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Article *in* Disasters · May 2016

DOI: 10.1111/disa.12198

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doi:10.1111/disa.12198

Mapping fires and American Red Cross aid using demographic indicators of vulnerability

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Social vulnerability indicators can assist with informing disaster relief preparation. Certain demographic segments of a population may suffer disproportionately during disaster events, and a geographical understanding of them can help to determine where to place strategically logistical assets and to target disaster-awareness outreach endeavours. Records of house fire events and American Red Cross aid provision over a five-year period were mapped for the County of Los Angeles, California, United States, to examine the congruence between actual events and expectations of risk based on vulnerability theory. The geographical context provided by the data was compared with spatially-explicit indicators of vulnerability, such as age, race, and wealth. Fire events were found to occur more frequently in more vulnerable areas, and Red Cross aid was found to have an even stronger relationship to those places. The findings suggest that these indicators speak beyond vulnerability and relate to patterns of fire risk.

Keywords: American Red Cross, disasters, home fires, National Fire Information and Reporting System (NFIRS), social vulnerability

Introduction

A key component of the mission of the American Red Cross is to help people prepare for disasters before they happen. Understanding the social vulnerability of the different communities it serves helps the Red Cross to accomplish its mission in at least two ways: (i) by allowing the organisation to distribute strategically logistical assets for pre-disaster placement based on expected need; and (ii) by determining the communities that could most benefit from outreach and education initiatives. This study focuses on validating demographic variables commonly identified as social vulnerability indicators with the goal of generating confidence in decision-making and a richer understanding of those served by the Red Cross. A distinction is also made between the first responses by fire departments and the aid that the Red Cross may supply subsequently.

Spatial patterns of response events become evident after geographically enabling records on both fire department 'runs' and Red Cross aid. If all households were at equal risk of fire, the expected distribution of fire would be correlated only with the presence of households across a landscape. Through an analysis of fire records,

Published by John Wiley & Sons Ltd, 9600 Garsington Road, Oxford, OX4 2DQ, UK and 350 Main Street, Malden, MA 02148, USA

however, studies have shown that fire risk varies depending on a number of factors, including the presence of smokers, the age of housing, the installation of smoke alarms, and related demographic characteristics such as wealth (Runyan et al., 1992; Warda, Tenenbein, and Moffat, 1999; Folz et al., 2011; Gaither et al., 2011). In addition, catastrophic incidents will disproportionately affect people depending on their vulnerability, which many studies have also related to some of these same characteristics (Morrow, 1999; King and MacGregor, 2000; Cutter, Boruff, and Shirley, 2003; Rygel, O'Sullivan, and Yarnal, 2006; Flanagan et al., 2011).

To understand better the communities assisted by the Red Cross in the County of Los Angeles, California, United States, fires and Red Cross aid were mapped over a five-year time period and compared with geographical data on demographic variables commonly associated with vulnerability. The initial aim of the exercise was to determine whether or not fires occur evenly among households across the county that represent different levels of these variables. For example, if Los Angeles was split into census block groups, and these groups were assigned to one of three median household income classes ('low', 'medium', or 'high'), would fire responses occur evenly in these three classes, or would they trend in an explainable direction? For which demographic variabilities will there be bias? When Red Cross aid events are examined in the same manner, are trends also observed? Will the biases generally be greater for aid cases than for fire responses?

This study does not take into account likely contributors to fire risk that are not purely demographic in nature, such as the age of housing or the crime rate. Its purpose is not to ascertain what causes fire, but to determine the kinds of demographic profiles of those who are affected by fire. The results are intended to assist organisations such as the Red Cross in understanding the communities they serve and help them to tailor better their approach to achieving their goals. The wider-reaching findings include a broader understanding of those who seek relief; not strictly populations that have been identified as vulnerable, but those who have found themselves in situations of distress.

Disaster risk and vulnerability

Disaster situations result in stresses for both organisations and individuals that hinder expected conditions of life, creating a greater demand for them than society may be capable of providing (Tierney, Lindell, and Perry, 2001). Some organisations and individuals suffer greater stress than others or may have more difficulty in restoring those expected conditions of life, leading to varying levels of vulnerability among different parties. While many definitions of vulnerability have made their way into the academic literature (see, for example, Cutter, 1996; Weichselgartner, 2001), it can be broadly defined as the potential for loss; the greater a person's potential for loss, the greater the vulnerability. Just as there are many definitions that have nuanced distinctions, there are various models for understanding disasters in which the concept of vulnerability plays an important role.

The Pressure and Release (PAR) Model heavily features vulnerability (Blaikie et al., 1994). It describes a disaster (or risk) formed from two sources of pressure: (i) the processes that create vulnerability; and (ii) the natural hazard or process that threatens a population (Blaikie et al., 1994). Elements of the PAR model have been used by the International Federation of the Red Cross and Red Crescent Societies for vulnerability and capacity assessments (Pelling, 2007). The processes that create the 'progression of vulnerability' are the interaction of vulnerabilities' root causes (consisting of limited access to resources and political and economic ideologies), dynamic pressures from society (consisting of the lack of social infrastructure and macro forces such as rapid population changes), and unsafe conditions (consisting of both physical and social elements of safety).

The hazards that interact with this progression of vulnerability are physical, such as earthquakes, fires, and floods. The magnitude of the disaster can be reduced via a release of pressure on the vulnerability side. A formulaic representation of this concept is $R = H \times V$, where R is risk, H is hazard, and V is vulnerability. The shortcomings of the model are the equal weighting of hazards and vulnerability in the production of risk (Adger, 2006), the failure to consider the vulnerability of biophysical subsystems, and the lack of consideration of the causal sequence of hazards and feedback mechanisms (Turner et al., 2003).

The risk of hazards comprises both the type of disaster and the probable frequency and magnitude of that event, while mitigation accounts for steps taken to ameliorate losses. These factors interact and form the hazard potential of the place, with risk increasing hazard potential and mitigation reducing it. Hazard potential is filtered for the geographical context and the social fabric of the place it affects, representing biophysical and social aspects of vulnerability, respectively. These two features of vulnerability are responsible for place vulnerability, which feeds back to alter both risk and mitigation strategies. This model is commonly cited in the disaster research literature (see, for example, Brenkert and Malone, 2005; Greiving, Fleischhauer, and Lückenkötter, 2006; Collins and Bolin, 2007; Holub and Fuchs, 2009) and has been used as a framework for the development of other models (see, for example, Borden et al., 2007; Zhou et al., 2009).

While there is no widespread consensus on the exact indicators that should be used to determine social vulnerability, there is general agreement that socioeconomic status has a significantly negative relationship with vulnerability. This alone cannot determine vulnerability (Kahn, 2005), but it may be among the strongest of influences (Eriksen and O'Brien, 2007; Cutter and Finch, 2008; Wood, Burton, and Cutter, 2010; McLeod and Kessler, 1990). This broad category of factors can include indicators such as a community's percentage of households below a federally-designated poverty level, the percentage of the population with less than high-school education, per capita income, and median house value.

In the most commonly cited study on a Social Vulnerability Index, Cutter, Boruff, and Shirley (2003) describe six key groups of vulnerability factors: (i) lack of access to resources and knowledge; (ii) limited access to political power and representation;

(iii) reduced social capital and social networks; (iv) building stock and age; (v) frailty and physical limitations of individuals; and (vi) the type and density of infrastructure and lifelines. Given that many of these parameters typically are measured by seeking data directly from people, social vulnerability mapping involves the use of demographic data, including previously collected census data (see, for example, Cutter, Boruff, and Shirley, 2003; Chakraborty, Tobin, and Montz, 2005) or the use of data collected from interviews and surveys (see, for example, Adger and Kelly, 1999; Collins, 2005).

In the work by Cutter, Boruff, and Shirley (2003), the Social Vulnerability Index was produced at the county level for the entire US. The model started with 250 variables as inputs, obtained from a variety of sources. These variables were narrowed to 85 after a test for multicollinearity was performed. They were furthered narrowed to 42 after a set of computations and normalisations were completed to format the data into appropriate percentages, per capita estimates, and density functions. From there, a principal component analysis was carried out to create a total of 11 factors, as shown in Table 1. The majority of these variables have been used consistently by other studies dealing with vulnerability to disaster (Morrow, 1999; King and MacGregor, 2000; Rygel, O'Sullivan, and Yarnal, 2006; Flanagan et al., 2011).

All of the aforementioned studies have demonstrated that people with less wealth suffer disproportionately in disasters. When broadly dividing disaster events into

Table 1. Eleven factors of social vulnerability

Factor	Name	Percentage variation explained	Dominant variable	Correlation
1	Personal wealth	12.4	Per capita income	0.87
2	Age	11.9	Median age	-0.90
3	Density of the built environment	11.2	Number of commercial establishments per square mile	0.98
4	Single-sector economic dependence	8.6	Percentage employed in extractive industries	0.80
5	Housing stock and tenancy	7.0	Percentage of housing units that are mobile homes	-0.75
6	Race: African-American	6.9	Percentage African-American	0.80
7	Ethnicity: Hispanic	4.2	Percentage Hispanic	0.89
8	Ethnicity: Native American	4.1	Percentage Native American	0.75
9	Race: Asian	3.9	Percentage Asian	0.71
10	Occupation	3.2	Percentage employed in service	0.76
11	Infrastructure dependence	2.9	Percentage employed in communications, public utilities, and transportation	0.77

Source: Cutter, Boruff, and Shirley (2003).

segments of preparedness, response, and recovery, wealth can play a huge role in resilience at all stages. Socioeconomic status has been shown to correlate negatively with preparedness behaviour (Turner et al., 1986). This lack of preparation appears to be independent of perceived risk, as lower socioeconomic status populations have been observed to have a heightened risk perception (Fothergill and Peek, 2004). This trend may be related to the cost of preparation, or to perceptions of how much control people feel they have over their own lives (Vaughan, 1995).

The second stage, response, can be related to wealth as well. In terms of the likelihood of a fire event, the most probable causes of residential fires are heating equipment or smoking materials such as cigarettes; tobacco smoking has been shown to be more common among low-income populations (Runyan et al., 1992; Jennings, 2013). Older and poorly maintained buildings are at greater risk, too. And in the last stage of this simplified disaster cycle, the ability of people to recover and restore their homes and lost possessions after a fire is related directly to their wealth and/or insurance.

For all of these reasons, this study looks closely at indicators of wealth as they relate to fire response and aid. Other variables examined here are associated with age and ethnicity (including language and race), owing to their identification as important to social vulnerability and the focus that the Red Cross puts on them when planning outreach activities. Age pertains to Red Cross training sessions that specialise in families and babysitters, whereas language receives special attention to ensure that the messages of disaster preparedness and disaster relief reach as many people as possible.

Methods

Fires are tracked by responding agencies to enable reporting on the services they provide. In the US, individual fire departments have the opportunity to report their responses to a national database to contribute to the larger picture of fire response in the country. This system, called the National Fire Information and Reporting System (NFIRS), is a rich and valuable data source for understanding the country's fires and how local fire departments respond to them. NFIRS data are made available to the public.

The American Red Cross also keeps a national database in which local chapters can report their activities. The Client Assistance System (CAS) tracks incidents where the organisation has supplied assistance to someone affected by any kind of disaster. In other words, CAS is not limited to fires. This database is not public and is used internally to understand better Red Cross responses and operations.

Both datasets track large amounts of information measured in terms of detail and volume. A thorough understanding of each is needed to maximise utility and improve interpretation. In particular, expert knowledge is needed to filter the databases so that they can be properly aligned and compared for spatial analysis. While both systems possess opportunities for tracking some demographic variables, these fields in the databases usually are blank. This is probably because of the volume of records produced by both databases and the priority accorded to essential elements, such as time and the number of people affected and organisations involved, when populating these databases.

The NFIRS

The National Fire Data Center initiated NFIRS in the 1970s. The system is currently at Version 5.0 and has evolved over the years to incorporate a greater wealth of information. The U.S. Fire Administration's NFIRS website[1] currently reports that about 23,000 fire departments from every state and Washington, DC, enter their incidents into the database, accounting for approximately 75 per cent of all reported fires that occur annually.

The NFIRS employs a three-tiered system composed of local fire departments, state fire agencies, and the federal government. When a fire occurs, a local fire officer will complete a fire report in a standard format provided by the NFIRS, creating a public legal record that will be reported first to the state and then to the national database. Furthermore, each state may set its own reporting requirements for the local agencies. For some states, reporting is voluntary. Examples of varied requirements include differences in which 'runs' get counted (such as fire responses only) or a dollar loss threshold due to a fire. Local communities may also have varying standards for what gets included (or not) (Ahrens, Stewart, and Cooke, 2003).

The fire report incorporates information such as the date and time that the incident occurred, estimated property damage, occupancy in the structures involved, and any resulting casualties. Finer levels of detail are also possible, including whether or not sprinklers and smoke detectors were found to be working. Information on the nature of the fire, such as its cause and origin, also may be captured (Ahrens et al., 2003). Some data in the NFIRS is made available through the website, but a public request for data can be issued to a fire agency representative of each state.

Selecting an appropriate set of attribute queries for the NFIRS database was an iterative process that required consulting with fire data specialists who work with the NFIRS regularly. The ultimate goal of the export was to have a tabular output with one record for each fire in Los Angeles County. An attribute-based geographic filter (that is, by fire department codes in Los Angeles County) and a time-based filter (that is, fires between 2007 and 2012) provided a start, but there were many more filters that needed to be applied. A basic query of fire events would yield multiple records for the same fire because multiple departments could respond to a single event, and each department would report its involvement as a record. A refined query removed the fire departments that were supplying 'mutual aid' to another department that was the primary responder.

Another goal was to analyse only records for fires to which the Red Cross might also have responded. Residences, including mobile homes, were included in the query, but other location types were excluded, such as commercial buildings, parked cars, and trash cans. The final component of the query filtered for incidents occurring in Los Angeles County using fire department identification codes.

An initial search of the NFIRS for fire events in 2011 was conducted using a less refined filter. This resulted in records for all fire department responses, including non-fire responses such as medical emergencies. Duplicate values owing to mutual aid entries were not removed and commercial property responses were included. This query produced 18,280 records for dispatches in Los Angeles County. The refined query for this year reduced the number of responses by 89 per cent to 2,092.

Even though the exclusion of certain 'mutual aid' values in the query was extremely helpful in removing multiple records for a single fire, there were still cases where this occurred. Regardless of mutual aid, this can arise if a house fire happens to spread from one structure to an adjacent one. Such 'duplicates' were manually removed from the input dataset for this analysis. While those records often are appropriate for inclusion in many types of analysis (for instance, when looking at the number of structures that received a fire response), they were not suitable in this case, as the focus here is on singular fire events captured by fire departments and the Red Cross.

The CAS

American Red Cross nomenclature designates any event that the organisation responds to as a 'disaster', including both large catastrophes like wildfires and events with smaller geographic footprints like house fires. When any *incident* occurs, the Red Cross may open a *case* for each household—the household will be composed of one or more *individuals* to be given assistance. As a result, a *case* is likely to be associated with several *individuals*, and multiple *cases* can be generated from an *incident*. For instance, a single *incident* involving an apartment building fire will generate multiple *cases* (that is, apartment units) and each case will help multiple *individuals*. The vast majority of disasters in the Los Angeles Region of the Red Cross are single-family house fires.

Information on assisted *individuals*, the *cases* to which they belong, and the *incidents* that instigated the response are stored in the CAS. This system is not open to the public and is used internally for reporting. The use of Red Cross data in this study is permitted through a local partnership whereby any data products that arise from the analysis are reviewed carefully to ensure that no sensitive information is released.

The CAS only tracks disasters in which the Red Cross has a role in responding. If there is a house fire and the affected party declines Red Cross assistance, the incident will not be recorded in the CAS. An example of assistance that could be provided is a small set of funds designated to help an individual purchase enough clothing to mitigate temporarily the loss of their closet in a fire. Red Cross assistance is not based on financial need but rather on damages incurred because of the incident. Since the amount of assistance typically is a small fraction of the total damages (that is, this assistance is far from comprehensive insurance) and requires effort to obtain, an assumption is made that this dataset represents individuals with greater financial need.

Red Cross disaster response cases were queried from the CAS for all fire-related events (including single-family fires, multi-unit residential fires, and wildfires) in Los Angeles County between 2007 and 2012. As the CAS records any event that can lead to the Red Cross providing aid (such as a building collapse, civil disturbance, explosion, flood, or landslide), non-fire event types were excluded from the query. With only the geographic and time-based filters applied, fires made up 87 per cent of Red Cross events in the county. After removing duplicate data points, a table was produced for analysis where each incident (such as a house fire) was represented by one record.

Both datasets were geo-coded using a variety of address locators to maximise the number of usable records. While the NFIRS database does include fields for latitude and longitude, they were sparsely populated. The absence of these data could be due to a large number of factors, including the lack of a global positioning system (GPS) unit in the field for acquiring coordinates and the cumbersome task of entering long strings of numbers weighed against immediate need. Moreover, data entry is not necessarily completed by someone with knowledge of geographical data or GIS skills. Given this lack of latitude/longitude coordinates, automatic geo-coding of addresses was performed, followed by manual iterations where unmatched addresses could be resolved by making small obvious changes. For instance, many intersections recorded by fire departments were written in the form of 'Main St. × Broadway Ave'., which had to be corrected to 'Main St. and Broadway Ave'.

Demographic variables

The analysis of demographic variables was done using data from the 2013 Business Analyst[2] software package compiled by Esri from a variety of sources, including the United States Census Bureau. The variables chosen reflect the most common indicators of vulnerability, related to age, ethnicity, and wealth. The census block group was chosen as the geographical unit for this study because it was the finest scale unit available with comprehensive data coverage. An attribute based query for block groups in Los Angeles County was performed in Business Analyst, yielding 6,422 block groups.

A total of 11 variables were selected, including one that considered language as an indicator and another that considered density (see Table 2). For each of these indicators, the expected correlation to vulnerability was determined and summary statistics were calculated. Tertiles were used to categorise each census block group as being either 'low' (L), 'medium' (M), or 'high' (H) for the county. The resulting dataset assigned each block group to a class (L, M, or H) for each of the 11 variables. For each variable, there was an approximately even distribution of block groups belonging to each of the three classes (that is, approximately one-third of the total block groups in each class).

The indicator in the language category, linguistic isolation, was not available through the Business Analyst application and was calculated using United States Census Bureau data. The calculation was based on the premise that a linguistically-isolated household has no member who is 14 or more years of age who (i) speaks only English or (ii) speaks a non-English language and speaks English 'very well' (United States Census Bureau, n.d.). This data was only available at the census tract level, and so 'low', 'medium', and 'high' categories were calculated for this coarser geographical unit,

Table 2. Demographic variables used in the analysis*

Expected correlation	Category	Variable	Min.	1st tertile	2nd tertile	Max.
Negative (-)	Age	More than 65 years old	0	9%	13%	100%
	Age	Median age	0	32	39	78
	Wealth	Median home value	0	$267,442	$368,122	$1,000,001
	Wealth	Median household income	0	$39,367	$61,133	$200,001
	Wealth	Per capita income	0	$15,618	$28,341	$103,910
Positive (+)	Age	Less than 20 years old	0	23%	30%	100%
	Density	Average household size	0	2.7	3.5	6.0
	Ethnicity	Hispanic population	0	25%	64%	100%
	Language	Linguistically-isolated households	0	8%	20%	84%
	Race	Black population	0	2%	6%	100%
	Race	Minority population	0	60%	93%	100%

Notes: * Tertile values were calculated for each variable in the county. All geographic units in the study area were assigned a rank of 'low', 'medium', or 'high' based on the three tertiles for each variable.
Source: authors.

and all subsequent analyses of this particular variable involved census tracts rather than block groups.

Spatial joins and expected distributions

Census block groups were identified for every location in the Red Cross and NFIRS datasets through a spatial join. Once the block group codes were matched to the fire and aid locations, the classes for each variable were also matched to each record. The result was an L, M, or H designation for each of the 11 variables at every location.

To determine how reality deviates from a *ceteris paribus* expectation of fire response/aid (that is, independent of indicators such as wealth), expected numbers of response/aid needed to be calculated. A common incorrect assumption of a *ceteris paribus* scenario would be that 33 per cent of fires occur in the L income block groups, 33 per cent occur in the M income block groups, and 33 per cent occur in the H income block groups. The more accurate assumption would be based on the number of households in each of these classes: if 55 per cent of households fall in the L income block groups, 55 per cent of house fires would occur there. The counts of households by block group were used, therefore, to calculate expected fire rates.

With 'expected' and 'actual' distributions for each variable, one can make a statistical comparison to determine how likely the two datasets differ by chance. A chi-squared test was selected as the statistical test where the null hypothesis is that the distributions are not different. The *p*-value for the chi-squared tests offers a determination for the statistical significance of the result.

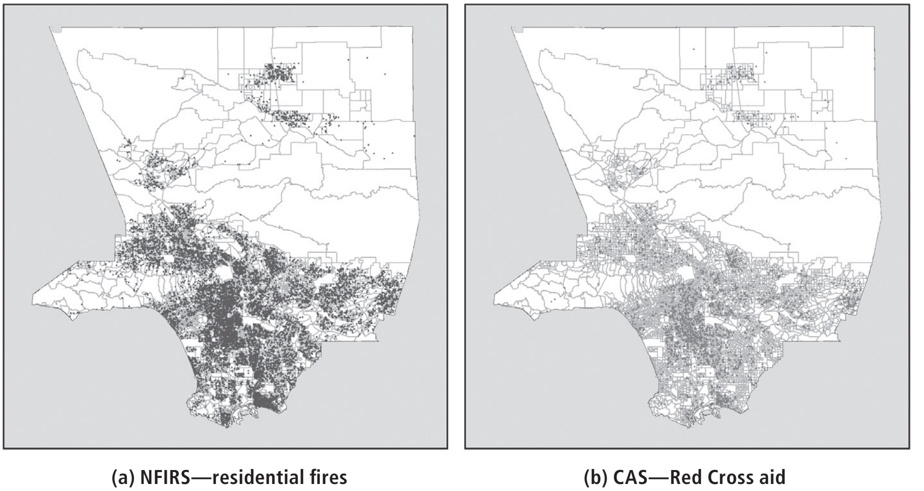
Results

The majority of fire and aid events could be geo-coded with automated services by using the addresses assigned to them in their respective databases, but a significant percentage of those records had incomplete address attributes or improper formatting. Manual correction of addresses increased geo-located aid events from 90 to 99 per cent (1,057 to 2,271 records) and fire events from 84 to 89 per cent (10,766 to 11,398 records). The process of fixing these addresses was time-consuming, with one of the more common problems being the blanket assignment of 'Los Angeles' as the city of record in a county that includes 88 cities. After corrections between the two datasets, a total of 13,669 of 15,067 records were successfully located to a street address (see Figure 1).

Most of the NFIRS data that was left unmatched came from the Los Angeles Fire Department (LAFD) and Los Angeles County Fire Department (LACoFD). This is unsurprising given the sheer volume of responses by these two entities; together, they account for 78 per cent of responses in the study time period. The LAFD was responsible (primary responder) for 41 per cent of events, whereas the LACoFD was responsible for 37 per cent of events. The next highest responses were the Long Beach Fire Department (eight per cent) and then the Glendale Fire Department (two per cent). On average, the LAFD and the LACoFD handled, respectively, 910 and 809 fires per year as primary responders.

Over the time frame queried, a total of 30 fire departments in Los Angeles County reported to the NFIRS. The largest number of departments reporting in a single year was 27 in 2008, whereas the fewest was 22 in 2011. There are 88 cities in the county, all of which either have their own fire department or have a partner agreement with

Figure 1. Geocoded NFIRS and CAS data for the County of Los Angeles



(a) NFIRS—residential fires

(b) CAS—Red Cross aid

Source: authors.

a nearby department (in most cases, the LACoFD). The total number of departments that can report to the NFIRS in the county is 55, although only 36 belong to a city or the county; the remaining 19 are fire departments for private organisations, such as aerospace companies, state recreation areas, and universities.

L, M, and H counts

After summing the number of households, fires, and aid events that fell into the L, M, and H classes for each variable, the same general trend was observed for every demographic indicator chosen: the majority of the county's households, even if slight, were in the block groups that were classed as having lower vulnerability according to that indicator (see Table 3). At the same time, the majority of both fire responses and Red

Table 3. A sample of representative variables with sums of population, households, response events, and aid for each H, M, and L class*

Variable	Class	Total population	Total households	Expected fire department responses	Actual fire department responses	Expected Red Cross aid	Actual Red Cross aid
Median age	H	2,922,938 (30%)	1,116,243 (34%)	3,873 (34%)	3,175 (28%)	620 (28%)	350 (16%)
	M	3,185,941 (32%)	1,136,401 (35%)	3,943 (35%)	3,604 (32%)	704 (32%)	623 (28%)
	L	3,795,462 (38%)	1,014,474 (31%)	3,520 (31%)	4,558 (40%)	890 (40%)	1,241 (56%)
Median household income	H	3,053,537 (31%)	1,116,800 (34%)	3,875 (34%)	3,029 (27%)	592 (27%)	259 (12%)
	M	3,332,468 (34%)	1,082,198 (33%)	3,755 (33%)	3,818 (34%)	746 (34%)	816 (37%)
	L	3,518,336 (36%)	1,068,120 (33%)	3,706 (33%)	4,490 (40%)	870 (40%)	1,139 (51%)
Percentage minority population	H	3,442,874 (35%)	915,398 (28%)	3,176 (28%)	4,316 (38%)	843 (38%)	1,226 (55%)
	M	3,452,837 (35%)	1,111,583 (34%)	3,857 (34%)	3,696 (33%)	722 (33%)	714 (32%)
	L	3,008,630 (30%)	1,240,137 (38%)	4,303 (38%)	3,325 (29%)	649 (29%)	274 (12%)
Total		**9,904,341**	**3,267,118**	**11,337**	**11,337**	**2,214**	**2,214**

Notes: * Expected fire department responses and Red Cross aid are calculated using the relative frequencies of total households and actual fire department responses, respectively. The expected fire department responses column and the expected Red Cross aid/median household income cell do not equal exactly the totals owing to the significant digits in the proportions used.

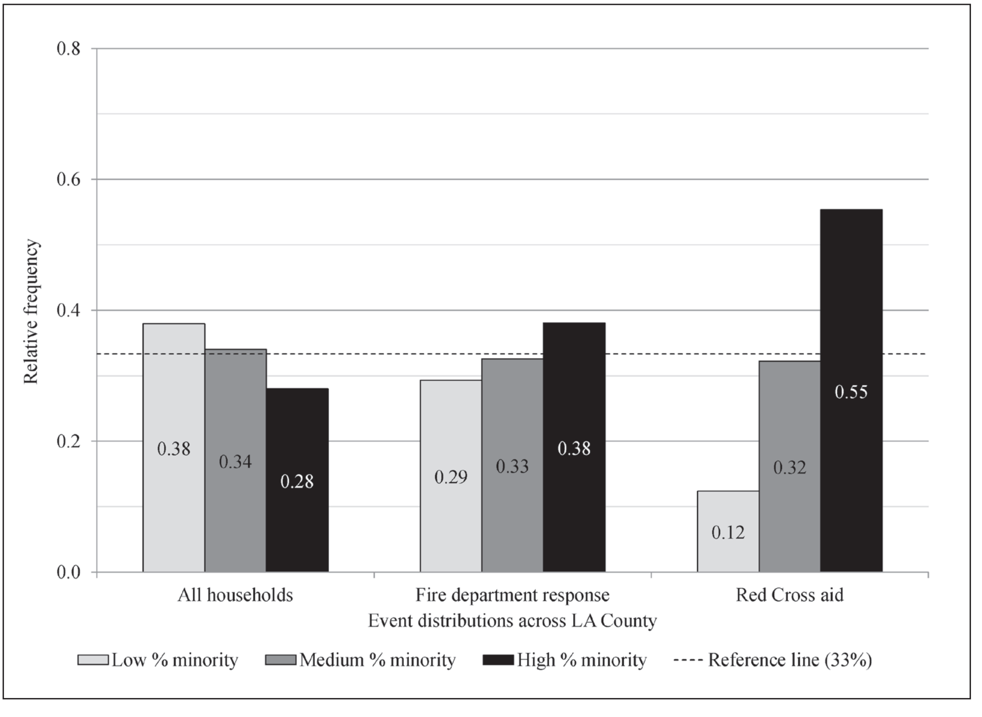
Source: authors.

Cross aid events occurred in the block groups with higher vulnerability as represented by each indicator. In the case of the 'median household income' variable, for instance, a small difference is seen in the counts for the classes, with 34 per cent in H, 33 per cent in M, and 33 per cent in L. When dividing the block groups into these three classes for this variable, 27 per cent of fires occurred in H, 34 per cent of fires occurred in M, and 40 per cent of fires occurred in L.

The relative frequency of households in the different classes for any variable sometimes demonstrated no trend from L to H. For instance, 31 per cent of households in the county fell in L census block groups for median age (less than 32 years old), 35 per cent fell in M block groups for median age (less than 39 years old), and 34 per cent fell in H block groups for median age (more than 39 years old); no definitive trend is seen here, as there is no large or small percentage of households for any class. However, for the variable 'percentage minority', the majority of block groups were classified as L, but the majority of fire department responses and Red Cross aid occurred in H block groups.

For nearly all fire department responses, the trend in the distribution of events was usually consistent with what might be expected of vulnerability indicators; more vulnerable populations experienced more fires. The only exception was linguistically-isolated households, which showed no clear trend. For Red Cross aid events, the trend

Figure 2. Relative frequencies of events, households, responses, and aid distributions by percentage of minority tertiles



Source: authors.

was always consistent with the expectation for socially-vulnerable households. In all cases, the Red Cross aid events demonstrated a stronger trend (that is, larger absolute value of slope in the regression) than that obtained for the fire responses. Minority population, for example, was a variable where more households in general were found in block groups with a smaller percentage of racial minorities, but households that suffered fire events and that received Red Cross aid were both situated in block groups with a greater percentage of minorities (see Figure 2).

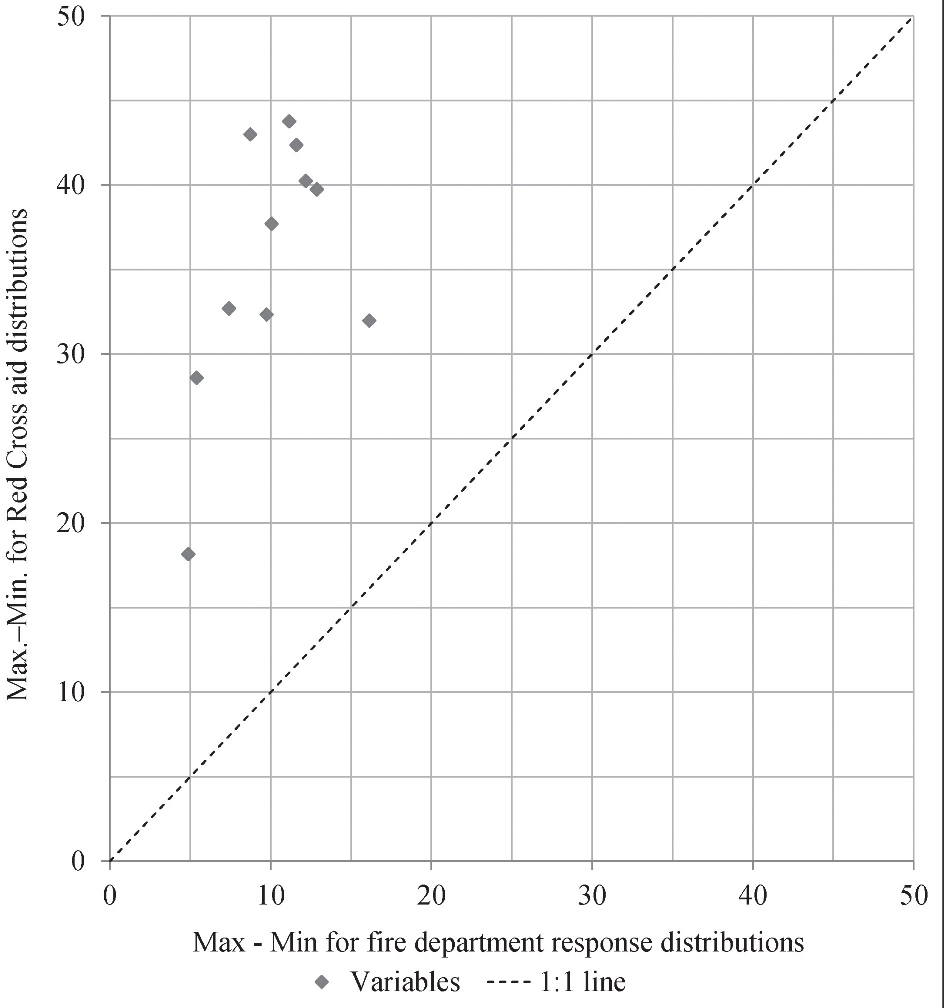
Comparing the CAS and the NFIRS

The similarities of the relative frequencies for the fire department response and Red Cross aid (examples of which are shown in Table 3) were also examined to determine if one dataset demonstrated stronger correlations with social vulnerability indicators than the other. This was generally measured by taking the smallest class percentage and subtracting it from the largest class percentage for each variable and using this 'Max.–Min.' value as an indicator of similarity. For instance, when looking at the fire data and average household size, 37 per cent of fires occurred in H block groups and 31 per cent occurred in L block groups, resulting in a Max.–Min. value of six percentage points. For the Red Cross data, 49 per cent of aid occurred in H block groups and 20 per cent occurred in L block groups, resulting in a Max.–Min. value of 29 percentage points. The Red Cross dataset always had a higher Max.–Min. value than the fire dataset (see Figure 3). Consequently, the trend towards expected distributions respective of social vulnerability indicators was stronger for Red Cross aid cases than for fire response events for each variable.

To determine whether or not there was a statistically significant difference between the Red Cross and fire datasets results, chi-squared tests were performed on the counts of fire and aid events using the L, M, and H classes. The p-value for each test for each demographic indicator was less than 0.01, indicating significant differences between the expected and actual datasets. In other words, the actual count of the NFIRS data as distributed in each variable was different from the expected count; the same was true for the CAS data.

Expected values were calculated by taking the proportions of households in each of the L, M, and H classes and multiplying by the total number of data points. For instance, 500 fires may have occurred in L block groups for per capita income out of a total of 1,000 fires. Yet, if only 29 per cent of Los Angeles County households are positioned in L block groups, the expected count of fires in those block groups would be 290 out of the 1,000 total. Using this method for determining expected values, fire events and Red Cross aid events were found to have a significantly different distribution than expected based on classifications by social vulnerability indicators. Furthermore, Red Cross aid events were found to have significantly different distributions than what would be expected if fire events were completely independent of these indicators. For this determination, the expected values of Red Cross aid were calculated using proportions provided by the distributions of fire events.

Figure 3. Max.–Min. values for Red Cross aid distributions versus fire department response distributions*



Notes: * The gap between the largest class percentage and the smallest class percentage was calculated for each variable as a measure of the evenness of the variables' relative frequencies. These Max.–Min. values were calculated for both fire responses and Red Cross aid and plotted against each other.

Source: authors.

The difference in L, M, and H distributions between the expected and actual results demonstrates the positive correlation between these demographic indicators and fire/aid occurrence. Fires and aid provision are both tilted towards the socially vulnerable, with aid being more strongly tilted than fires. These results lend support to the strategy of preparing for disasters based on certain indicators; a disproportionate risk should be addressed by a disproportionate response.

Discussion and conclusions

The distributions of these datasets when organised by demographic variables indicated that fire events in Los Angeles County were more likely to have occurred in block groups that demonstrate elements of greater social vulnerability. Specifically, indicators of age, race, and wealth were examined and found to be associated with a higher incidence rate for fires. Moreover, these demographic characteristics are even more strongly related to populations that will receive aid from the American Red Cross following a fire.

The results surrounding the Red Cross dataset are not as surprising as they are reaffirming; aid is supplied based on need, and need is related to capacity for recovery. The results pertaining to the NFIRS dataset, though, may suggest that socially-vulnerable populations face a higher risk of fire in an urban area. This makes sense as such populations may live in older buildings where fire potential is greater. While the NFIRS database allows for the recording of information such as ignition source or effectiveness of smoke alarms, these fields are sparsely populated. Further study of the reasons for this skewed distribution of fire occurrences may be aided by information on building age and quality. In addition, important indicators of vulnerability such as disability status and household structure were not considered as variables in this study. A more comprehensive collection of vulnerability indicators can be used with the NFIRS and Red Cross data to determine their relations with fire occurrence and the need for aid.

These individual demographic indicators certainly do not explain vulnerability comprehensively. Factors such as wealth, although important, cannot eliminate vulnerability on their own, as certain types of resources may be inaccessible during or following a disaster (Adger and Kelly, 1999). Furthermore, wealthy individuals who lack traditional knowledge of disaster preparedness and response potentially can be more affected by a catastrophic event than less wealthy individuals who possess it (Eriksen and O'Brien, 2007). Regardless of these possibilities, the indicators utilised in this study can be used for exploratory analysis or rapid planning and response in the absence of robust models of vulnerability. Existing models, while more comprehensive (see, for example, Cutter, Boruff, and Shirley, 2003; Rygel, O'Sullivan, and Yarnal, 2006; Flanagan et al., 2011), can certainly take days or even weeks to produce if datasets, software, or technical expertise is lacking.

The adoption of digital information infrastructures, such as the NFIRS, has streamlined data reporting, and the programme's long history makes for a relatively comprehensive collection of records. What is more, recent open data initiatives have increased accessibility and enabled the general public to make visualisations and maps out of bulk tabular exports. Such data sources give humanitarian aid workers and volunteers an opportunity to create timely information-driven solutions to immediate disaster needs (Miller, 2006; Troy et al., 2008; Liu and Palen, 2010). Yet, a problem still exists with regard to the quality of that information. Much of the data processing involved in this study was devoted to 'clean up' and data sanitisation.

Thus, even in well-established databases such as the NFIRS, there can be a need to improve the format in which data is distributed and the ease of data querying. The sanitisation employed in this study can help to guide future researchers interested in NFIRS data, and could be used to produce streamlined workflows to access commonly requested data.

Regardless of the progress left to be made in preparing the quality of these datasets, the American Red Cross can use such existing information to plan better places to prepare. Many groups have been found to be affected by fires, so diverse tactics for planning and preparedness have already been recommended (DiGuiseppi et al., 2000). However, the affirmation that social vulnerability indicators have been shown quantitatively to correlate with actual fire and aid events helps to justify targeted outreach initiatives. General reporting of such information can also aid members of the public in understanding how they can be affected by a disaster and how people similar to them have been impacted in the past.

Acknowledgements

The authors would like to thank those people at the American Red Cross who helped in providing information on the CAS: Corey Eide, Stephanie Landess, Greg Tune, Scott Underwood, and Lauren Vail. Additional thanks go to Kirsti Fong at California Department of Forestry and Fire Protection (CAL FIRE) and Benjamin Steers at the Santa Monica Fire Department for assisting with the NFIRS data.

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Endnotes

[1] See https://www.nfirs.fema.gov/ (last accessed on 9 March 2016).

[2] See http://www.esri.com/software/businessanalyst (last accessed on 10 March 2016).

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