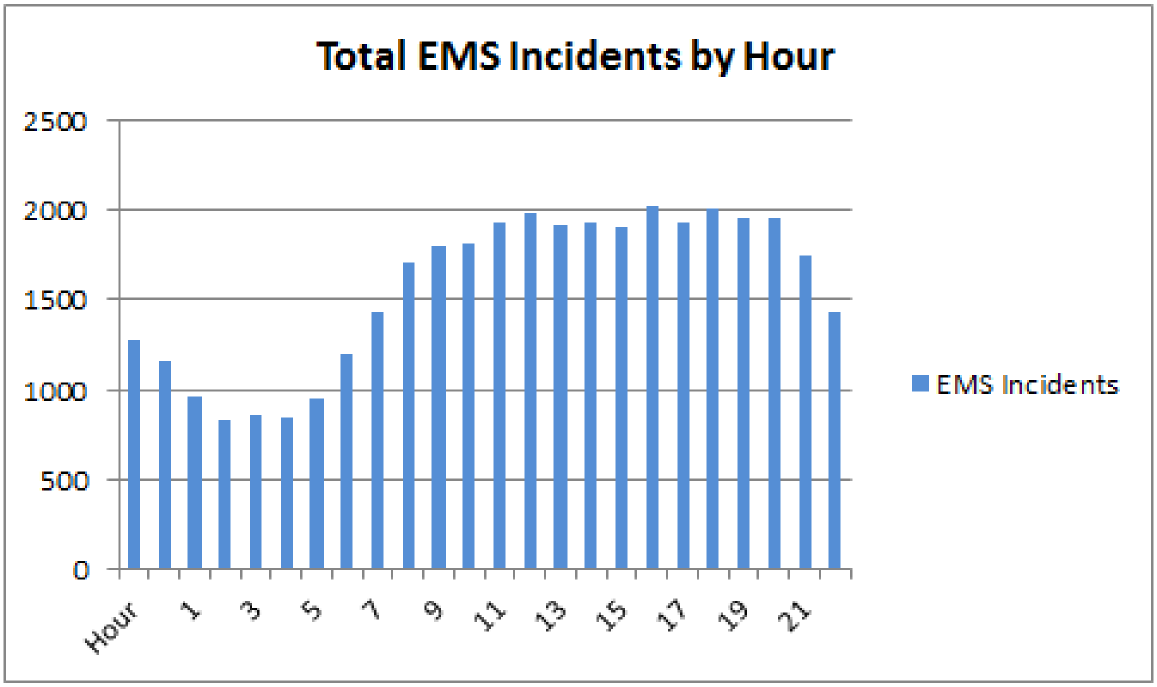


1. Hourly Distribution Summary Analysis

Analyzing the hourly maps involved reviewing how density changed from one image to the next. Specific areas were inspected one at a time throughout the displays. This afforded a comparison of smaller areas over time to see potential patterns. A bar graph of the total quantity of EMS calls by hour (see Figure 14) was also created to help illustrate how a particular area varies from the patterns of the entire coverage area. The total quantity of EMS calls follows a very clear pattern that mirrors a diurnal circadian rhythm. Call volume is lowest from 11:00 P.M. to 7:00 A.M. before it steadily climbs to a peak around 6:00 P.M., and then tapers off after 11:00 P.M. The heat maps show this trend, as well. The hottest portions of the heat maps appear from 6:00 P.M.–7:00 P.M. and the coolest portions between 2:00 A.M. and 3:00 A.M. Some areas still show considerable density in those early morning hours yet proportional decreases from the busiest times of the 24-hour cycle.

As depicted in Figure 14, call volume steadily increases during the day until its peak in the evening. Diving further into the hourly values, the graph reveals that city wide, 66 percent of emergency medical calls occur in a 12-hour span between 10:00 A.M. and 10:00 P.M. In the Fresno Fire Department coverage area, two-thirds of the medical calls in the community occur during half of the day. Any discussion of increasing resources could focus on the surge of EMS calls between 10:00 A.M. and 10:00 P.M.

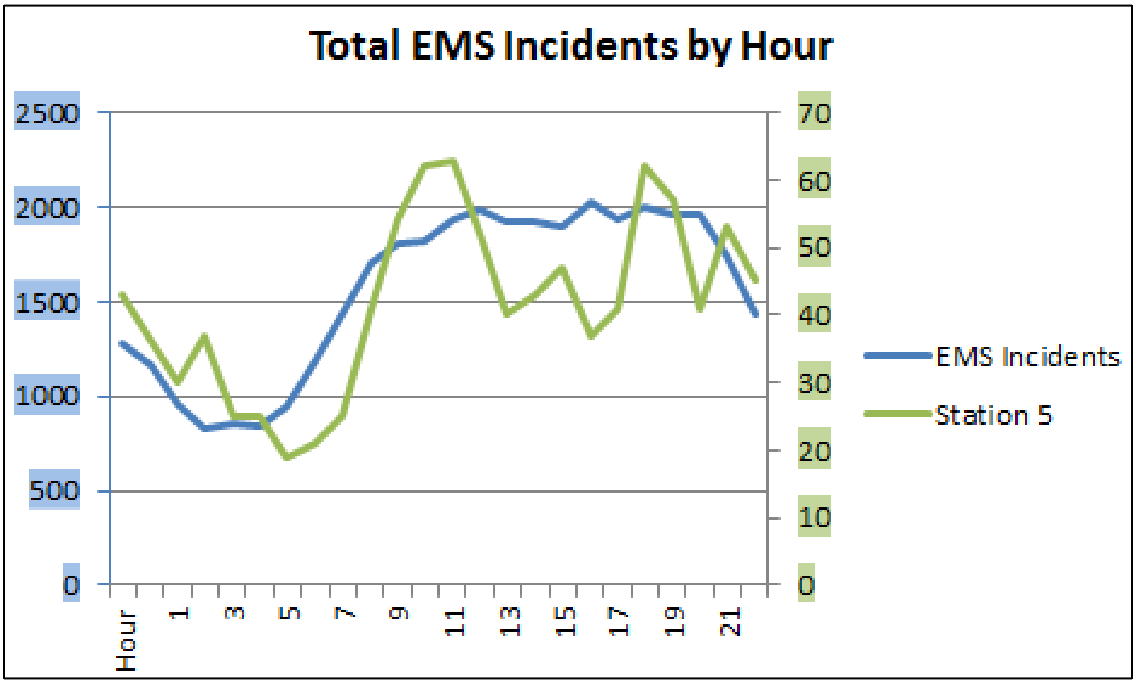
Figure 14. Total EMS Calls for the Fresno City Fire Department



2. Blackstone Corner

Not all of the coverage area requests for service follow a daytime circadian rhythm. One area, the "Blackstone Corner" at the intersection of Blackstone and Dakota avenues, stood out as having a nominally different pattern than the rest of the city. The typical pattern of hourly distribution, as seen in Figure 15, shows heavy call volume during the afternoon into the evening, but the Blackstone Corner experiences declines in volume during the afternoon. The area also shows a distinctive uptick in volume during the early morning hours, which stands in opposition to the balance of the coverage area.

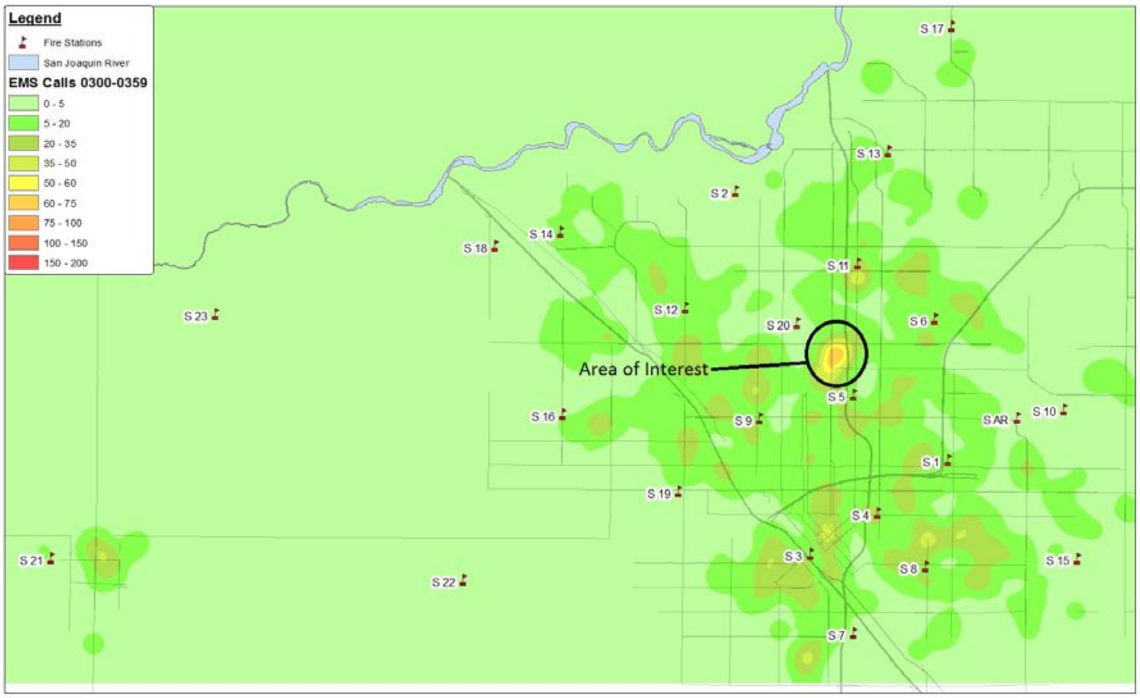
Figure 15. Total EMS Calls Compared to Station 5 EMS Calls



Fire Station 5 is located in the center of Fresno along the main artery of Blackstone, running north and south of Highway 41. Station 5 has one of the busiest engines historically, and throughout the study period, it responded to nearly 6,000 EMS incidents. The composite map in Figure 13 depicts an hourly call distribution for Station 5 that resembles the rest of the city with its call density following a diurnal circadian rhythm.

The hourly heat map, as seen in Figure 16, shows a distinctive pattern of call volume in the Blackstone Corner. While most of the coverage area shows relatively lower activity after 11:00 P.M., this one pocket actually increases in activity. The increase in activity extends until the 4:00 to 5:00 A.M. window, when call density drops to that of the surrounding areas. After 7:00 A.M., call density picks up steadily until 1:00 P.M. and, then, unlike the rest of the city, drops 20 percent after the lunch hour. While the rest of the coverage area ramps up with activity between 1:00 P.M. and 5:00 P.M., this area appears to cool off. See Figure 16 for a chart of the activity of this area relative to the broader temporal trend in the coverage area. The Blackstone Corner exhibits a distinctive hourly distribution of calls.

Figure 16. Blackstone Corner



Observing the spatiotemporal trends provides a window into the various microclimates of EMS call density through the Fresno Fire Department's coverage area. However, it provides only the opening chapter to a story about the underlying causes for the observed patterns. The data in Figure 15 shows a quantitative assessment of the discrepancy between the Blackstone Corner near Station 5 and the coverage area as a whole. To further understand the dynamics, analysts would need to access a much broader dataset. One possible explanation may be found in the police department's RMS dataset. Among the Fresno fire personnel, this spatiotemporal anomaly is a well-known location for prostitution. Police RMS data may reveal similar trends to those seen by the Fire Department. Further research could analyze police RMS data and associate them with Fresno Fire Department RMS data to investigate any coincident spatiotemporal patterns. If there is any kind of causal connection, it is reasonable to assume that if the prostitution problem is addressed, call volume will decrease.

3. Conclusion

Throughout the coverage area for Fresno Fire Department, hourly call volume follows a clear cyclical pattern of ebb and flow. The slowest times occur through the early hours of the morning while approximately two-thirds of the EMS call volume occurs between 10:00 A.M. and 10:00 P.M. The effect on the static deployment plan is a surge of activity during a 12-hour period when the largest number of apparatuses is committed to EMS incidents. The hourly spatiotemporal analysis also showed that spatially, the ebbs and flows of density remain proportional. In other words, the relative density of calls in specific areas remains constant. The composite maps illustrate this point in that, generally speaking, each of the circular plots of temporal distribution appears very similar. Though the quantities of calls may change from one station to the other, the temporal distribution of the call volume is extremely similar; it follows a diurnal circadian rhythm. In terms of community risk, the surges in risk across the entire coverage area follow a similar pattern, while the quantity of apparatuses deployed to mitigate this risk remains static.

Further analysis should investigate how the surge in EMS call volume affects availability of apparatuses. Analysts may find that the EMS demand exceeds a threshold for a committed apparatus. For example, if policy makers determine that 50 percent of resources committed for 30 minutes or longer is the lowest threshold of risk that the department is willing to accept, and during the busiest hours of the day, the department routinely passes that threshold, then analysts and leaders would need to discuss deployment of additional apparatuses.

Spatiotemporal analysis of EMS call volume depicts a significant impact to the deployment plan. EMS calls for service may also not necessarily need the full complement of four firefighters from a fire engine. Analysis of the EMS datasets might determine that a percentage of the surge in EMS calls stems from calls that could be handled with a smaller crew on a smaller piece of equipment in place of a fire engine. Should analysts determine that an alternative piece of equipment is capable of managing a portion of the call volume surge, it is possible that deployment of an alternative apparatus could relieve the pressure of lower level emergencies on fire engines.

C. CALL DENSITY BY MONTH OF THE YEAR

Call density by month of the year breaks total EMS calls into 12 separate heat maps (shown in Figures 17 and 18). The maps start in January and extend to December; each map represents one month's worth of calls. The monthly map sets use density ranges from 0–15 calls per square mile, represented by pale green, and up to 350–400 calls per square mile, indicated in red.

Twelve heat maps depicting monthly EMS call volume provided insight into a stable volume distribution over the course of two years despite an expectation that migratory work and seasonal illnesses would drive fluctuations in call volume. Surprisingly, across the entire coverage area, call volume remained stable from month to month. The heat maps illustrate no seasonal fluctuations, and the month-to-month call volume is notably stable.

Figure 17. Call Density by Month of Year from January through June

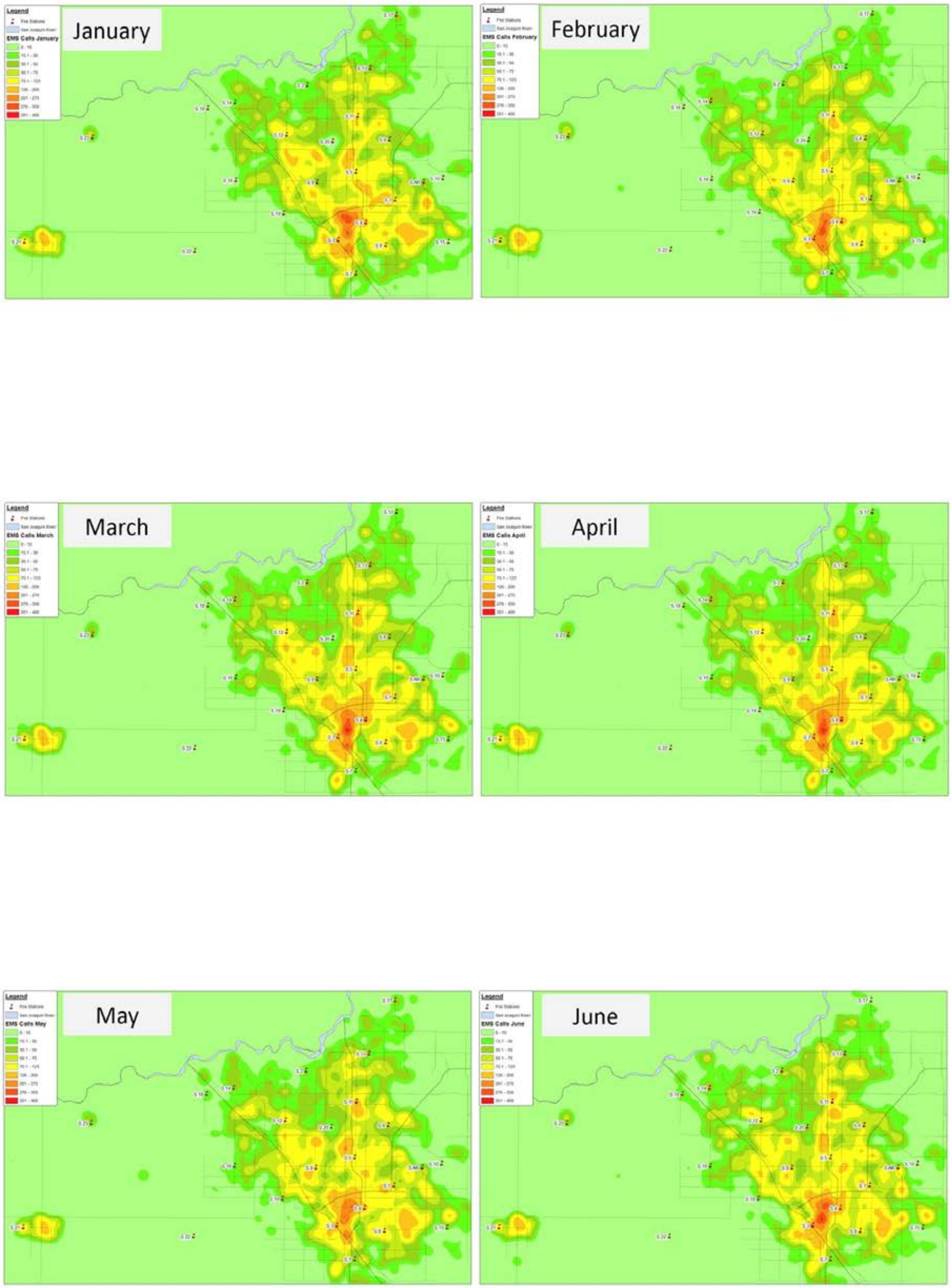
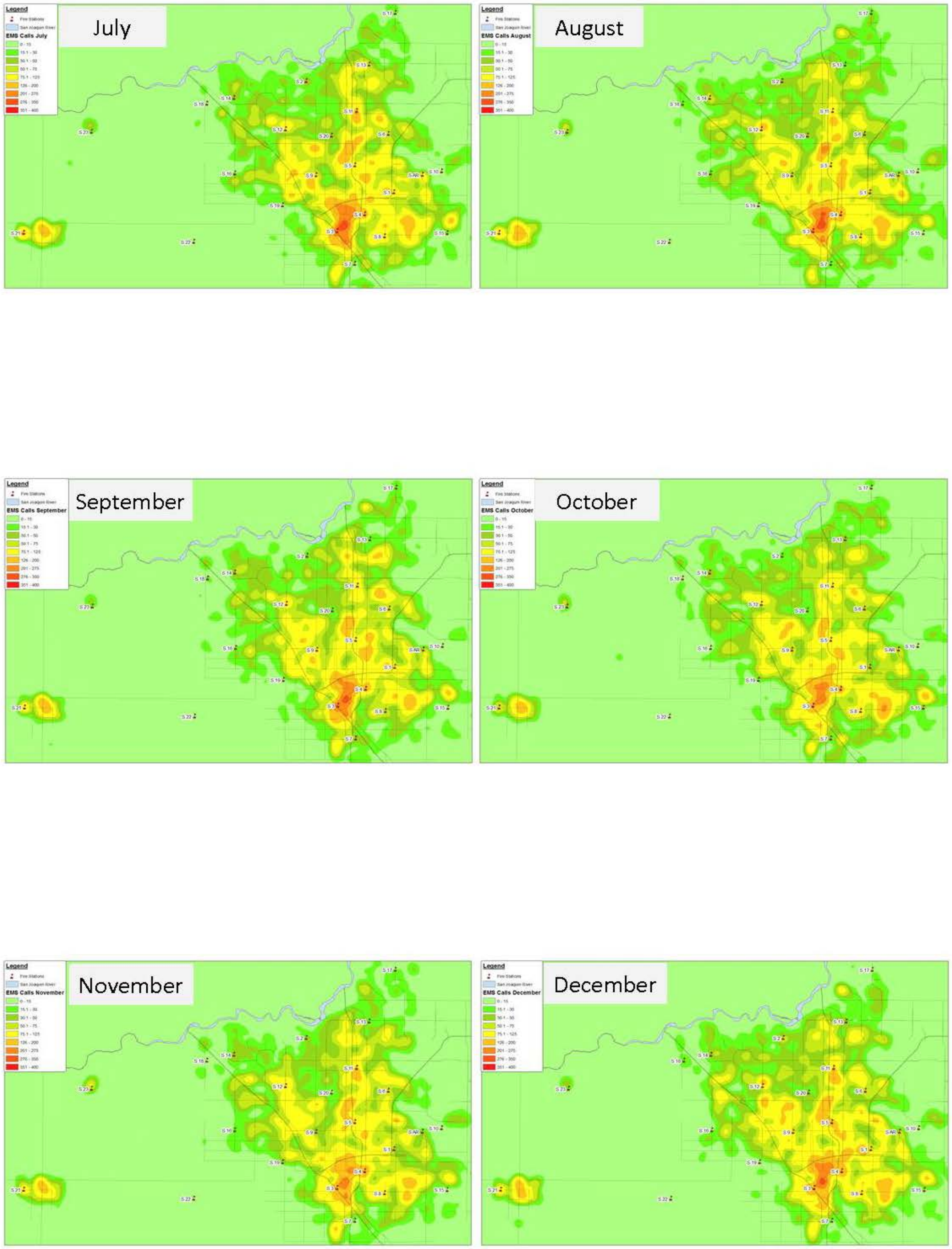


Figure 18. Call Density by Month of Year from July through December



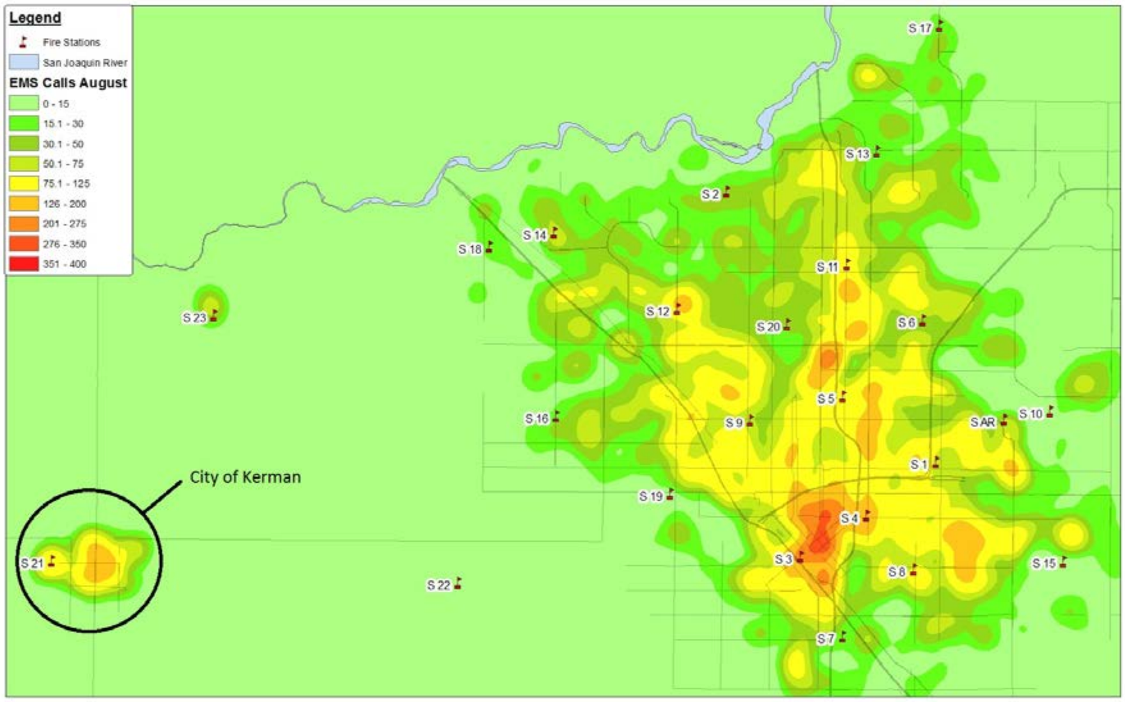
1. Monthly Distribution Analysis

As depicted in the heat maps, call volume remained stable from month to month across the coverage area and, seasonal fluctuations were not noted. The monthly changes across the coverage area were minute. Overall call volume fluctuated by approximately 12–15 percent, but no particular area showed significant signs of shifting density. The data appear to show that when overall call volume dropped, it did so across the entire district.

The expectation for month-to-month call volume was to identify significant seasonal, if not monthly, variations. Seasonal illnesses, such as the flu and asthma, should have registered fluctuations to match outbreaks. In addition to seasonal illnesses, Fresno, which is situated in the San Joaquin Valley, depends largely on an agricultural economy. Agricultural businesses and workers tend to follow the seasonal crop harvests. The hypothesis for the monthly call distribution was that there would be statistically significant seasonal or monthly variations in call volume driven by seasonal illnesses and the agricultural economy.

A second hypothesis regarding the rural areas west of Fresno was debunked. It was that, in alignment with agricultural harvests, monthly distribution of call volume would follow stronger seasonal trends than would the metropolitan areas. However, the area around Fire Station 21 in the city of Kerman, as seen in Figure 19, showed remarkable consistency from month to month, more so even than the metropolitan area.

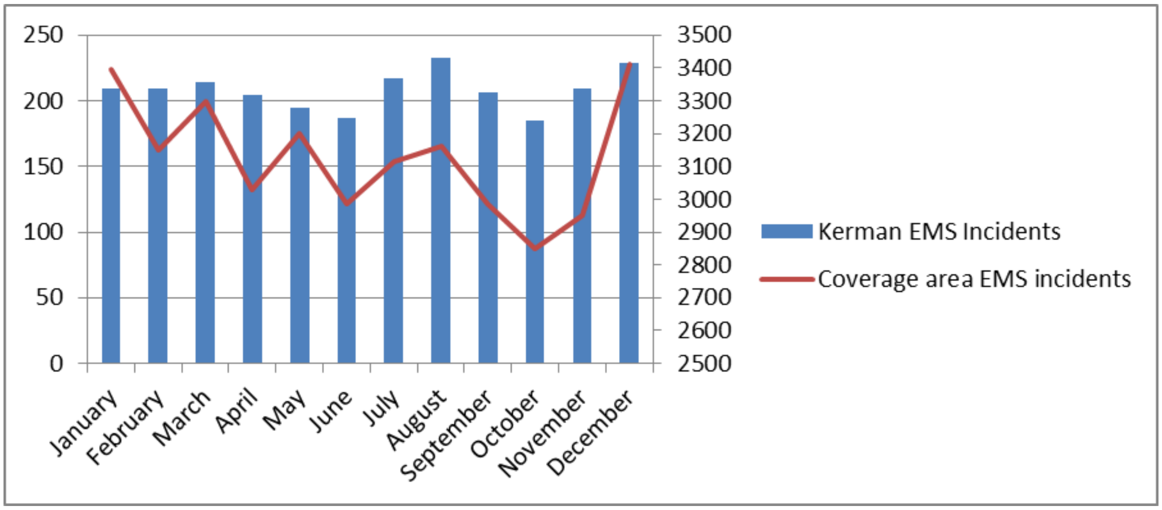
Figure 19. Call Volume by Month with the City of Kerman Highlighted



2. Kerman Monthly Analysis

The Fresno Fire Department protects approximately 600,000 people across 320 square miles and includes the community of Kerman, home to approximately 14,000 citizens. Many residents of Kerman, a agricultural community, commute to surrounding commercial areas for work. The production of crops such as grapes, pistachios, and cotton support migrant farm labor as well as commercial enterprises. The seasonal nature of agricultural work prompted a working hypothesis that Kerman would experience monthly or seasonal fluctuations in call volume associated with a potentially transient labor force. The results, however, defied the hypothesis. Kerman had a more stable call volume throughout the months than did the coverage area as a whole. The range of monthly totals was only 19 percent. When the highest and lowest values were removed (August and October), the range shrunk to 13 percent. Of the 12 months, seven of them were within 10 calls of one another, approximately a five percent range. Figure 20 shows the monthly call volume for Station 21 in Kerman in which fluctuations were less than the coverage area as a whole.

Figure 20. Monthly Call Volume for Kerman and Entire Coverage Area



In contrast to assumptions about transient agricultural communities, the monthly call volume for Station 21 fluctuated far less than expected. The quantitative analysis from spatiotemporal modeling illustrates that community risk in the city of Kerman shows very little volatility from month to month. The static deployment of fire apparatuses, therefore, matches the consistent nature of the community risk.

3. Conclusion

The data across the coverage area of the Fresno Fire Department appear to show a consistent volume of calls each month of the year, which probably speaks to a lack of population volatility or mobility. The people in the coverage area seem to stay relatively stationary, if call volume is any indicator of population fluctuations. One could reasonably expect that if the population were to change, there would be a correlated fluctuation in the volume of requests for service.

One could posit that fluctuations in weather patterns affect call volume, especially for emergency medical services. The flu season in the winter and asthmatic episodes in the summer typically provide fodder for news coverage, but the monthly fluctuations in EMS call volume fail to follow any distinguishable seasonal pattern. The summer months see a slight uptick, from 2,900 calls in June to 3,200 calls in July and August, and, then, a decline to 2,900 calls in September. This fluctuation does not seem substantial and is probably statistically insignificant. December and January see an increase to approximately 3,400 calls for service, but this only represents a 5.8 percent increase from the high months of July and August and a 12 percent increase from June and September. This stability in call volume speaks to some underlying cause and may mask more focused patterns in types of medical emergency that are not present in the fire department's data.

The stability in EMS calls over the months suggests an important component in community risk. Spatiotemporal modeling can show risk dynamics over time, and in the case of the data from Fresno Fire Department, the risk associated with emergency medical service calls is very consistent. This is important to fire department staffing because it shows explicitly and quantitatively that, at least across seasons and months, the requests for service are extremely consistent. Therefore, a static deployment model is appropriate for what appears to be a static risk factor.

D. ANALYSIS SUMMARY

Synthesizing the analysis across three different time increments provides a view into how risk changes over space and time. Spatiotemporal modeling provided an image of incident density changes for three time increments: calls by hour of the day, day of the week, and month of the year. For each time increment, a set of heat maps was created, and a fourth was added for depicting spatiotemporal distribution of calls by hour. Analysis of the data concluded that across the days of the week and months of the year, there was notable consistency. In days-of-the-week modeling, the distribution across each day showed a relatively even spread. Distribution across the months was more evenly spread than the days of the week. The hourly distribution of calls, however, showed a strong temporal distribution that followed diurnal circadian rhythms. Call volume peaked in the late afternoon and evening and then reached its nadir in the early morning hours. Analysis of the spatiotemporal trends can drive important proactive and reactive policy decisions.

The findings in the spatiotemporal modeling provide the impetus for analysis of two areas: proactive preventative measures and reactive deployment efforts. Understanding the causal factors is a step toward creating proactive measures. Spatiotemporal models provide the first look at a comparison of deployment models to community risk. Further analysis would determine whether deployment plans match actual community risk.

Several examples in the analyses for the different increments were noted for their break from the broader spatiotemporal trends. The day-of-week trends, for instance, showed broad continuity across the coverage area with a few notable exceptions: the downtown core, the Fort Washington area, and the Airport Industrial area. These areas depicted unique localized spatiotemporal distributions of call density and provide excellent opportunities for future analysis into the causal factors. The broader trend, however, depicts a consistent level of risk throughout the coverage area. From a deployment standpoint, this means that the current static deployment model matches the overall uniformity of call volume across the days of the week.

Spatiotemporal distribution across the months of the year showed strong continuity. The fluctuation from the month with lowest call volume to the highest volume showed statistically insignificant variation. In spite of the absence of seasonal and monthly variations, spatiotemporal modeling should be the beginning of the analysis. Seasonal outbreaks of flu and asthma are known problems in Fresno, yet the EMS call data do not reflect seasonal illness trends. This discrepancy should lead analysts to investigate the underlying reasons. We may find that the Fire Department's RMS data does not have the resolution to visualize seasonal outbreaks. It is possible that summer and fall outbreaks of asthma present in a similar way to winter outbreaks of flu in the Fire Department RMS data. To determine whether seasonal data is hidden in the Fire Department data, analysts may need to look further into alternate datasets such as EMS records.

Analysis of spatiotemporal trends across the Fresno Fire Department equips leaders with the necessary quantitative information to assess deployment plans and develop proactive measures. The largely insignificant fluctuation of call volume over days and months justifies the current static deployment models as adequate to mitigate the mostly static risk levels.

Contrary to monthly and daily trends, spatiotemporal patterns of the hourly call volume depict a clear call volume fluctuation. For Fire Department leaders, this provides the impetus for analyzing data further and also assessing current deployment models. Static deployment may not be the most appropriate answer for what is clearly a dynamic risk. Hourly call volume data indicate that the most appropriate deployment would be a dynamic model possessing surge capacity for the daily fluxes in call volume. It is these daily surges that drive down apparatus availability. In a dynamic deployment model, additional apparatuses would be assigned during the busiest portions of the day to provide needed surge capacity.

Spatiotemporal modeling provides valuable analysis of call volume distribution throughout the coverage area. The analysis should drive research into causal factors for preventative and reactive measures. The spatiotemporal trends across months and days for the Fresno Fire Department show little change, while the hourly flux depicts dynamic risk across the entire coverage area. The observed patterns provide the nucleus for further research into proactive measures as well as justification for reactive mitigation efforts.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. IMPLEMENTATION

Spatiotemporal modeling provides an enhanced view of community risk by showing how it changes over time and space. Many methods in the literature show time or spatial distribution, but few discuss how space and time changes coincide. For the fire service, spatiotemporal modeling of community risk, as Ceyhan, Ertugay, and Duzgun suggest, gives leaders and policy makers a view of actualized risk within the community to create both "proactive and reactive" mitigation measures.[42] Spatiotemporal modeling of community risk shows policy makers that oftentimes, dynamic features of risk fluctuate over time and geography. Understanding how risk changes can help drive fire departments to refine deployment and operate efficiently in a changing political environment.

Three separate factors over the last decade are driving changes to operational models for the fire service. First, fires are occurring less frequently across the country while other calls for service are increasing.[43] The most notable changes have come in the increase of emergency medical calls and incidents requiring specialized equipment.[44] Second, budgets have been squeezed significantly since 2008, which has caused city leaders to rethink the costs associated with fire departments. Firefighting is no longer the sacred service that it was many years ago. Author Jonathan Walters knows about shrinking budgets; he points to the words of public safety professional Tom Wieczorek: "For the fire service to continue to perform in these leaner times … it is now going to have to actively embrace change."[45] Walters describes the change needed, specifically in the area of data analysis of call volume. Third,

[42] Ceyhan, Ertugay, and Duzgun, "Exploratory and Inferential Methods."

[43] The USFA stats show an approximately 20 percent reduction in fires between 2002 and 2011. See, "U.S. Fire Statistics, Trends in Fires, Deaths, Injuries and Dollar Loss," USFA, last modified January 6, 2016, https://www.usfa.fema.gov/data/statistics/#tab-1.

[44] "Fire Department Calls," National Fire Protection Association, last updated September 2014, http://www.nfpa.org/research/reports-and-statistics/the-fire-service/fire-department-calls/fire-department-calls.

[45] Walters, "Firefighters Feel the Squeeze."

technology has provided immense computing power and data that allow policy makers to see the true nature of fire department activities and actualized risk within communities. These three factors provide both the means and the impetus for creating change, and spatiotemporal modeling is a tool to get there. Producing spatiotemporal products involves an investment of time and resources in a series of interconnected processes.

Changing call volume, decreasing budgets, and increasing availability of data analysis are pushing fire departments to adapt operations. The availability of fire service data can provide the means for departments to adapt their efforts to the shifting operational sands. The reduction of fire volume combined with an increasing overall call volume means the risk environment is transitioning. In order to transition with the risk environment, fire departments have at their disposal data and processing power to understand the risk profile and develop corresponding deployments. Spatiotemporal modeling provides visualization of community risk and how that risk fluctuates through space and time. Analyzing community risk dynamics provides the nucleus for deployment models, which answer the demands of the changing operational and political environment in which the modern fire service finds itself.

Fire service leaders have access to community risk data available in CAD and RMS platforms. Most dispatch centers use digital dispatching systems with integrated GPS systems, noting the most basic geographic, temporal, and incident type information. Furthermore, most departments already have an NFIRS-compliant RMS system, which provides the nucleus for analyzing actualized risk data. Actualized risk data from RMS systems gives analysts the start point for conducting spatiotemporal modeling. The RMS data, with its geographic, time-stamped incident information, is uploaded into a GIS database where computing power can yield modeling results.

Spatiotemporal modeling of actualized risk requires specialized software. ESRI is a ubiquitous name in the geographic information systems (GIS) industry and provides an array of tools and services by which departments with the appropriate resources can conduct spatiotemporal analysis. ESRI has a library of resources available to fire departments that are initiating a GIS system. These documents help departments structure the data and guide them in building databases that they can analyze.[46] ESRI also produces ArcMap 10.2, which has a set of tools called Spatial Analyst. Spatial Analyst has multiple methods for creating the heat maps, which are the baseline product for spatiotemporal visualization. Some departments, however, find they lack the resources or the interest in building out their own GIS platforms, but still require the necessary analysis. In those cases, outside consulting companies have produced detailed analysis for departments across the country.[47]

Spatiotemporal modeling of community risk provides policy makers a unique view of actualized risk. Fire service leaders, from both management and labor, have largely embraced the idea that the modern American fire service responds to all manner of emergencies, not solely fires. This thesis has presented two ideas that should be considered by all departments: first, that all emergencies represent the true nature of community risk and second, that the extent of community risk can be modeled through spatiotemporal methods. Spatiotemporal modeling of actualized risk provides the analytical underpinnings of refined deployments.

Finally, as policy makers in individual departments adopt spatiotemporal modeling as a tool for understanding actualized community risk, a standardized methodology needs to be created. As discussed in Chapter II, the spatial analyst tool settings were provided with a wide range of potential options for presenting the data in a meaningful visualization. Settings, such as color scales, call categorization, and time partitioning, were selected based on the presentation of

---

[46] Mike Price, *Fire Mapping: Building and Maintaining Datasets in ArcGIS* (Redlands, CA: Environmental Systems Research Institute, 2012).

[47] "Fire Service Emerging Trends: 'The View from the Road," PowerPoint Presentation, Citygate Associates; for a good analysis of a consultant's ability to analyze a department's service call, see System Planning Corporation, *Fire Service and Resource Deployment Analysis City of Oceanside Ca* (Arlington, VA: System Planning Corporation, 2012).

the particular dataset used. If another department used the same settings for a different dataset, it might find the presentation less than useful. However, analytical comparisons across jurisdictions provide fire service leaders context for their particular community's risk and potential mechanisms for mitigating those risks. Standardizing spatiotemporal methods will allow departments to compare data objectively across jurisdictions.

A combination of the correct data, the right tools, and receptive policy makers will provide the fertile ground on which an enhanced understanding of community risk can grow. Implementing spatiotemporal modeling is less a technical hurdle than an intellectual movement, one toward understanding that contemporary deployment models are static while the risk they are designed to mitigate is inherently dynamic. Depicting actualized risk in a spatiotemporal fashion illuminates the reality of dynamic community risk.

V. FUTURE RESEARCH

The preceding chapters covered spatiotemporal visualization of call volume for emergency medical service calls within the Fresno Fire Department. Spatiotemporal visualization provides immense analytical understanding of dynamic actual risk, but spatial or temporal statistics that could explain the underlying causal factors were outside the scope of this thesis. Fire departments could benefit from further research into the statistical underpinnings of the observed spatial and temporal patterns. In addition, this thesis modeled a single partition of the entire dataset, emergency medical service calls. Continuing to model the entire dataset would depict a broader visualization of risk within the coverage area, specifically for fires. Fires no longer represent a significant portion of call volume by number, but they still account for nearly half of the injuries and time committed by fire crews. Researching and visualizing time commitments to incidents is paramount to gaining a full understanding of all risks within the community. Analyzing all risk involves reviewing risk and the underlying data for causal factors. The underlying data also can provide insight into the potential risks within a community. Spatiotemporal modeling can assist in planning for potential risks and should be incorporated into future research.

Spatiotemporal modeling creates a visualization of the geographic and temporal distribution of incidents, but it lacks a statistical framework that explains the source for spatiotemporal distribution. Incidents can occur in complete spatial randomness or cluster according to patterns derived from underlying causal factors. Ceyhan, Ertugay, and Duzgun, in their research on structure fires in Ankara, Turkey, reference procedures within spatial analysis for distinguishing between complete randomness and clustering.[48] Future research should investigate the underlying causes of the distribution. Ceyhan, Ertugay, and Duzgun determined through statistical methodology that fires in the study were

[48] Ceyhan, Ertugay, and Duzgun, "Exploratory and Inferential Methods."

not random but exhibited first-order clustering based on some unknown commonality.[49] In their study that analyzed spatiotemporal patterns of fire distribution in Toronto, Canada, Asgary, Ghaffari, and Levy called for additional research into the sociological factors driving the underlying patterns in fire types. In their conclusions, the researchers suggest taking what author Jennings refers to as the "ecological approach" to discovering the underlying distribution patterns.[50] Spatiotemporal modeling provides clarity to distribution patterns across space and time but further research needs to delve into the root causes. Comprehending the underlying factors for incident distribution gives fire service leaders the ability to pursue proactive measures of risk mitigation while creating reactive deployment models.

Integrating additional datasets into the statistical analysis is needed to understand the causal factors of various patterns. The city of Fresno possesses several data sets that could prove relevant to the study. Those pertinent data sources include the U.S. Census, building and housing unit types, city zoning categories, transit routes, and tax records. It is possible that when demographic information is analyzed for correlations in spatial and temporal distribution, patterns could appear that may lead departments to proactive measures. For example, additional studies of existing population density and illness patterns may predict future seasonal spread of disease outbreaks. As the causal factors are determined for spatiotemporal distribution, proactive solutions may become evident to reduce the risk factors in the community.

Follow-on studies of the Fresno Fire Department should also include a spatiotemporal model of the entire dataset. This study analyzed the largest portion of the dataset, emergency medical calls, to depict spatiotemporal modeling. Modeling all call types could provide immense value to any organizations. The most significant potential for intervention exists within the study of fire occurrence in Fresno. Fires represent the single greatest

[49] Ceyhan, Ertugay, and Duzgun, "Exploratory and Inferential Methods," 232.

[50] Asgary, Ghaffari, and Levy, "Spatial and Temporal Analyses," 54.

expenditure of time and a significant source of injuries each year to personnel. It is possible that spatiotemporal modeling could illuminate patterns of distribution that have very specific causal factors—in other words, they are not randomly distributed. One potential causal factor is the link between the homeless population and temperature. It appears that when temperatures drop in the fall and winter, the number of fires in vacant and boarded-up homes increases significantly. Spatiotemporal visualization correlated with weather patterns could drive deployments when temperature drops below a certain threshold. Proactive measures may also emerge to reduce the vacant structure fire problem, such as warming centers and homeless shelters.

Structure fires represent a small number of total Fresno city incidents, approximately 10 percent of total call volume, compared with EMS calls, which represent approximately 60 percent of total incidents. Structure fires, however, consume almost 40 percent of the total time fire apparatuses are committed to incidents. EMS calls also represent approximately 40 percent of total time committed while all other calls combined only represent 20 percent. Accompanying the large volume of time committed to suppressing fires are enormous sums of money and many firefighter injuries. According to the National Fire Protection Association, 43 percent of injuries occurred during fire calls in 2014.[51] Spatiotemporal modeling of fire incidents should be part of future research to understand the causal factors, but the visualization lacks a component for specifically analyzing the time committed.

Future research into time committed to various incident types, especially for fires, could provide valuable insights. A framework for the study could go as follows. For the concept that many ambulance companies call “time-on-task,” (TOT)[52] analysts could calculate how long an ambulance crew spends on each

---

51 Hylton J.G. Haynes and Joseph L. Molis, “U.S. Firefighter Injuries in 2014,” *nfpa Journal*, November 2, 2015, 6.

52 Fitch and Associates, “How to Explain UHU from UFOs to Your City Manager,” EMS1, November 8, 2012, https://www.ems1.com/ems-management/articles/1365144-How-to-explain-UHU-from-UFOs-to-your-city-manager/.

call then correlate the call type with various other data points, including location and number of crew members, to determine dynamic ambulance deployment models. The time-on-task concept could be applied to the fire-service call volume segregated by call type. One method for TOT studies would be to incorporate TOT into spatiotemporal visualization. The KDE tool referenced in Chapter II can utilize a z variable that weights incidents on commit time as well as density.

The CAD system keeps track of each apparatus assigned to an incident and how long it stays committed. In the RMS and GIS systems, the total time committed for all apparatuses on an incident is calculated and added to the RMS files. One could use TOT as the *z* variable when building KDE heat maps. The *z* factor would cause the incidents with longer TOTs to show up as hotter spots on the maps than those with lower TOTs. Areas that have significant fire problems would appear hotter. Furthermore, the apparatuses with larger coverage areas experiencing longer response and wait times for ambulances would also appear hotter on the heat maps. In addition to adding nuance to the heat maps for incident density, it could be found that different incident types require different average TOTs. For instance, hazardous materials incidents do not occur often but their durations tend to last for hours and require several apparatuses to mitigate the hazard. It could be that resources do not adequately meet the demand of the Fresno area.

This thesis had a fundamental emphasis on incorporating all incidents into a spatiotemporal modeling visualization. The purpose was two-fold. First, it acknowledged that the fire service responds to all manner of hazards and risks in the community. From fires to car crashes, the fire department provides emergency care. Second, each of the hazards to which the fire service responds requires different types of equipment. The Fresno Fire Department, similar to many urban departments, has ladder trucks, water tenders, off-road engines, a hazardous materials apparatus, an aircraft rescue firefighting apparatus, urban search and rescue units, water rescue resources, a communications support vehicle, a large building mobile ventilation unit, a mobile air and light unit, and 24 engines. Each piece of equipment is designed for a different type of hazard. Spatiotemporal modeling of incidents specific to each type of equipment could help fire service leaders visualize the extent of the risk associated with those apparatuses. In some cases, the Fresno Fire Department (FFD) may need significantly more equipment. For some community risks, the department may decide that the specialized equipment is located in the wrong areas. Finally, FFD face risks for which there are no answers. Understanding the spatiotemporal distribution of all community risks provides the backdrop for discussion about the mitigation measures FFD needs to employ.

The last area of future research involves the data necessary to derive the causal factors from actualized risk to evaluate potential risk, the probability of emergencies that have yet to occur. Jennings illustrates this idea perfectly when explaining that "a community must not ignore a major hazard simply because it hasn't yet experienced a major consequence, but at the same time it must not ignore or undervalue the real and recurring patterns of risk that may be responsible for the lion's share of incidents, property losses and casualties."[53]

This thesis modeled emergency medical service incidents due to the large volume of calls during the time period in question (40,553 incidents in 27 months). During this research, several data sources surfaced that presented risk factors for which there has never been an emergency. Some potential risks present significant consequences. A prime example is a train derailment.

In reviewing transit line data underlying the EMS call distributions, it became clear that the two major railways traveling through Fresno present a significant problem if a train were to derail. Housing density, population density, emergency travel routes, and prevailing winds all point to a significant potential risk should a train derail. An emergency of this nature has never occurred in Fresno, but it represents such a significant consequence that it deserves attention. Evaluating the potential risk of such a scenario involves studying the

---

[53] Jennings, "Evaluating and Managing Risks," 73.

data that also drives causal factors of spatiotemporal modeling. In addition, spatiotemporal modeling could be used in a train derailment scenario to visualize the impacts of such an event, such as plume modeling, evacuation routes, and damage estimates.

Future research into spatiotemporal methods and causal factors could extend into many directions. This thesis offered visualization of a specific portion of the available dataset, emergency medical service calls, but stopped short of delving into the underlying spatial statistics describing the analytical framework of the distribution. The analytical framework for the spatiotemporal distribution, when correlated with other datasets, can provide causal factors. These areas are ripe for future analysis. Spatiotemporal modeling should also reflect the true nature of risk within the community and encompass all calls for service. Visualizing risk and determining causal factors of actual risk also provide the data and analytical framework for researching potential risk and mitigation measures. Community risk will constantly evolve and drive future research into the relationship between the fire departments and the challenges they are employed to overcome.

APPENDIX A. NFIRS INCIDENT CODE GUIDE

Excerpted from United States Fire Administration, *National Fire Incident Reporting System: Complete Reference Guide* (Washington, DC: FEMA, July 2010), Section C, 3-21 – 3-28.

C. Incident Type

Incident Type was known as Type of Situation Found in NFIRS 4.1.

Definition

This is the actual situation that emergency personnel found on the scene when they arrived. These codes include the entire spectrum of fire department activities from fires to EMS to public service.

The type of incident reported here is not always the same as the incident type initially dispatched.

Purpose

This critical information identifies the various types of incidents to which the fire department responds and allows the fire department to document the full range of incidents it handles.

This information can be used to analyze the frequency of different types of incidents, provide insight on fire and other incident problems, and identify training needs.

This element determines which modules will subsequently be completed.

Entry

Enter the three-digit code and a written description that best describes the type of incident. This entry is generally the type of incident found when emergency personnel arrived at the scene, but if a more serious condition developed after the fire department arrival on the scene, then that incident type should be reported. The codes are organized in a series:

SERIES HEADING

100 Fire

200 Overpressure Rupture, Explosion, Overheat (No Fire)

300 Rescue and Emergency Medical Service (EMS) Incidents

400 Hazardous Condition (No Fire)

500 Service Call

600 Good Intent Call

700 False Alarm and False Call

800 Severe Weather and Natural Disaster

900 Special Incident Type

For incidents involving fire and hazardous materials or fire and EMS, use the fire codes. Always use the lowest numbered series that applies to the incident. You will have an opportunity to describe multiple actions taken later in the report.
For vehicle fires on a structure, use the mobile property fire codes (130–138) unless the structure became involved.

The P denotes a required field.
C
For fires in buildings that are confined to noncombustible containers, use codes 113–118 of the structure fire codes when there is no flame damage beyond the noncombustible container.
Example
Fire in food on the stove that was confined to the pot (113).
C
Incident Type 131 Food on the stove
Incident Type
INCIDENT TYPE CODES
Fire. Includes fires out on arrival and gas vapor explosions (with extremely rapid combustion).
Structure fire
111 Building fire. Excludes confined fires (113–118).
112 Fire in structure, other than in a building. Included are fires on or in piers, quays, or pilings: tunnels or underground connecting structures; bridges, trestles, or overhead elevated structures; transformers, power or utility vaults or equipment; fences; and tents.
113 Cooking fire involving the contents of a cooking vessel without fire extension beyond the vessel.
114 Chimney or flue fire originating in and confined to a chimney or flue. Excludes fires that extend beyond the chimney (111 or 112).
115 Incinerator overload or malfunction, but flames cause no damage outside the incinerator.
116 Fuel burner/boiler, delayed ignition or malfunction, where flames cause no damage outside the fire box.
117 Commercial compactor fire, confined to contents of compactor. Excluded are home trash compactors.
118 Trash or rubbish fire in a structure, with no flame damage to structure or its contents.
Fire in mobile property used as a fixed structure. Includes mobile homes, motor homes, camping trailers.
121 Fire in mobile home used as a fixed residence. Includes mobile homes when not in transit and used as a structure for residential purposes; and manufactured homes built on a permanent chassis.

122 Fire in a motor home, camper, or recreational vehicle when used as a structure. Includes motor homes when not in transit and used as a structure for residential purposes.
123 Fire in a portable building, when used at a fixed location. Includes portable buildings used for commerce, industry, or education and trailers used for commercial purposes.
120 Fire in mobile property used as a fixed structure, other.
Mobile property (vehicle) fire. Excludes mobile properties used as a structure (120 series). If a vehicle fire occurs on a bridge and does not damage the bridge, it should be classified as a vehicle fire.
131 Passenger vehicle fire. Includes any motorized passenger vehicle, other than a motor home (136) (e.g., pickup trucks, sport utility vehicles, buses).
132 Road freight or transport vehicle fire. Includes commercial freight hauling vehicles and contractor vans or trucks. Examples are moving trucks, plumber vans, and delivery trucks.
133 Rail vehicle fire. Includes all rail cars, including intermodal containers and passenger cars that are mounted on a rail car.
134 Water vehicle fire. Includes boats, barges, hovercraft, and all other vehicles designed for navigation on water.
135 Aircraft fire. Includes fires originating in or on an aircraft, regardless of use.
136 Self-propelled motor home or recreational vehicle. Includes only self-propelled motor homes or recreational vehicles when being used in a transport mode. Excludes those used for normal residential use (122).
137 Camper or recreational vehicle (RV) fire, not self-propelled. Includes trailers. Excludes RVs on blocks or used regularly as a fixed building (122) and the vehicle towing the camper or RV or the campers mounted on pickups (131).

The P denotes a required field.
C
138 Off-road vehicle or heavy equipment fire. Includes dirt bikes, specialty off-road vehicles, earth-moving equipment
(bulldozers), and farm equipment.
130 Mobile property (vehicle) fire, other.
Natural vegetation fire. Excludes crops or plants under cultivation (see 170 series).
141 Forest, woods, or wildland fire. Includes fires involving vegetative fuels, other than prescribed fire (632), that occur in an area in which development is essentially nonexistent, except for roads, railroads, power lines, and the like. Also includes forests managed for lumber production and fires involving elevated fuels such as tree branches and crowns. Excludes areas in cultivation for agricultural purposes such as tree farms or crops (17xseries).

142 Brush or brush-and-grass mixture fire. Includes ground fuels lying on or immediately above the ground such as duff, roots, dead leaves, fine dead wood, and downed logs.
143 Grass fire. Includes fire confined to area characterized by grass ground cover, with little or no involvement of other ground fuels; otherwise, see 142.
140 Natural vegetation fire, other.
Outside rubbish fire. Includes all rubbish fires outside a structure or vehicle.
151 Outside rubbish, trash, or waste fire not included in 152–155. Excludes outside rubbish fires in a container or receptacle (154).
152 Garbage dump or sanitary landfill fire.
153 Construction or demolition landfill fire.
154 Dumpster or other outside trash receptacle fire. Includes waste material from manufacturing or other production processes. Excludes materials that are not rubbish or have salvage value (161 or 162).
155 Outside stationary compactor or compacted trash fire. Includes fires where the only material burning is rubbish.
Excludes fires where the compactor is damaged (162).
150 Outside rubbish fire, other.
Special outside fire. Includes outside fires with definable value. Excludes crops and orchards (170 series).
161 Outside storage fire on residential or commercial/industrial property, not rubbish. Includes recyclable materials at dropoff points.
162 Outside equipment fire. Includes outside trash compactors, outside HVAC units, and irrigation pumps. Excludes special structures (110 series) and mobile construction equipment (130 series).
163 Outside gas or vapor combustion explosion without sustained fire.
164 Outside mailbox fire. Includes dropoff boxes for delivery services.
160 Special outside fire, other.
Cultivated vegetation, crop fire
171 Cultivated grain or crop fire. Includes fires involving corn, wheat, soybeans, rice, and other plants before harvest.
172 Cultivated orchard or vineyard fire.
173 Cultivated trees or nursery stock fire. Includes fires involving Christmas tree farms and plants under cultivation
for transport off-site for ornamental use.
170 Cultivated vegetation, crop fire, other.
Fire, other
100 Fire, other.
Overpressure Rupture, Explosion, Overheat (No Fire). Excludes steam mistaken for smoke.
Overpressure rupture from steam (no ensuing fire)
211 Overpressure rupture of steam pipe or pipeline.
212 Overpressure rupture of steam boiler.
213 Overpressure rupture of pressure or process vessel from steam.
210 Overpressure rupture from steam, other.

Overpressure rupture from air or gas (no ensuing fire). Excludes steam or water vapor.
221 Overpressure rupture of air or gas pipe or pipeline.
222 Overpressure rupture of boiler from air or gas. Excludes steam-related overpressure ruptures.

The P denotes a required field.
C
223 Overpressure rupture of pressure or process vessel from air or gas, not steam.
220 Overpressure rupture from air or gas, other.
Overpressure rupture from chemical reaction (no ensuing fire)
231 Overpressure rupture of pressure or process vessel from a chemical reaction.
Explosion (no fire)
241 Munitions or bomb explosion (no fire). Includes explosions involving military ordnance, dynamite, nitroglycerin, plastic explosives, propellants, and similar agents with a UN classification 1.1 or 1.3. Includes primary and secondary high explosives.
242 Blasting agent explosion (no fire). Includes ammonium nitrate and fuel oil (ANFO) mixtures and explosives with a UN Classification 1.5 (also known as blasting agents).
243 Fireworks explosion (no fire). Includes all classes of fireworks.
240 Explosion (no fire), other.
Excessive heat, scorch burns with no ignition
251 Excessive heat, overheat scorch burns with no ignition. Excludes lightning strikes with no ensuing fire (814).
Overpressure rupture, explosion, overheat, other
200 Overpressure rupture, explosion, overheat, other.
Rescue and Emergency Medical Service Incident
Medical assist
311 Medical assist. Includes incidents where medical assistance is provided to another group/agency that has primary EMS responsibility. (Example, providing assistance to another agency-assisting EMS with moving a heavy patient.)
Emergency medical service incident
321 EMS call. Includes calls when the patient refuses treatment. Excludes vehicle accident with injury (322) and pedestrian struck (323).
322 Motor vehicle accident with injuries. Includes collision with other vehicle, fixed objects, or loss of control resulting in leaving the roadway.
323 Motor vehicle/pedestrian accident (MV Ped). Includes any motor vehicle accident involving a pedestrian injury.
324 Motor vehicle accident with no injuries.
Lock-In

331 Lock-in. Includes opening locked vehicles and gaining entry to locked areas for access by caretakers or rescuers, such as a child locked in a bathroom. Excludes lock-outs (511).
Search for lost person
341 Search for person on land. Includes lost hikers and children, even where there is an incidental search of local bodies of water, such as a creek or river.
342 Search for person in water. Includes shoreline searches incidental to a reported drowning call.
343 Search for person underground. Includes caves, mines, tunnels, and the like.
340 Search for lost person, other.
Extrication, rescue
351 Extrication of victim(s) from building or structure, such as a building collapse. Excludes high-angle rescue (356).
352 Extrication of victim(s) from vehicle. Includes rescues from vehicles hanging off a bridge or cliff.
353 Removal of victim(s) from stalled elevator.
354 Trench/Below-grade rescue.
355 Confined space rescue. Includes rescues from the interiors of tanks, including areas with potential for hazardous atmospheres such as silos, wells, and tunnels.
356 High-angle rescue. Includes rope rescue and rescues off of structures.
357 Extrication of victim(s) from machinery. Includes extrication from farm or industrial equipment.
350 Extrication, rescue, other.

The P denotes a required field.
C
Water and ice-related rescue
361 Swimming/Recreational water areas rescue. Includes pools and ponds. Excludes ice rescue (362).
362 Ice rescue. Includes only cases where victim is stranded on ice or has fallen through ice.
363 Swift-water rescue. Includes flash flood conditions.
364 Surf rescue.
365 Watercraft rescue. Excludes rescues near the shore and in swimming/ recreational areas (361). Includes people
falling overboard at a significant distance from land.
360 Water and ice-related rescue, other.
Electrical rescue
371 Electrocution or potential electrocution. Excludes people trapped by power lines (372).
372 Trapped by power lines. Includes people trapped by downed or dangling power lines or other energized electrical equipment.

370 Electrical rescue, other.

Rescue or EMS standby

381 Rescue or EMS standby for hazardous conditions. Excludes aircraft standby (462).

Rescue, emergency medical service (EMS) incident, other

300 Rescue and EMS incident, other.

Hazardous Condition (No Fire)

Combustible/Flammable spills and leaks

411 Gasoline or other flammable liquid spill (flash point below 100 degrees F at standard temperature and pressure [Class I]).

412 Gas leak (natural gas or LPG). Excludes gas odors with no source found (671).

413 Oil or other combustible liquid spill (flash point at or above 100 degrees F at standard temperature and pressure (Class II or III)).

410 Combustible and flammable gas or liquid spills or leaks, other.

Chemical release, reaction, or toxic condition

421 Chemical hazard (no spill or leak). Includes the potential for spills or leaks.

422 Chemical spill or leak. Includes unstable, reactive, explosive material.

423 Refrigeration leak. Includes ammonia.

424 Carbon monoxide incident. Excludes incidents with nothing found (736 or 746).

420 Toxic chemical condition, other.

Radioactive condition

431 Radiation leak, radioactive material. Includes release of radiation due to breaching of container or other accidental release.

430 Radioactive condition, other.

Electrical wiring/Equipment problem

441 Heat from short circuit (wiring), defective or worn insulation.

442 Overheated motor or wiring.

443 Breakdown of light ballast.

444 Power line down. Excludes people trapped by downed power lines (372).

445 Arcing, shorted electrical equipment.

440 Electrical wiring/equipment problem, other.

Biological hazard

451 Biological hazard, confirmed or suspected.

Accident, potential accident

461 Building or structure weakened or collapsed. Excludes incidents where people are trapped (351).

462 Aircraft standby. Includes routine standby for takeoff and landing as well as emergency alerts at airports.

463 Vehicle accident, general cleanup. Includes incidents where FD is dispatched after the accident to clear away

debris. Excludes extrication from vehicle (352) and flammable liquid spills (411 or 413).

460 Accident, potential accident, other.

C
Explosive, bomb removal
471 Explosive, bomb removal. Includes disarming, rendering safe, and disposing of bombs or suspected devices. Excludes bomb scare (721).
Attempted burning, illegal action
481 Attempt to burn. Includes situations in which incendiary devices fail to function.
482 Threat to burn. Includes verbal threats and persons threatening to set themselves on fire. Excludes an attempted burning (481).
480 Attempted burning, illegal action, other.
Hazardous condition, other
400 Hazardous condition (no fire), other.
Service Call
Person in distress
511 Lock-out. Includes efforts to remove keys from locked vehicles. Excludes lock-ins (331).
512 Ring or jewelry removal, without transport to hospital. Excludes persons injured (321).
510 Person in distress, other.
Water problem
521 Water (not people) evacuation. Includes the removal of water from basements. Excludes water rescues (360 series).
522 Water or steam leak. Includes open hydrant. Excludes overpressure ruptures (211).
520 Water problem, other.
Smoke, odor problem
531 Smoke or odor removal. Excludes the removal of any hazardous materials.
Animal problem or rescue
541 Animal problem. Includes persons trapped by an animal or an animal on the loose.
542 Animal rescue.
540 Animal problem or rescue, other.
Public service assistance
551 Assist police or other governmental agency. Includes forcible entry and the provision of lighting.
552 Police matter. Includes incidents where FD is called to a scene that should be handled by the police.
553 Public service. Excludes service to governmental agencies (551 or 552).
554 Assist invalid. Includes incidents where the invalid calls the FD for routine help, such as assisting a person in returning to bed or chair, with no transport or medical treatment given.
555 Defective elevator, no occupants.

550 Public service assistance, other.
Unauthorized burning
561 Unauthorized burning. Includes fires that are under control and not endangering property.
Cover assignment, standby at fire station, move-up
571 Cover assignment, assist other fire agency such as standby at a fire station or move-up.
Service call, other
500 Service call, other.
Good Intent Call
Dispatched and canceled en route
611 Dispatched and canceled en route. Incident cleared or canceled prior to arrival of the responding unit. If a unit arrives on the scene, fill out the applicable code.

3-27 NFIRS 5.0 COMPLETE REFERENCE GUIDE
CHAPTER 3 • BASIC MODULE (NFIRS-1)
The P denotes a required field.
C
Wrong location, no emergency found
621 Wrong location. Excludes malicious false alarms (710 series).
622 No incident found on arrival at dispatch address.
Controlled burning
631 Authorized controlled burning. Includes fires that are agricultural in nature and managed by the property
owner. Excludes unauthorized controlled burning (561) and prescribed fires (632).
632 Prescribed fire. Includes fires ignited by management actions to meet specific objectives and have a written, approved prescribed fire plan prior to ignition. Excludes authorized controlled burning (631).
Vicinity alarm
641 Vicinity alarm (incident in other location). For use only when an erroneous report is received for a legitimate incident. Includes separate locations reported for an actual fire and multiple boxes pulled for one fire.
Steam, other gas mistaken for smoke
651 Smoke scare, odor of smoke, not steam (652). Excludes gas scares or odors of gas (671).
652 Steam, vapor, fog, or dust thought to be smoke.
653 Smoke from barbecue or tar kettle (no hostile fire).
650 Steam, other gas mistaken for smoke, other.
EMS call where party has been transported
661 EMS call where injured party has been transported by a non-fire service agency or left the scene prior to arrival.
HazMat release investigation w/no HazMat found

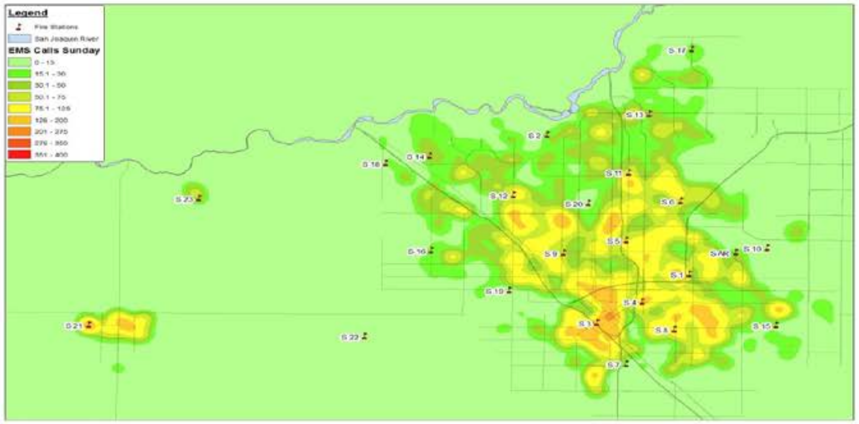
671 Hazardous material release investigation with no hazardous condition found. Includes odor of gas with no leak/gas found.
672 Biological hazard investigation with no hazardous condition found.
Good intent call, other
600 Good intent call, other.
False Alarm and False Call
Malicious, mischievous false alarm
711 Municipal alarm system, malicious false alarm. Includes alarms transmitted on street fire alarm boxes.
712 Direct tie to fire department, malicious false alarm. Includes malicious alarms transmitted via fire alarm system directly tied to the fire department, not via dialed telephone.
713 Telephone, malicious false alarm. Includes false alarms transmitted via the public telephone network using the local emergency reporting number of the fire department or another emergency service agency.
714 Central station, malicious false alarm. Includes malicious false alarms via a central-station-monitored fire alarm system.
715 Local alarm system, malicious false alarm. Includes malicious false alarms reported via telephone or other means as a result of activation of a local fire alarm system.
710 Malicious, mischievous false alarm, other.
Bomb scare
721 Bomb scare (no bomb).
System or detector malfunction. Includes improper performance of fire alarm system that is not a result of a proper system response to environmental stimuli such as smoke or high heat conditions.
731 Sprinkler activated due to the failure or malfunction of the sprinkler system. Includes any failure of sprinkler
equipment that leads to sprinkler activation with no fire present. Excludes unintentional operation caused by damage to the sprinkler system (740 series).
732 Extinguishing system activation due to malfunction.
733 Smoke detector activation due to malfunction.
734 Heat detector activation due to malfunction.
735 Alarm system activation due to malfunction.
736 Carbon monoxide detector activation due to malfunction.
730 System or detector malfunction, other.

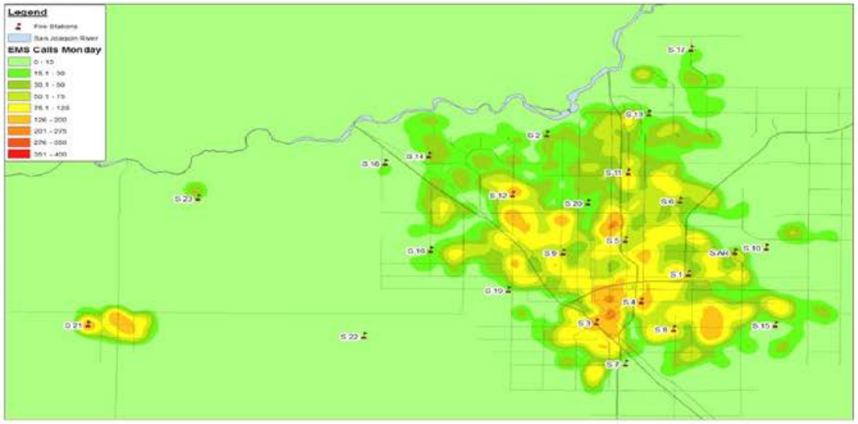
The P denotes a required field.
D
Unintentional system or detector operation (no fire). Includes tripping an interior device accidentally.
741 Sprinkler activation (no fire), unintentional. Includes testing the sprinkler system without fire department notification.

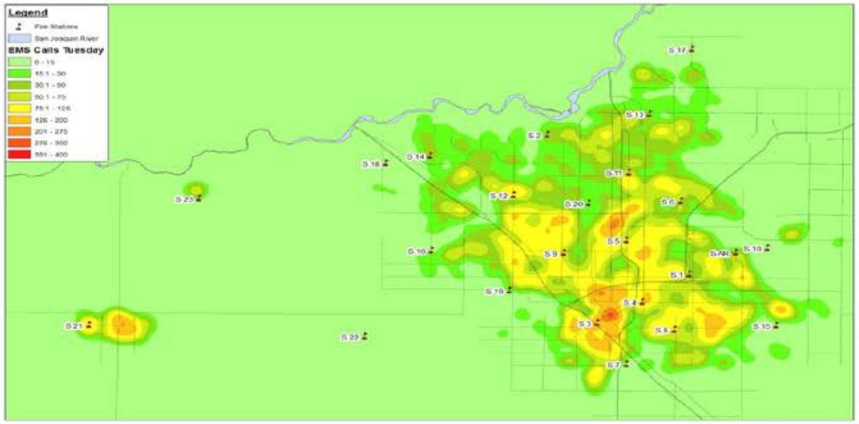
742 Extinguishing system activation. Includes testing the extinguishing system without fire department notification.
743 Smoke detector activation (no fire), unintentional. Includes proper system responses to environmental stimuli such as non-hostile smoke.
744 Detector activation (no fire), unintentional. A result of a proper system response to environmental stimuli such as high heat conditions.
745 Alarm system activation (no fire), unintentional.
746 Carbon monoxide detector activation (no carbon monoxide detected). Excludes carbon monoxide detector malfunction.
740 Unintentional transmission of alarm, other.
Biohazard scare
751 Biological hazard, malicious false report.
False alarm and false call, other
700 False alarm or false call, other.
Severe Weather and Natural Disaster
811 Earthquake assessment, no rescue or other service rendered.
812 Flood assessment. Excludes water rescue (360 series).
813 Wind storm. Includes tornado, hurricane, or cyclone assessment. No other service rendered.
814 Lightning strike (no fire). Includes investigation.
815 Severe weather or natural disaster standby.
800 Severe weather or natural disaster, other.
Special Incident Type
Citizen complaint
911 Citizen’s complaint. Includes reports of code or ordinance violation.
Special type of incident, other
900 Special type of incident, other.

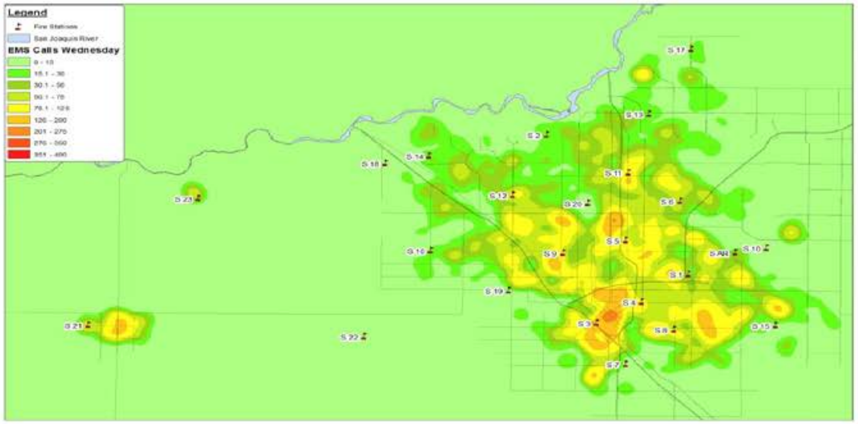
THIS PAGE INTENTIONALLY LEFT BLANK

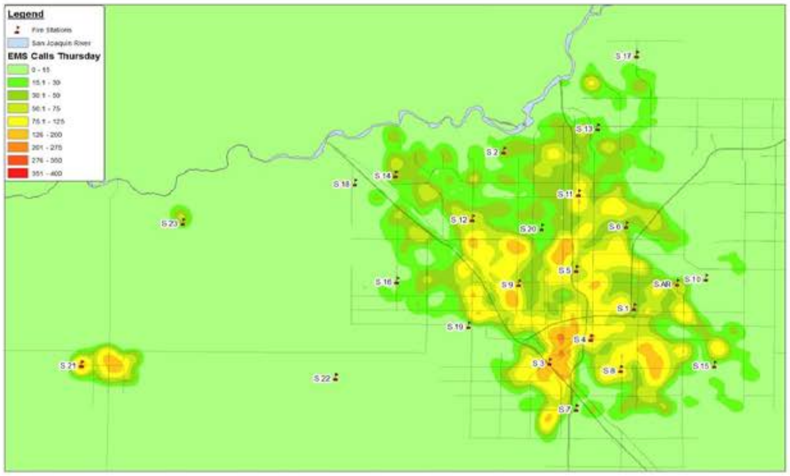
APPENDIX B. DAILY CALL DISTRIBUTION

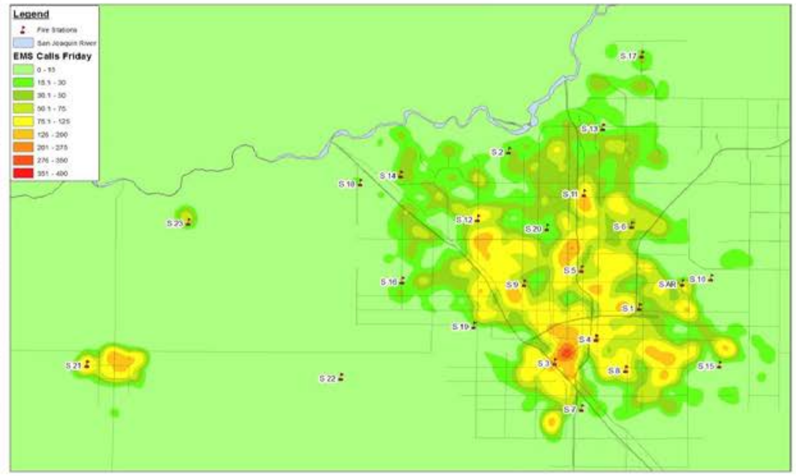


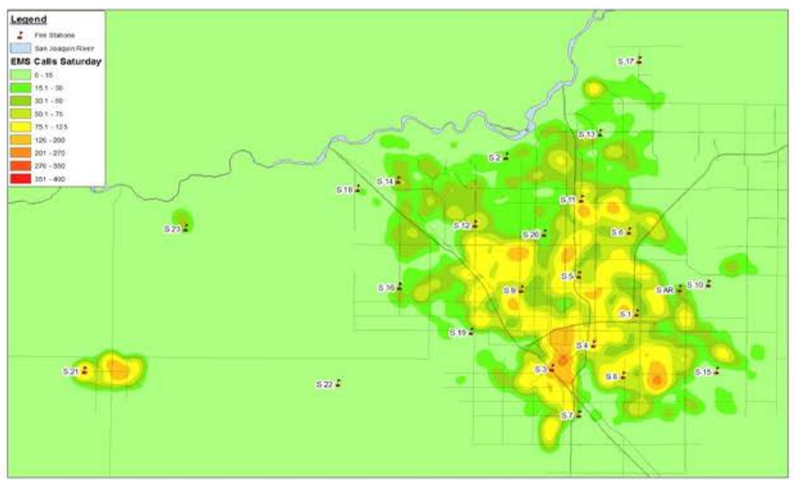




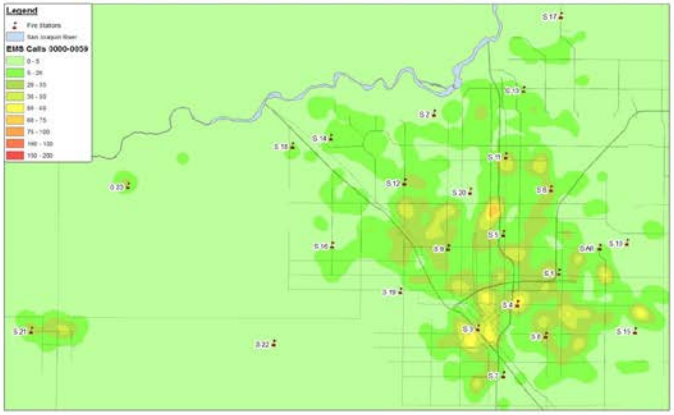


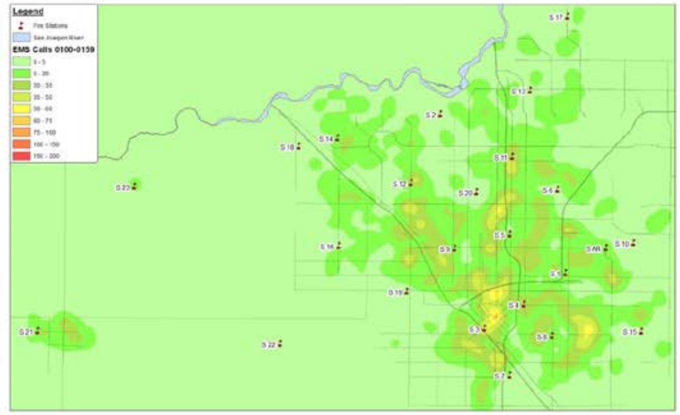

Legend
Fire Stations
San Joaquin River
EMS Calls Thursday
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 5
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

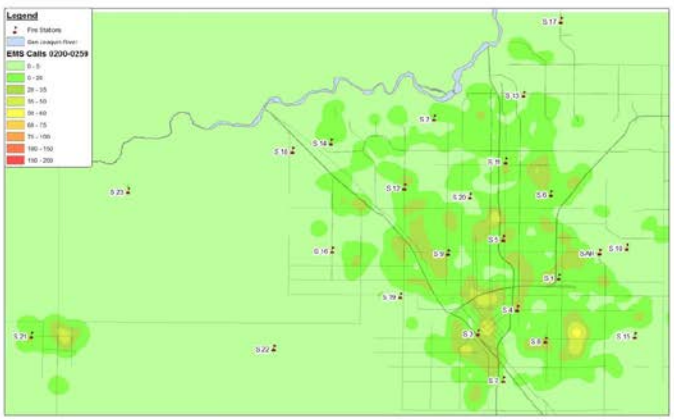

Legend
Fire Stations
San Joaquin River
EMS Calls Friday
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 5
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

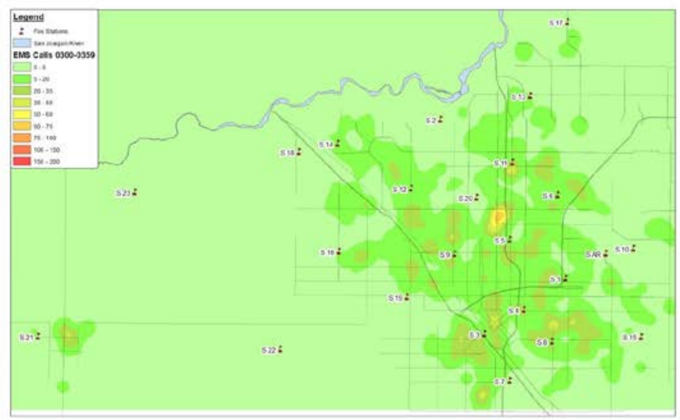

Legend
Fire Stations
San Joaquin River
EMS Calls Saturday
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 5
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

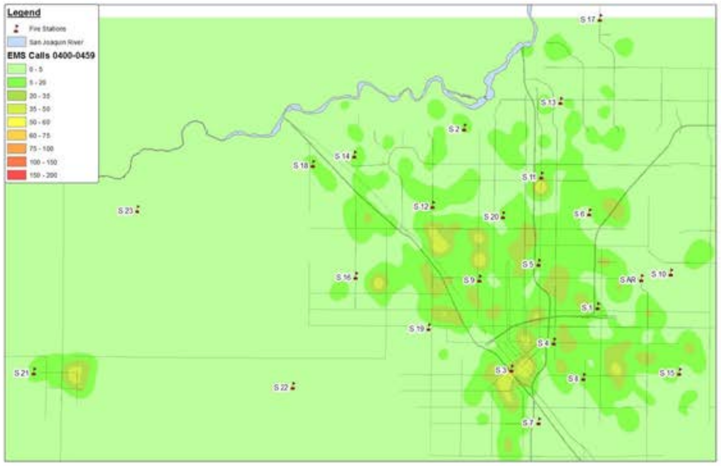
APPENDIX C. HOURLY CALL DISTRIBUTION

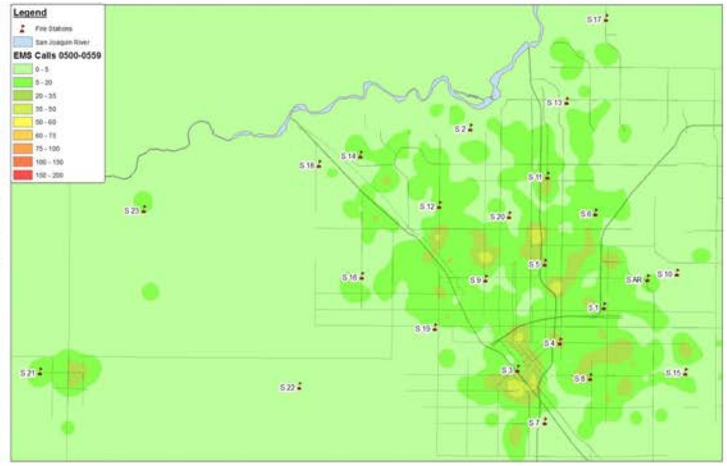


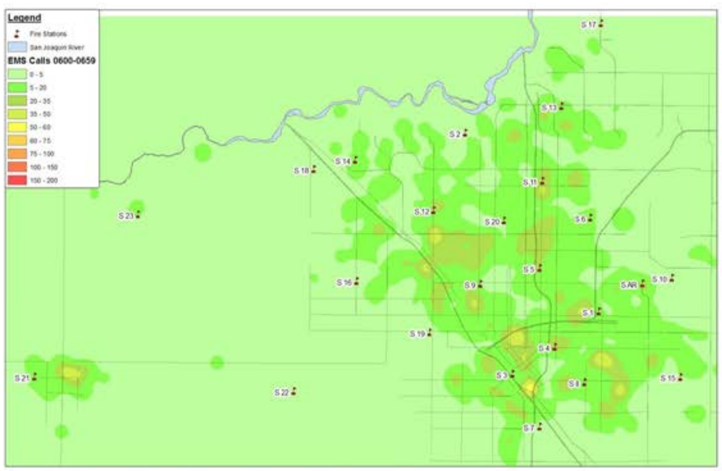


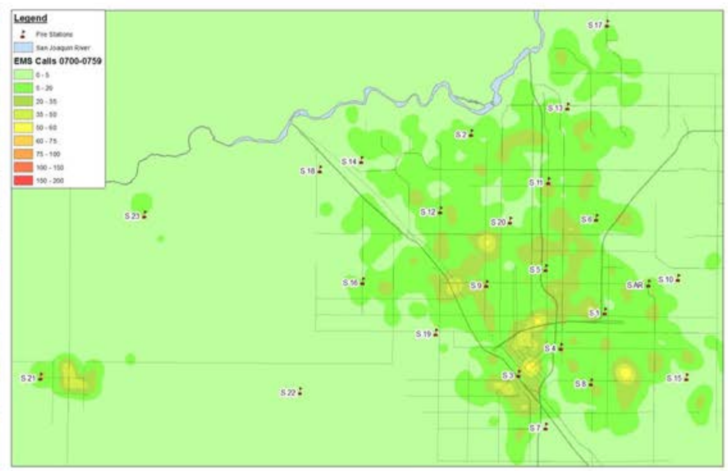


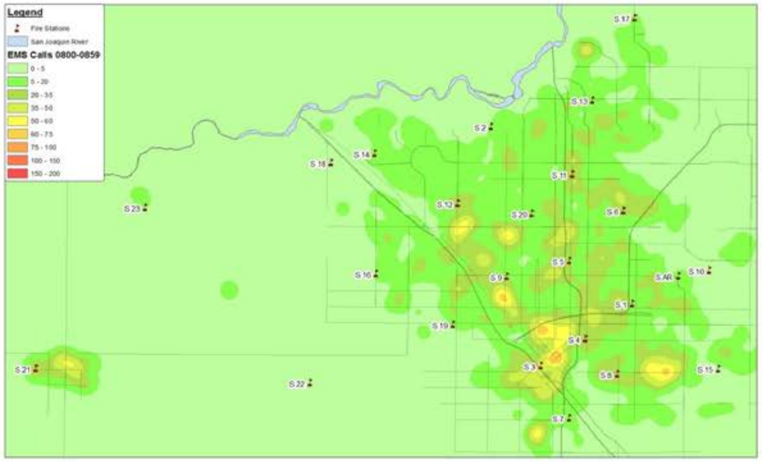


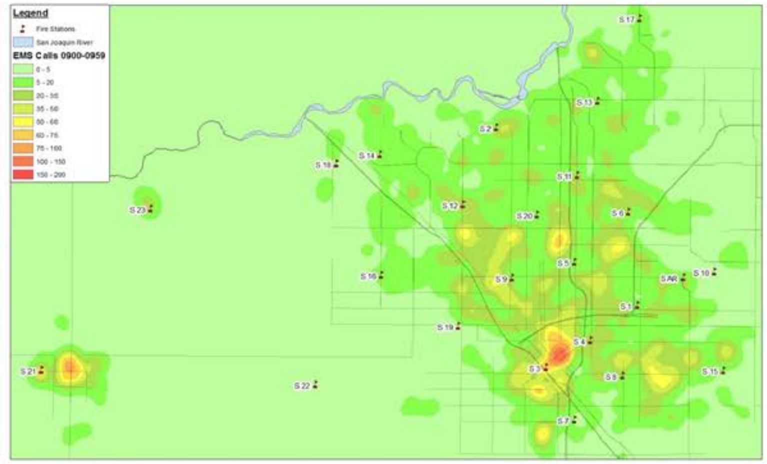

Legend
Fire Stations
San Joaquin River
EMS Calls 0400-0459
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

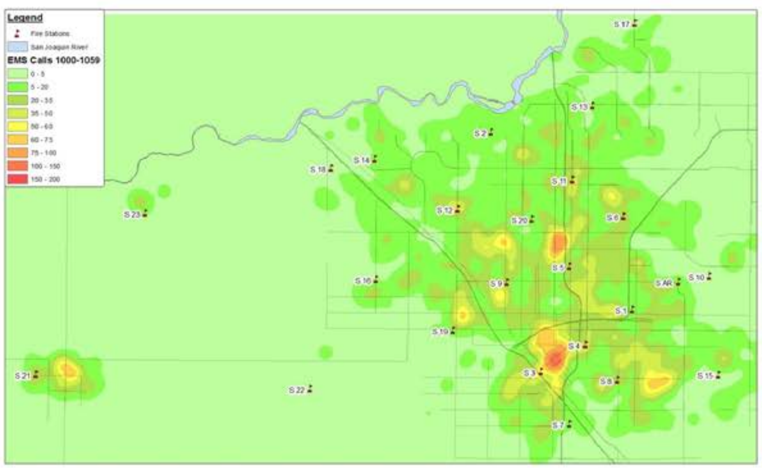

Legend
Fire Stations
San Joaquin River
EMS Calls 0500-0559
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

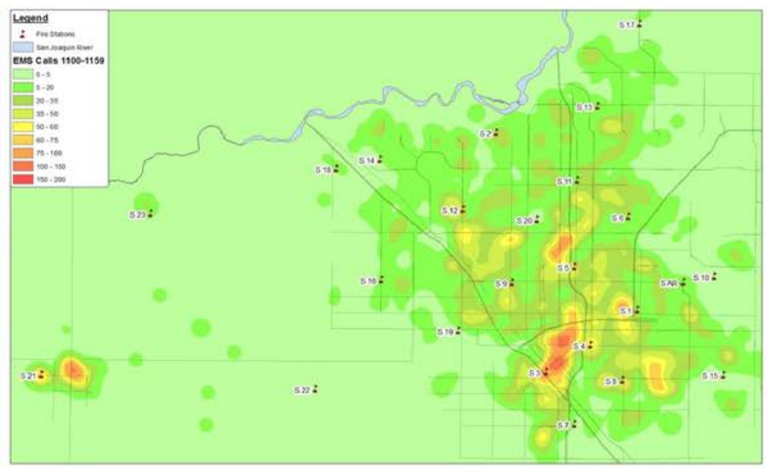

Legend
Fire Stations
San Joaquin River
EMS Calls 0600-0659
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

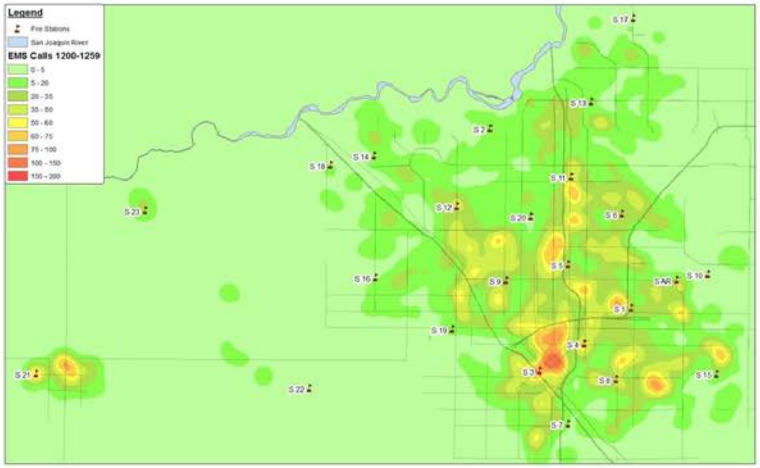

Legend
Fire Stations
San Joaquin River
EMS Calls 0700-0759
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

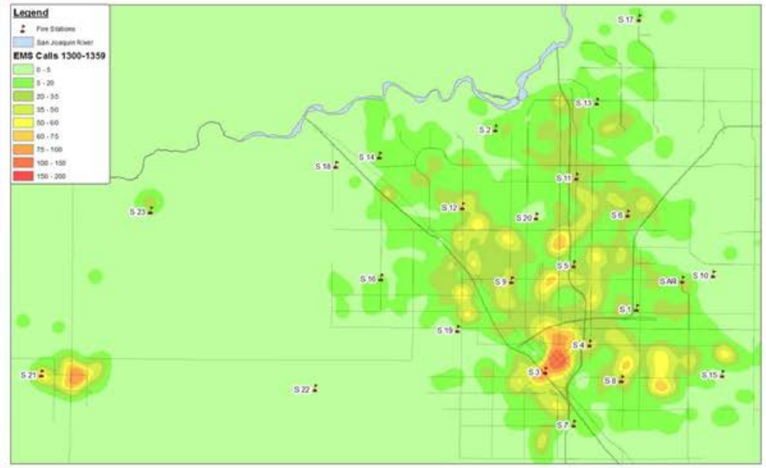

Legend
Fire Stations
San Joaquin River
EMS Calls 0800-0859
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 5
S 16
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 8
S 15
S 22
S 7

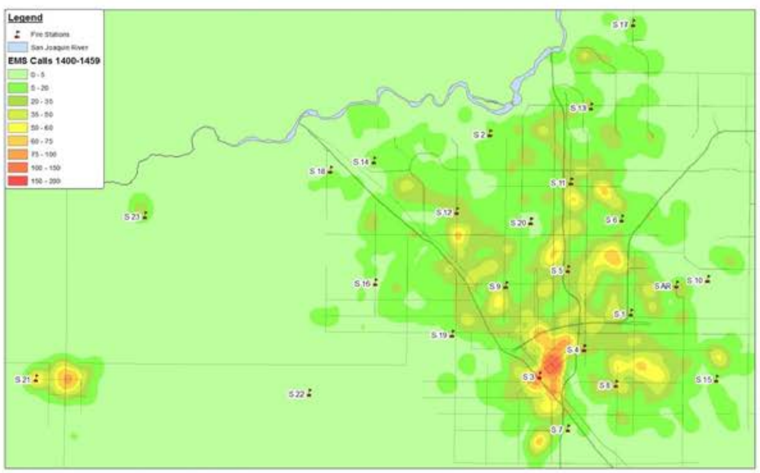

Legend
Fire Stations
San Joaquin River
EMS Calls 0900-0959
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 5
S 16
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 8
S 15
S 22
S 7

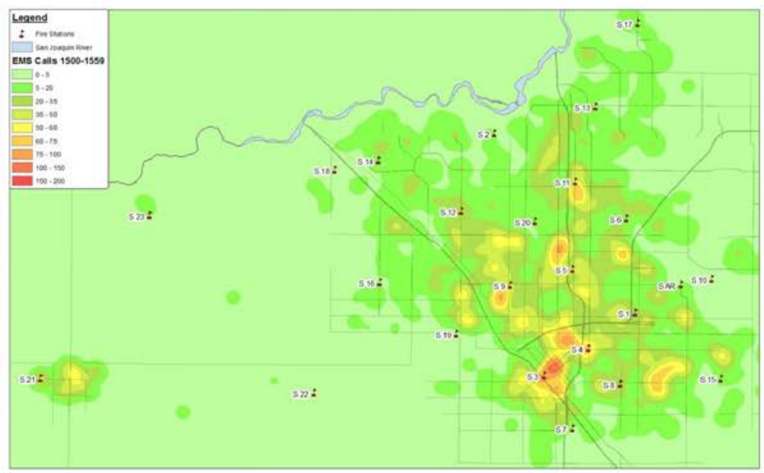

Legend
Fire Stations
San Joaquin River
EMS Calls 1000-1059
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 5
S 16
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 8
S 15
S 22
S 7

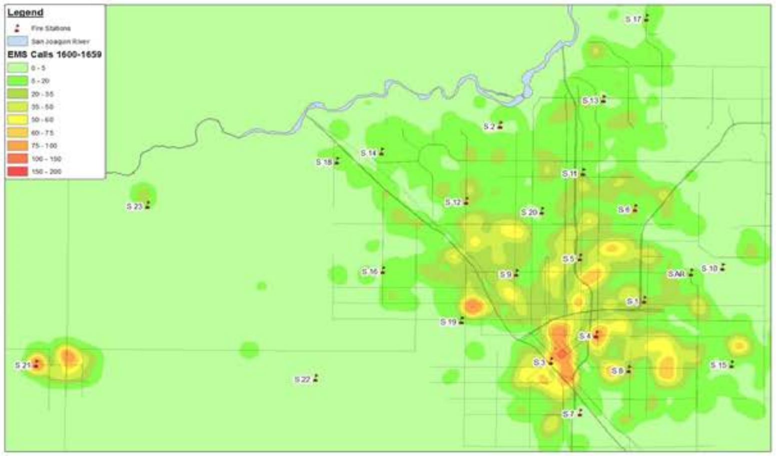

Legend
Fire Stations
San Joaquin River
EMS Calls 1100-1159
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 5
S 16
S 9
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 8
S 15
S 22
S 7

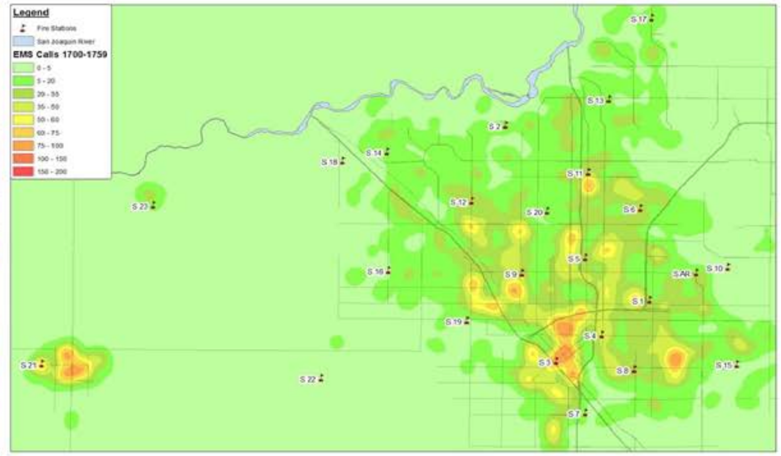

Legend
Fire Stations
San Joaquin River
EMS Calls 1200-1259
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 9
S 5
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

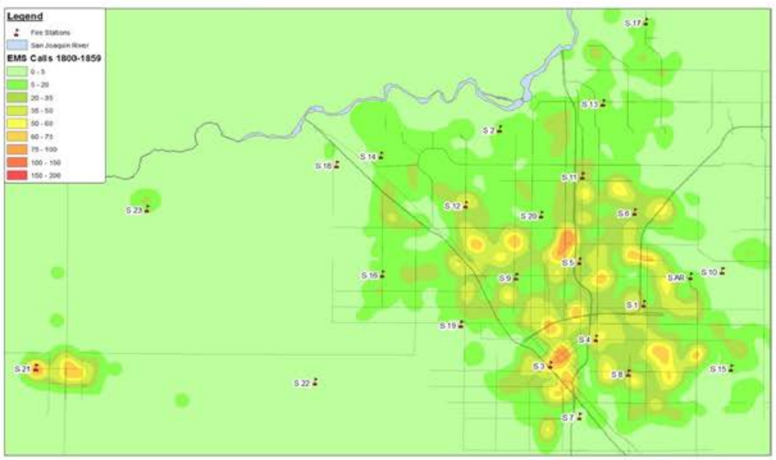

Legend
Fire Stations
San Joaquin River
EMS Calls 1300-1359
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 9
S 5
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

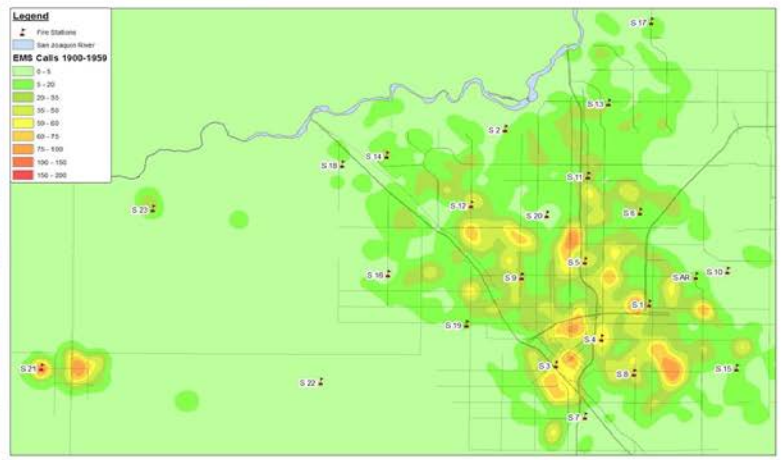

Legend
Fire Stations
San Joaquin River
EMS Calls 1400-1459
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 9
S 5
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

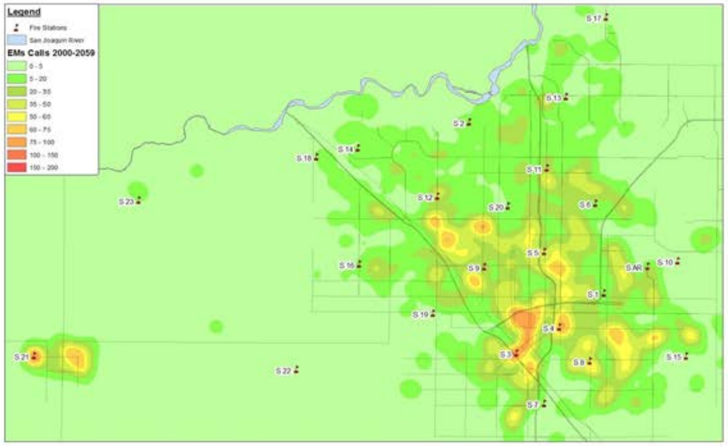

Legend
Fire Stations
San Joaquin River
EMS Calls 1500-1559
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200
S 17
S 13
S 2
S 14
S 18
S 11
S 23
S 12
S 20
S 6
S 16
S 9
S 5
S AR
S 10
S 1
S 19
S 4
S 21
S 3
S 22
S 8
S 15
S 7

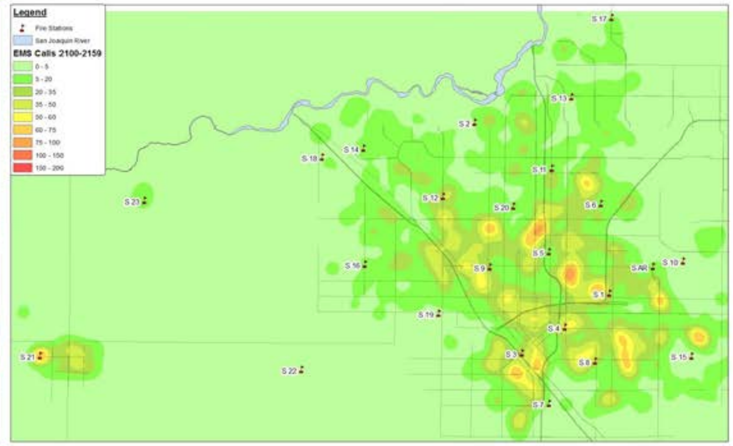

Legend
Fire Stations
San Joaquin River
EMS Calls 1600-1659
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

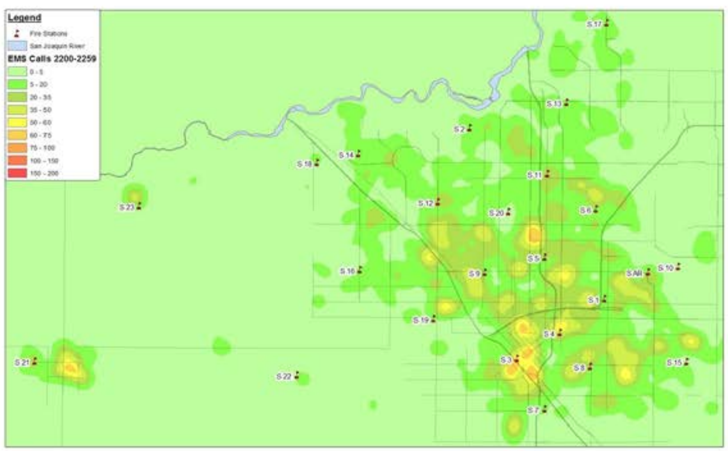

Legend
Fire Stations
San Joaquin River
EMS Calls 1700-1759
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

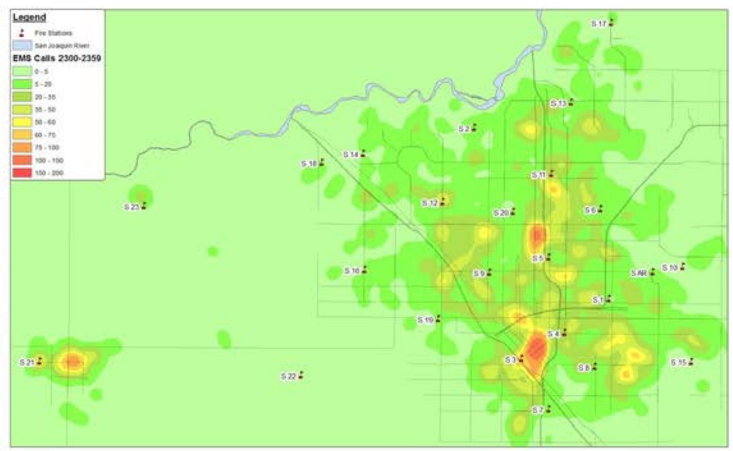

Legend
Fire Stations
San Joaquin River
EMS Calls 1800-1859
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200


Legend
Fire Stations
San Joaquin River
EMS Calls 1900-1959
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

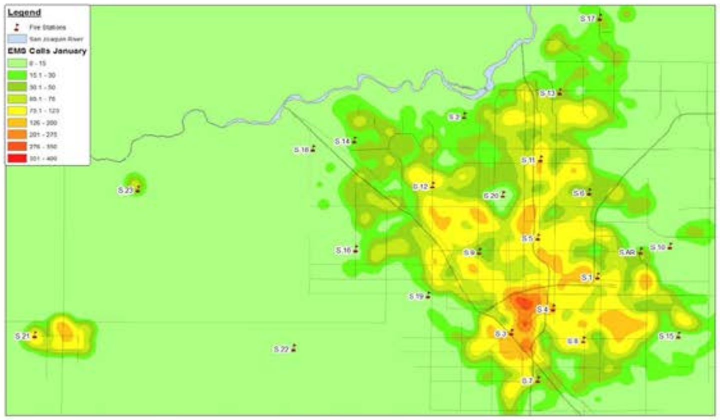

Legend
Fire Stations
San Joaquin River
EMs Calls 2000-2059
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

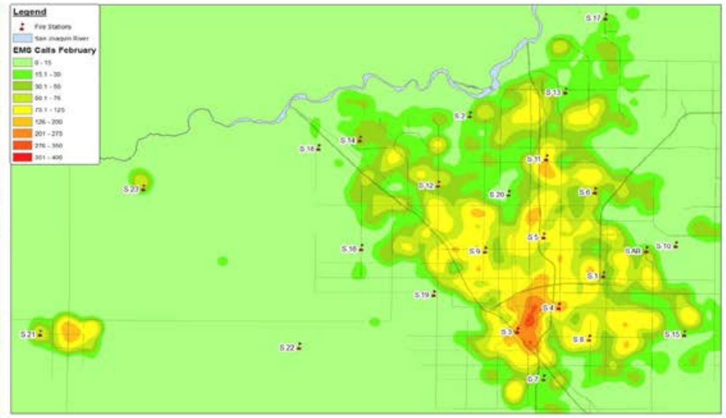

Legend
Fire Stations
San Joaquin River
EMS Calls 2100-2159
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

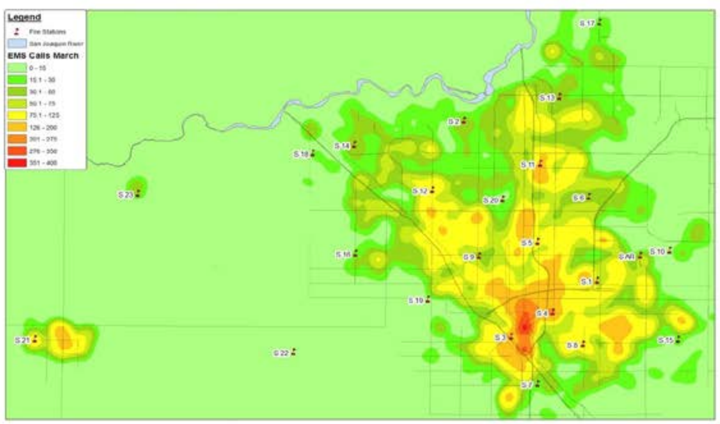

Legend
Fire Stations
San Joaquin River
EMS Calls 2200-2259
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

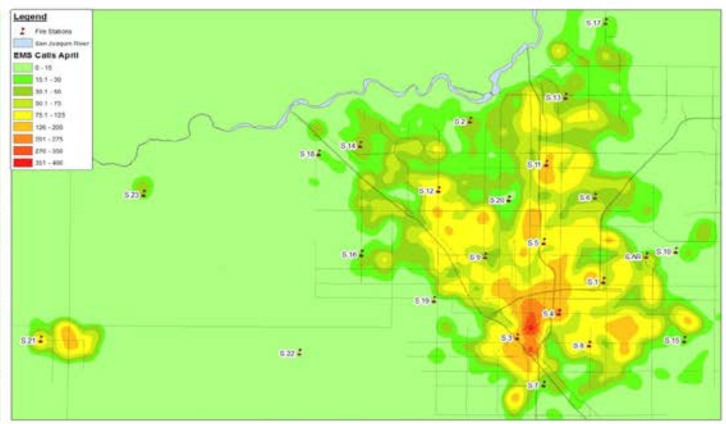

Legend
Fire Stations
San Joaquin River
EMS Calls 2300-2359
0 - 5
5 - 20
20 - 35
35 - 50
50 - 60
60 - 75
75 - 100
100 - 150
150 - 200

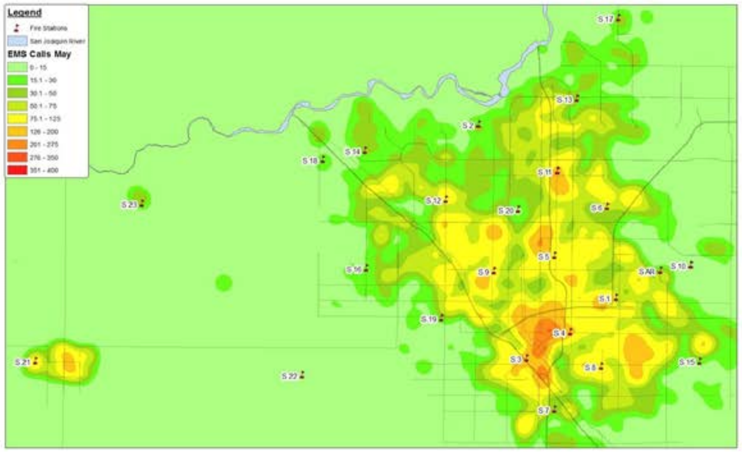
APPENDIX D. MONTHLY CALL DISTRIBUTION IN FRESNO, CA, FROM JANUARY 2012 TO MARCH 2014

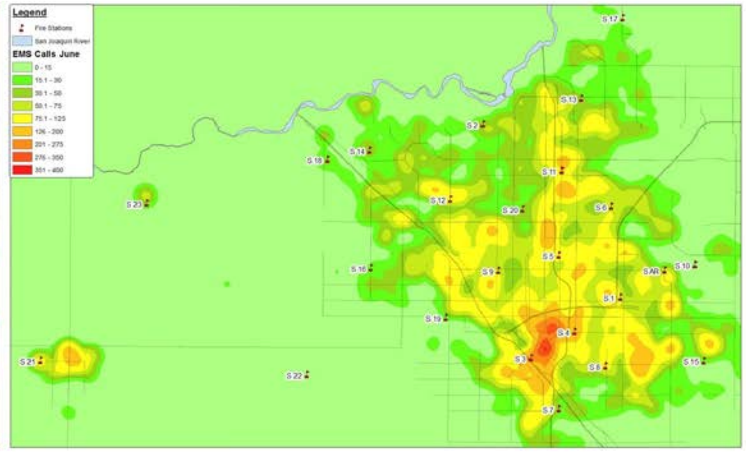


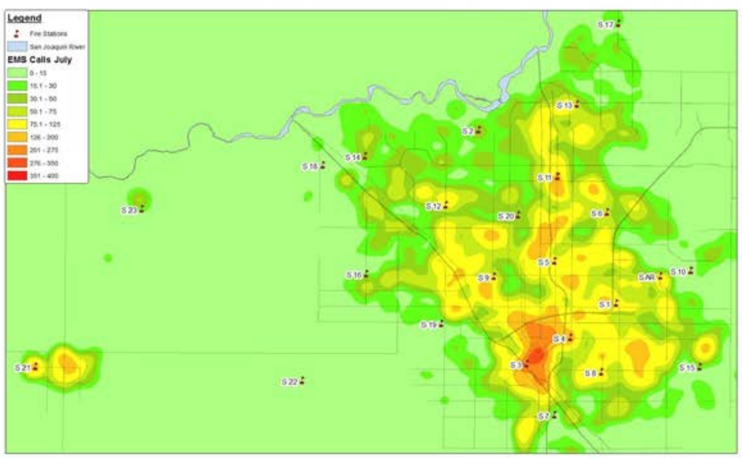


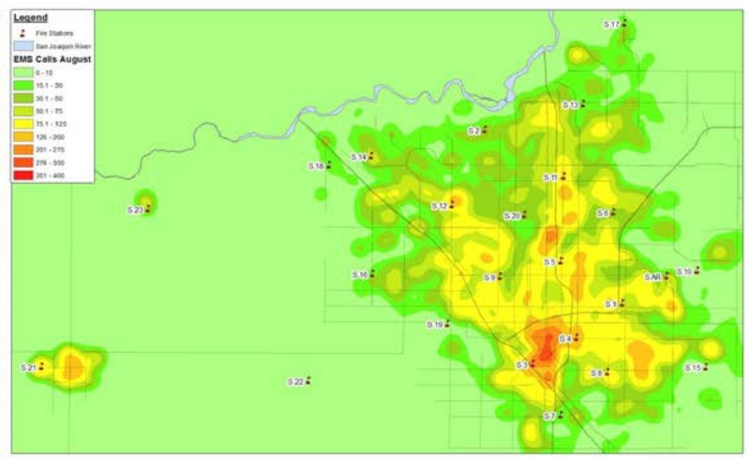


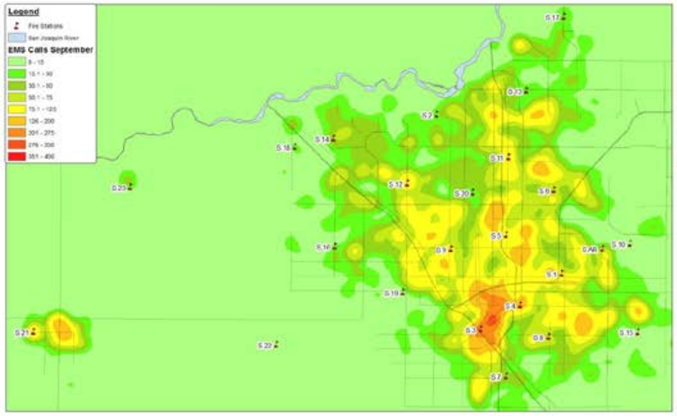


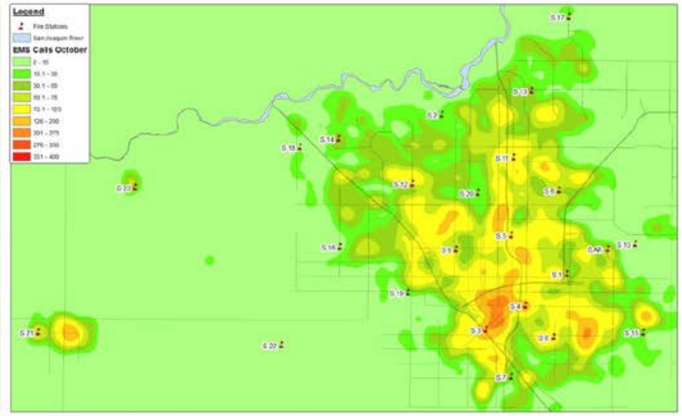

Legend
Fire Stations
San Joaquin River
EMS Calls May
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400

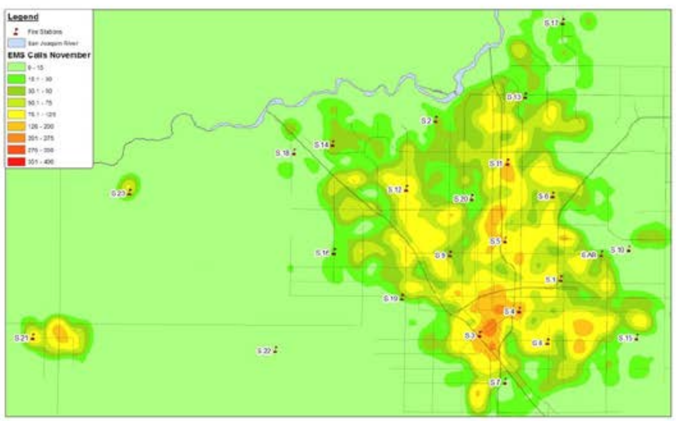

Legend
Fire Stations
San Joaquin River
EMS Calls June
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400

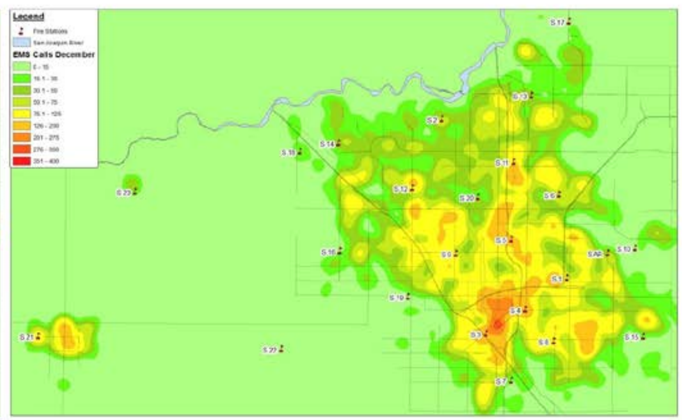

Legend
Fire Stations
San Joaquin River
EMS Calls July
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400


Legend
Fire Stations
San Joaquin River
EMS Calls August
0 - 15
15.1 - 30
30.1 - 50
50.1 - 75
75.1 - 125
126 - 200
201 - 275
276 - 350
351 - 400


Legend
Fire Stations
San Joaquin River
EMS Calls September


Legend
Fire Stations
San Joaquin River
EMS Calls October


Legend
Fire Stations
San Joaquin River
EMS Calls November


Legend
Fire Stations
San Joaquin River
EMS Calls December

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

ArcNews. “Charlotte Fire Department Links Live Data, Multiple Systems.” Summer 2012, http://www.esri.com/news/arcnews/summer12articles/charlotte-fire-department-links-live-data-multiple-systems.html.

Asgary, Ali, Alireza Ghaffari, and Jason Levy. “Spatial and Temporal Analyses of Structural Fire Incidents and their Causes: A Case of Toronto, Canada.” *Fire Safety Journal* 45, no. 1 (January 2010): 44–57.

Ceyhan, Elvan, Kivanc Ertugay, and Sebnem Duzgun. “Exploratory and Inferential Methods for Spatio-Temporal Analysis of Residential Fire Clustering in Urban Areas.” *Fire Safety Journal* 58, no. 2013 (2013): 226–239.

Citygate Associates. “Fire Service Emerging Trends: ‘The View from the Road.’” PowerPoint presentation. Folsom, CA: Citygate Associates.

Craig, Allen M, Richard P. Verbeek, and Brian Schwartz. “Evidence-based Optimization of Urban Firefighter First Response to Emergency Medical Services 9-1-1 Incidents.” *Prehospital Emergency Care* 14 (2010): 109–117.

———. “How Kernel Density Works.” Accessed March 21, 2016. http://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/how-kernel-density-works.htm.

———. “Space-time Cluster Analysis,” accessed February 9, 2014, http://resources.arcgis.com/en/help/main/10.1/index.html#//005p00000056000000.

FirefighterCloseCalls.com. “Firefighter Staffing.” Accessed February 1, 2016. http://firefighterclosecalls.com/firefighter-staffing/.

Fitch and Associates. “How to Explain UHU from UFOs to Your City Manager.” EMS1. November 8, 2012. https://www.ems1.com/ems-management/articles/1365144-How-to-explain-UHU-from-UFOs-to-your-city-manager/.

Haynes, Hylton J.G., and Joseph L. Molis. “U.S. Firefighter Injuries in 2014,” *nfpa Journal*. November 2, 2015.

Jennings, Charles R. “Evaluating and Managing Local Risks.” In *Managing Fire and Emergency Services*, 1st edition, edited by Adam K. Thiel and Charles R. Jennings, 63–92. Washington, DC: International City/County Management Association, 2012.

———. *The Promise and Pitfalls of Fire Service Deployment Analysis Methods*. Alexandria, VA, Institution of Fire Engineers, 1999.

National Fire Protection Association. “Fire Department Calls.” Last updated September 2014. http://www.nfpa.org/research/reports-and-statistics/the-fire-service/fire-department-calls/fire-department-calls.

Northern Ireland Fire and Rescue Service. *Integrated Risk Management Plan 2012–2015*. Lisburn, Northern Ireland: Northern Ireland Fire and Rescue Service, 2012.

Office of the Deputy Prime Minister. *Using FSEC to Develop an Integrated Risk Management Plan*. London: Office of the Deputy Prime Minister, 2003.

Price, Mike. *Fire Mapping: Building and Maintaining Datasets in ArcGIS*. Redlands, CA: Environmental Systems Research Institute, 2012.

Rosenshein, Lauren. “Extending Your Map with Spatial Analysis.” Environmental Systems Resource Institute. Accessed February 8, 2016. http://resources.arcgis.com/en/communities/analysis/017z00000015000000.htm.

Shekhar, Shashi, Zhe Jiang, Reem Y. Ali, Emre Eftelioglu, Xun Tang, Venkata M. V. Gunturi, and Xun Zhou. “Spatiotemporal Data Mining: A Computational Perspective.” *ISPSR International Journal of Geo-Information* 4, no. 4 (2015): 2306–2338. doi: 10.3390;ijgi4042306.

Stone, Martin*. Update of Response Time Loss Relationships for the Fire Service Emergency Cover Toolkit* (Fire Research Report 3/2010). Reading, United Kingdom: Greenstreet Berman, 2010.

System Planning Corporation*. Fire Service and Resource Deployment Analysis City of Oceanside Ca*. Arlington, VA: System Planning Corporation, 2012.

Tomaszewski, B. M. “Developing Geo-Temporal Context from Implicit Sources with Geovisual Analytics.” Presented at the ICA Commission on Visualization and Virtual Environments Annual Meeting, Helsinki, Finland, August 2, 2007.

United States Fire Administration. *National Fire Incident Reporting System: Complete Reference Guide*. Washington, DC: FEMA, July 2010.

———. “U.S. Fire Statistics, Trends in Fires, Deaths, Injuries and Dollar Loss.” Last modified January 6, 2016. https://www.usfa.fema.gov/data/statistics/#tab-1.

Walters, Jonathan. "Firefighters Feel the Squeeze of Shrinking Budgets." Governing. January 2011. http://www.governing.com/topics/public-workforce/firefighters-feel-squeeze-shrinking-budgets.html.

Wicks, John*. Fire Service Emergency Cover: Presentation Strategy Toolbox* (Research Report No. 4/2003). London: Office of the Deputy Prime Minister, 2003.

Yuan, May. "Temporal GIS and Spatio-Temporal Modeling." University of Oklahoma, April 18, 2007. http://geosensor.net/temp/yuan1996.pdf.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California