Abstract This paper outlines a statistical analysis of United States fire department response times to fires in 1-2 family residential dwellings between the years 2002-2017. Using data from the National Fire Incident Reporting System (NFIRS), it is shown that a log-normal distribution provides a reasonable approximation of the empirical distribution of response times. Furthermore, this paper investigates the effect of increasing respoonse times on several different measures of fire severity, including the reported fire spread category, the estimated monetary property and contents losses, and the reported flame damage. It was found that all averaged measures of fire severity increase over the interval of 3-13 minutes of response time, which is primarily due to the increased likelihood of very severe fire incidents at longer response times. An analysis was conducted to assess the effect of NFPA 1710 compliance on the severity of fire outcomes in a community. It was found that department response times were most strongly correlated with the fraction of fires that do "extreme" damage to at least one story and the fraction of the property value lost. It has been proposed that a power law distribution is appropriate for modeling the distribution the burned areas in urban fires. In order to assess whether this proposition is supported by United States data, a Monte-Carlo methodology has been developed to estimate the burned area indirectly from NFIRS data. Finally, several methods are presented for evaluting data consistiency and quality from the NFIRS reports.

1 Introduction

Quantifying the performance of fire departments is necessary for several reasons. First of all, a meaningful ranking of fire departments could identify the departments with the best practices that could serve as models for other departments. Also, comprehensive performance measures coupled with appropriate standards can help departments identify and correct performance deficienies, which would make them more effective at minimizing property damage, deaths, and injuries. Furthermore, trends in performance over time could provide insight into the effect of changing practices and staffing.

According to the National Fire Protection Agency (NFPA) [1], A proper performance evalutation requires the comparison of achieved outcomes compared to desired outcomes. For a fire department, the desired outcome is the maximum preservation of property and human life; however quantifying this preservation is difficult for several reasons. First of all, determining the amount of property or human life preserved during a fire incident would require knowing the amount of property damage and loss of life for the same fire had there been no fire department intervention, which is obviously impossible. Furthermore, even if this information were somehow available, it is not clear how performance would be evaluated. One might think that a suitable performance metric would then be the monetary difference in property damage between the hypothetical fire that would have occured with no fire department intervention and the actual fire that occured. However, an important attribute of any performance metric is that it should encourage equitable coverage in the protected community, and a simple evaluation of monetary property damage prevented could reward departments that prioritize protecting the properties of highest value, which is problematic.

A workaround to the aforementioned issues is the use of time to evaluate the efficacy of fire department intervention. This is the standard practice in the United States, and NFPA 1710 [2] and NFPA 1221 [3] provide performance objectives in terms of times to complete various tasks required for fire suppression. The assumption is that minimizing the time a fire is active also minimizes its ability to grow and inflict damage to the property. However, the relationship between fire department intervention times and fire damage is not well understood, especially for fire incidents in the United States. Särdqvist et al [4] conducted a study of 307 non-residential fires in London, and concluded that the time from igntion to fire department intervention is not correlated with fire area, unless the fire is still spreading when the fire department arrives. A study conducted by Holborn et al [5] uses response time data from the London Fire Brigade to estimate fire growth rates, and their findings illustrate the multitude of factors that can influence fire growth, including fuel load layouts, type of first ignited, intensity of heat source among others. The uncertainty associated with many of the factors that influence the growth of a fire highlights the need to describe fire outcomes probabalistically. Instead of correlating fire area with response time as previous studies had done, Challands [6] examines the fraction of fires that are reported as "large" (flame damage exceeding 30 m^2) as a function of response time based on New Zealand fire incidents. This approach reveals a clearer relationship, indicating that delays in response time should be thought of as increasing the probability of a severe fire, rather than increasing fire size in a deterministic sense. Lu et al [7] analyzed fire incidents from Japan and China and concluded that fire area for a given response time follows a power-law distribution, whose parameters are correlated with response time. However, no similar analyses have been conduted for U.S. fire reports despite the large amount of data provided in the National Fire Incident Reporting System (NFIRS).

The analyses presented in this paper examine the relationship between response time and fire severity for residential fire incidents in the United States. In addition to providing insight into the merit of time-based performance metrics, understanding this relationship could aid fire department decision makers who must allocate resources in a manner that effectively serves their community. For example, a community-scale analysis that accounts for the relationship between response time and fire severity could identify ideal locations for fire stations. Furthermore, an understanding this relationship offers a means to validate models that describe the growth of structure fires as a function of time.

2 Methodolgy

All analyses presented in this paper are based on incident reports available in the National Fire Incident Reporting System (NFIRS). NFIRS provides three relevant timestamps that give insight into promptness of response: the time at which the alarm is received by the department (alarm time), the time at which the first unit arrived on scene (arrival time), and the time at which it was determined that the fire would not grown beyond its containment perimeter (incident controlled). Though other reporting systems, such as the National Fire Operations Reporting System, take advantage of computer automated reporting, the NFIRS data is subject to the limitations of manual entry. The timeline of the events associated with a fire incidents are shown in Figure 1.

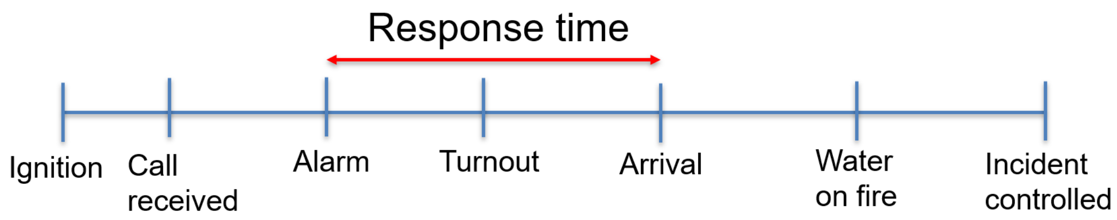


Fig. 1 A timeline summarizing the major events assoicated with a fire incident.

Given that the focus on this paper is on determining the effect of the response of the fire departments on the severity of the associated fires, it is important to choose parameters and queries that minimize the influence of noise factors, i.e. factors that influence fire severity that are outside the control of a fire department. First of all, a parameter must be chosen that adequately quantifies the promptness of the fire department. Given the parameters reported in NFIRS, one may think that the best parameter to use would be the time from "alarm" to "incident controlled." However, the time at which the incident was deemed to be under control is a subjective metric and the use of this parameter to demonstrate the effect of fire department response could result in the wrong direction of causality. For example, a fire that is large due to extraneous factors, such as fuel load density or ventilation conditions, could take longer to contain, regardless of the performance of the fire department. Instead, this paper uses response time to quantify the promptness of the fire department response because it is far more likely that the resulting correlations would incidate meaningful causality; in other words, it is far more likely that longer response times cause more severe fires than it is that the larger fires cause the department to take longer to arrive on scene. As a result, any effect associated with delays in response time give insight into the effect of the department's response on the fire, even though this time does not capture the entire fire timeline shown in Figure 1.

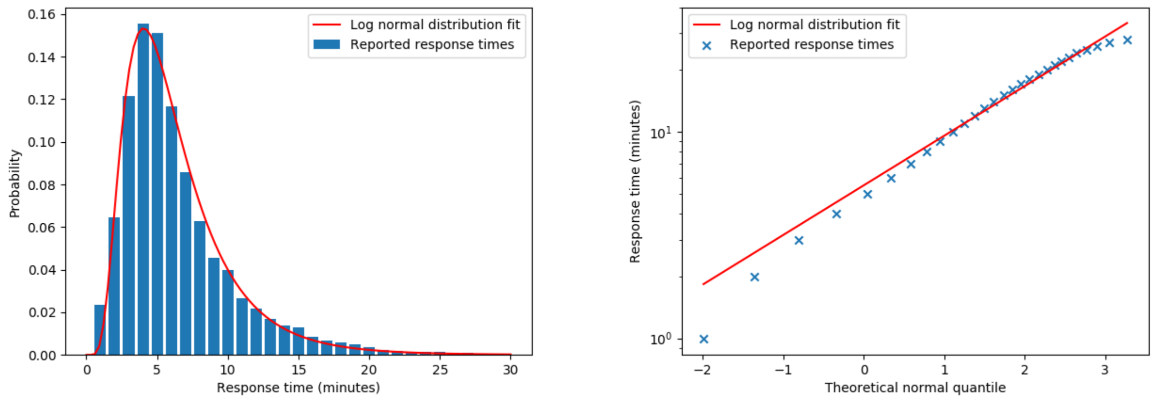
The analyses described in this paper are limited to incident reports from 1-2 family residential fires occuring between 2002 and 2017. In order to ensure that the incidents required fire department intervention, only incidents that have "extinguishment by fire service personel" as a reported action are considered. Also, incidents with a reported automatic extinguishing system are excluded for similar reasons. Finally, because some incidents are reported multiple times when one department offers aid to another department, any incident that is reported as offering aid to another department is exluded.

3 Distribution of response times

Before investigating the effect of response time on fire severity, it is worth discussing the distribution of response times based on the NFIRS incidents. Chen et al. [8] that the arrival time distribution for fire incidents in Japanese fire data resembles a log-normal distribution. This finding could be useful for Monte-Carlo simulations that require response time as an input because it would allow for the use of draws from a well defined distribution. The empirical distribution of relevant response times is shown in the normalized histogram in Figure 2(a).

In order to determine whether the United States distribution of response times is well modeled by a log-normal distribution, least squares optimization was performed to determine the two parameters of a log-normal distribution which produce the best fit to the histogram of response times. This optimization is based on the fact that the width of the bins of the historgram is one, which means that the value of the probability distribution function at a given response time is approximately equal to the integral of the function over an interval of width one.

A quantile-quantile (Q-Q) plot was also generated (Figure 2(b)) to examine how well the empirical distribution adheres to a log-normal distribution. This is done by calculating the fraction of incidents that are at or below a given response time (cumulative probability), and then determining the corresponding value from a standard normal distribution. For example, if 2.5% of indicents were at or below a response time t, the theoretical normal value would be -1.96. When plotting the actual response time against the theoretical normal value on a log-scale, a high level of linearity indicates adherence to a log-normal distribution.



(a) Normalized histogram

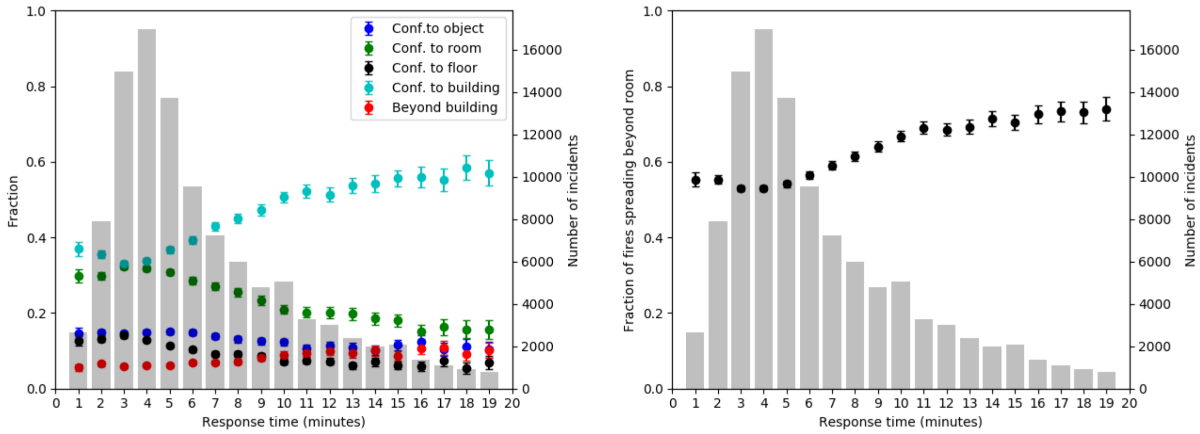
(b) Quantile-quantile plot

Fig. 2 a) The normalized historgram of response times for fire incidents involving 1-2 family residential dwellings. The red curve indicates the log-normal distribution with the best fit with $\mu = 1.7$ ln(minutes) and $\sigma = 0.54$ ln(minutes) with $R^2 = 0.988$. b) The quantile-quantile plot with a semi-log scale to indicate how well the distribution adheres to a log-normal distribution. It is important to note that the error in the fit line is visually exaggerated at small times due to the logarithmic nature of the y-axis.

The large R^2 value (0.988) of the log-normal distribution fit indicates that the empirical distribution of response times is well modeled by a log-normal distribution. Although the Q-Q plot appears fairly linear for response times of less than 15 minutes, curvature becomes apparent at large response times. This indicates that a log-normal distribution would have a heavier tail than the emprical distribution, meaning that the use of a log-normal distribution to approximate the distribution of response times would overestimate the frequency of extremely long response times. One potential method to mitigate this shortcoming is to truncate the distribution at a sufficiently large response time, such as 20 minutes.

4 Fire spread

One that is commonly used to characterize the size of the fire is the "fire spread" entry, which bins fires into one of five categories- 1. confined to object of origin, 2. confined to room of origin, 3. confined to floor of origin, 4. confined to building of origin, and 5. spread beyond building of origin. It seems reasonable to assume that the larger spread categories are reflective of larger fires, but there are several sources of error. First of all, this categoriziation is heavily dependent on quantities that are not known such as the room and building sizes. For example, a large fire could be considered "confined to room" if it occurs in a very large or open room. Also, for small buildings such as sheds that consist of only one room, it is ambiguous whether a fire should be classified as confined to building or confined to room. To mitigigate this source of error, the analysis described here is limited to incidents that reported a main floor area that falls between 10 and 450 m^2. Furthermore, a fire does not necessisarily evolve sequentially through the fire spread categories, especially if it starts on the exterior of the structure, in which case it could easily become classified as spreading beyond the struture of origin without ever being considered "confined to floor of origin." Perhaps the most meaningful binning of these data is to consider fires that spread beyond the room of origin (categories 3, 4, and 5) versus those that do not spread beyond the room of origin (categories 1 and 2). The assumption is that most fires that spread beyond the room of origin flashover that room, so those fires are more severe.



(a) All spread categories

(b) Fraction that spread beyond room

Fig. 3 a) The fraction of incidents reported as each fire spread category as a function of response time and b) the fraction of incidents that spread beyond room as a function of response time. Also shown is the number of incidents for each response time evaluated. In total, 110,255 incidents were used for this analysis.

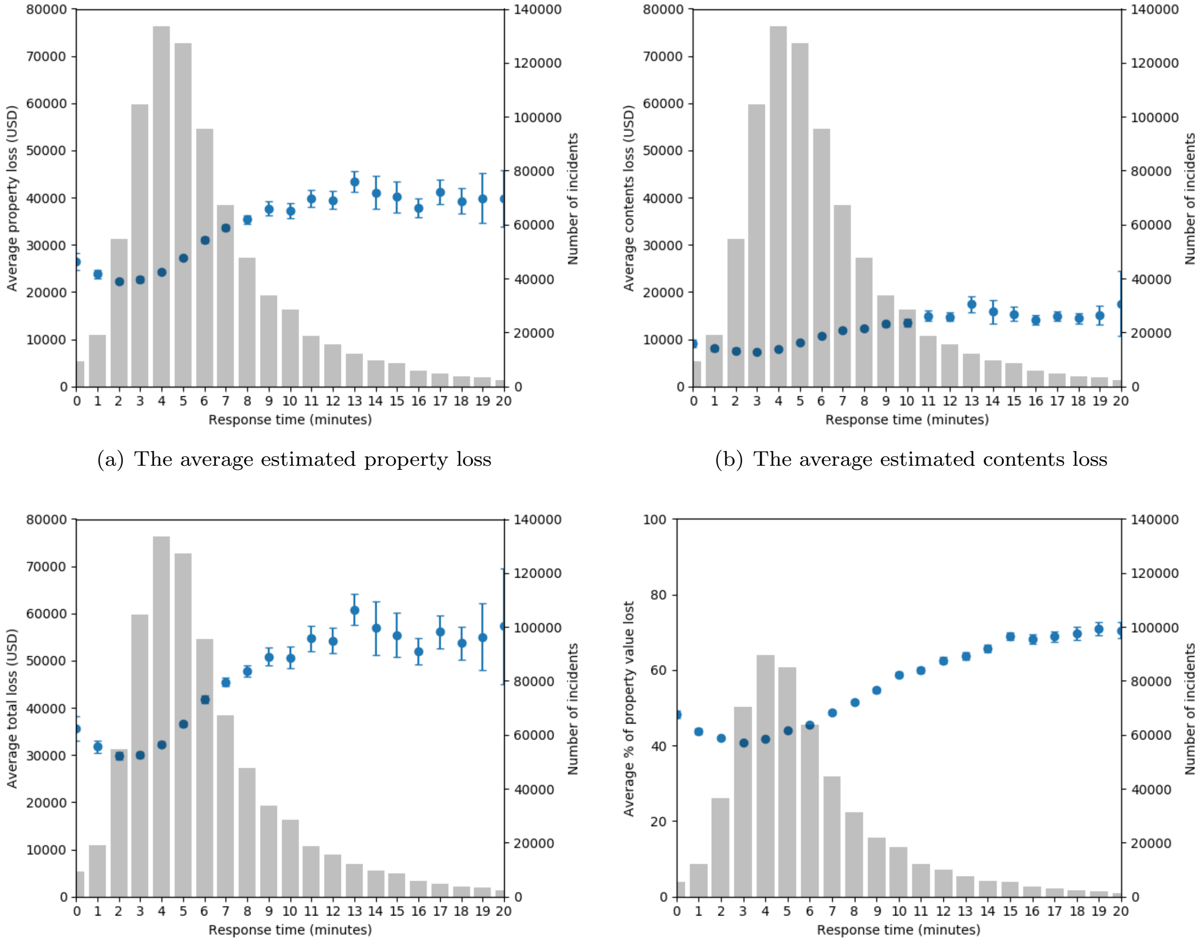
Figure 3(b) shows that the fraction of fires that spread beyond the room of origin increases with increasing response time over the interval 4-11 minutes from about 53% to about 70%. Figure 3(a) shows that this trend is due to the fact that fewer fires are classifed as “confined to room” and more fires are classified as “confined to building” over this interval. Interestingly, the fraction of other spread categories is relatively constant across all response times. There is only a slight increase in the fraction of fires that are classified as “spread beyond building”, indicating that the primary risk associated with delays in response time is to the structure of origin rather than structures near it.

5 Estimated monetary loss

Another metric available in NFIRS is the estimated property loss and contents loss caused by the fire, smoke, water, and overhaul. These figures are rough estimates based on the amount of damage that occured and the construction cost of the building [9]. The estimate of the total losses can also be calculated by summing the property and contents loss estimates for a given fire incident. It is also important to note that these values do not necessarily indicate the size of the fire; a large fire in a low-value property can cause less monetary loss than a smaller fire in a high-value property. In light of this limitation, a fractional loss metric has also been calculated for incidents that also report a property value which is calculated by dividing the reported property loss by the reported property value. The property value is not reported for all incidents; as a result, the percentage of property value lost can be evaluated for fewer incidents than Figure 4 shows the average property loss, contents loss, total loss, and the fractional property loss as a function of response time.

Figures 4 shows that the averaged measures of monetary loss increase over the interval of 3-13 minutes of response time. Monetary damage appears to decrease from 0-2 minutes, though it is not clear why. Perhaps incidents that are listed with response times of 1 or 2 minutes are not accurately reported. For response times greater than 13 minutes, the uncertainity on the average losses becomes quite large, but it appears that the average monetary losses are approximately constant for very large response times.

It is important to note that the metrics plotted in Figure 4 are averaged across many incidents and that enormous scatter exists between incidents that have the same response time due to a multitude of other factors including the source of the fire, the ventilation conditions, the fuel load density, among many others. In reality, there is a distribution of monetary losses for each response time and it is informative to understand how these distribution evolve with increasing response times. In order to visualize how the distribution of total losses evolves with increasing response times, cumulative probability density plots were generated for the total losses at various response times are shown in Figure 5.



(a) The average estimated property loss

(b) The average estimated contents loss

(c) The average estimated total loss

(d) The average estimated fraction of property value lost

Fig. 4 The average property loss (a), contents loss (b), total loss (c), and fractional loss (d) plotted against response time. Also provided are the number of incidents (right axes) that were considered for generating the average at each minute of response time. Only 1-2 family residential fire incidents were considered and the incidents were filtered according to the criteria described in the "Methods" section of this paper. 816,744 total incidents were used to generate (a)-(c) and 538,001 were used to generate (d).

Figure 5 shows that the distributions are very similar for the lowest 40% of total losses for each response time. Even the medians of the distributions (the 50th percentile) are not more than \$6,000 apart. The most apparent differences occur at the upper tails of the distributions; for example, the 90th percentile of total losses for fires with response times of 3 minutes is \$75,000 compared to \$147,300 for fires with response times of 12 minutes. The vertical distance between 1.0 and the cumulative probability at a loss amount indicates the probability of an incident exceeding that loss amount. For example, there is about a 16% chance of a fire with a 3 minute response time exeeding \$50,000 of loss, but about a 28% chance for fires with 12 minute response times. This finding demonstrates that the effect of short response times is only apparent when the damage threshold is sufficiently high. For example, the probablity of a fire causing more than \$5,000 of losses is roughly uniform across all response times, but the probabilty of a fire exceeding $50,000$ of losses varies significantly.

6 Story damage

Another parameter reported in NFIRS is the number of stories that were damaged by flame, which is shown in 6.

For structures with multiple stories, there are many possibly entries for the reported stories damaged. In order to understand the reporting trends, a simple analysis was conducted of residences with only one story in total and that story recieved some classification of damage per Figure 6. The fraction of each damage classification is shown as a function of response time in Figure 7.

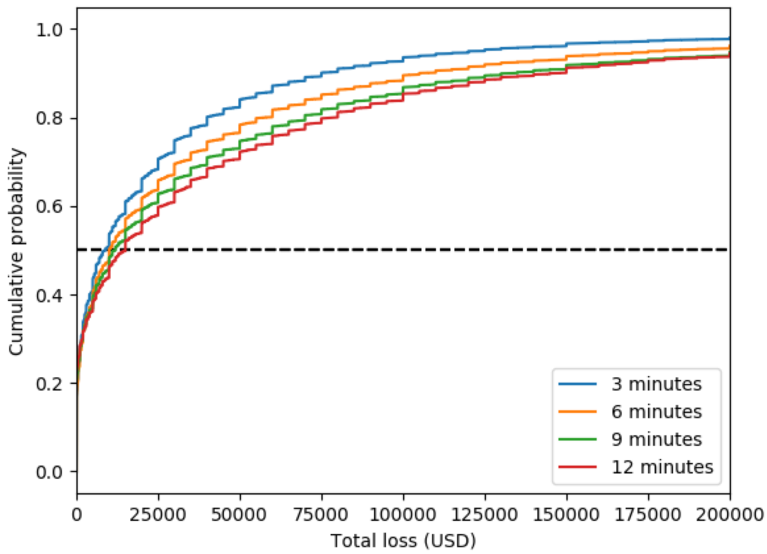
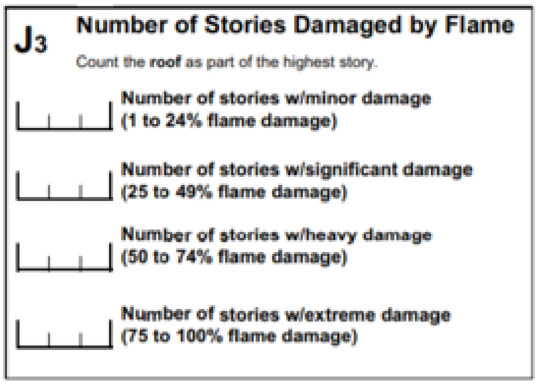


Fig. 5 The cumulative probability distributions of total losses for response times of 3 minutes (blue), 6 minutes (orange), 9 minutes (green), and 12 minutes (red). The dashed black line represents the median loss of the response times shown.



J3 **Number of Stories Damaged by Flame**

Count the **roof** as part of the highest story.

Number of stories w/minor damage (1 to 24% flame damage)

Number of stories w/significant damage (25 to 49% flame damage)

Number of stories w/heavy damage (50 to 74% flame damage)

Number of stories w/extreme damage (75 to 100% flame damage)

Fig. 6 The NFIRS field that provides the number of stories recieving each bin of damage as it appears to department personel.

The general trend of Figure 7 is that over the interval of 4-14 minutes of response time, there is an increasing fraction of incidents classified as "extreme" damage, while the fractions associated with all other damage classifications decreases, most notably among incidents classified as "minimal" damage. These results support the conclusion that the primary consequence of delays in response time is an increase in risk of very severe fire incidents.

7 Estimating burned area

7.1 Method

In many cases, the fire damage is quantified by the amount of floor area that received flame damage. Knowing the distribution of flame areas for the population of United States fires is useful because it allows for comparison to these other datasets and also, it is a common output for models that predict fire evolution. Although this parameter is reported directly in some countries such as Japan and China [7], it is not reported directly in the NFIRS dataset and no estimate of this distribution has been carried out for the United States. However, it is possible to generate an estimate of this distribution through the use of the reported storys damaged.

Recall the story damage field reported in NFIRS (shown in Figure 6). Every story that receives flame damage is placed into one of four bins- minimal damage (0-24% burned area), signficant damage (25-49%

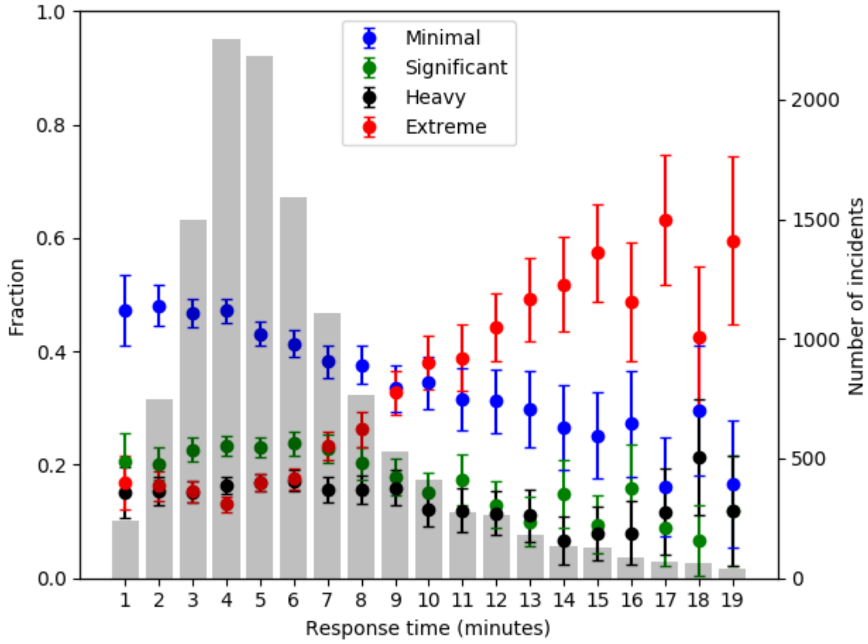


Fig. 7 The fraction of each damage classification for one story residences whose only story recieved some classification of damage whose floor area was reported as between 10 and 450 m^2. In 12,893 incidents were analyzed.

burned area), heavy damage (50-74% burned area), extreme damage (75-100% burned area). Also the area of the main floor is either reported directly or it can be easily calculated from its reported length and width. If one assumes that every story has the same area as the main floor, then the burned area for each story can be bounded based on the aforementioned damage bins.

As a simple example, one could imagine that for a specific fire incident, it is reported that there was one story recieving heavy damage and the main floor area is 100 m^2. It is not known which story recieved damage, but if one assumes that it has the same area as the main floor, then it received at least 50 m^2 of damage (50% of 100 m^2) and at most 74 m^2 of damage (74 % of 100 m^2). The actual amount of flame damaged this story recieved could fall anywhere in this interval, and without any additional information, any area in this interval is equally likely. Therefore, the best representation of the actual burned area for that story is a uniform probability distrubion from 50 to 74 m^2. If this is the only story that was reported as damaged, then this distribution also represents the distribution of possible values for the total burned area of the incident.

If the incident has more than one reported story receiving damage, then the estimation of the incident's burned area becomes more complicated. As an example, one could imagine a fire incident with one story reported as receiving significant damage (story A), one story receiving heavy damage (story B), and a reported main floor area of 100 m^2. This means that story A recieved between 25 and 49 m^2 of damage and story B received between 50 and 74 m^2 of damage, which allows for the generation of two uniform distributions, namely one for the uncertainity of the burned area of each story. The total burned area for the incident is by definition the sum of the burned areas for all stories damaged; therefore generating the distribution that captures the uncertainty of the total burned area requires the convolution of the uniform distributions that describe the uncertainties on the burned areas of each story.

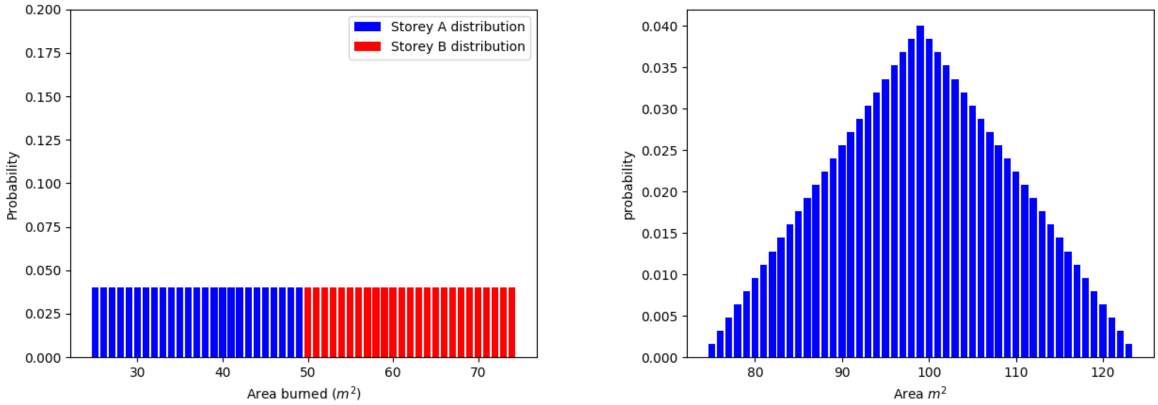
Let A_A and A_B represent the burned area of story A and story B such that $p_A(A_A)$ and $p_B(A_B)$ represent the probability that story A received A_A amount of damage and the probability that story B received A_B amount of damage respectively. Also recall that $p_A(A_A)$ is a distribution ranging from $A_{A,min} = 25m^2$ to $A_{A,max} = 49m^2$ with uniform density of $d_A = \frac{1}{A_{A,max} - A_{A,min}}$ and similarly $p_B(A_B)$ is a distribution ranging from $A_{B,min} = 50m^2$ to $A_{B,max} = 74m^2$ with uniform density of $d_B = \frac{1}{A_{B,max} - A_{B,min}}$. If $A_{total} = A_A + A_B$, and A_A and A_B are independent, then $p_{total}(A_{total})$ can be obtained through the convolution of the distributions for the burned area of each story, shown in equation 1.

$$p_{total}(A_{total}) = \int_{-\infty}^{\infty} p_A(A_A) p_B(A_{total} - A_A) dA_A \tag{1}$$

The convolution of two uniform distributions has been described elsewhere [10] and results in a triangular distribution defined over the interval $(A_{A,min} + A_{B,min}, A_{A,max} + A_{B,max})$ shown in equation 2.

$$p_{total}(A_{total}) = \begin{cases} d_A d_B(A_{total} - A_{B,min} - A_{A,min}) & A_{total} \leq A_{A,max} + A_{B,min} \\ d_A d_B(A_{A,max} - A_{total} + A_{B,max}) & A_{total} > A_{A,max} + A_{B,min} \end{cases} \quad (2)$$

The uniform distributions for the damage done to each story in the example case is shown in 8(a), and the resulting distribution for the overall incident is shown in 8(b). Note that the distribution is discretized into intervals of 1 m^2 for ease of calculations.



(a) Distributions of burned area for the individual stories

(b) The distribution of burned area for the incident

Fig. 8 a) The uncertainty distributions for the burned areas of story A, which received “significant damage” and story B, which received “heavy damage” and b) the resulting uncertainity distribution for the burned area of the incident.

The aforementioned methodology was used on all incidents involving 1-2 family residential dwellings with one or two stories for the year 2014, shown in Figure 9. The incidents were filtered based on the same criteria described in the “Methodology” section.

7.2 Burned area as a power law

The distribution shown in Figure 9 shows the expected result that the burned area for most incidents is small, but there is a heavy tail to the right. As previously stated, Lu et al [7] concluded that the burned areas for incidents at fixed response times in Japan and the Jiangxi Province of China follow a power law distribution over the interval 1-100 m^2 whose governing equation is shown in equation 3

$$p(X = x_i|t_a) = a(t_a)x_i^{b(t_a)} \quad (3)$$

where t_a is the arrival (response time) of the fire department, x_i is a is a burned area, $p(X = x_i|t_a)$ is the probability that the actual burned area for an incidents, X, is equal to x_i at a given arrival time (t_a). $a(t_a)$ and $b(t_a)$ are the parameters of the power law fit. According to Lu et al, these parameters are functions of the arrival time.

To examine whether it is reasonable that the United States burned area distribution follows a power law, the distributions of burned areas for all incidents with a reported response time of 2 minutes and 7 minutes is shown on log-log axes in Figure 10. A power law distribution should appear linear on these axes, and the 7 minute response time fit lines from Lu et al are also shown.

An inspection of Figure 10 reveals that in the United States estimate of flame areas, the frequency decays much more slowly than the the data for Japan or China for burned areas that are less than $25m^2$. This is likely an artifact of using uniform distributions to represent the uncertainty due to the the binning of flame areas in the NFIRS reports. Many of the incidents that add weight to the small values for burned area are incidents with only one story recieving “minimal” damage. As previously stated, this means that the burned area for the incident was somewhere between 0-24% of a floor area, and a uniform distribution is assigned over this interval. In the example case of a floor area of 100 m^2, this corresponds to a uniform distribution between 0 and 24 m^2 of damage; however, if the true distribution is actually a power law, then smaller values in this interval are more likely than larger ones, and this effect is strongest for fires with one story receiving minimal damage because the power law distribution becomes flatter for larger burned

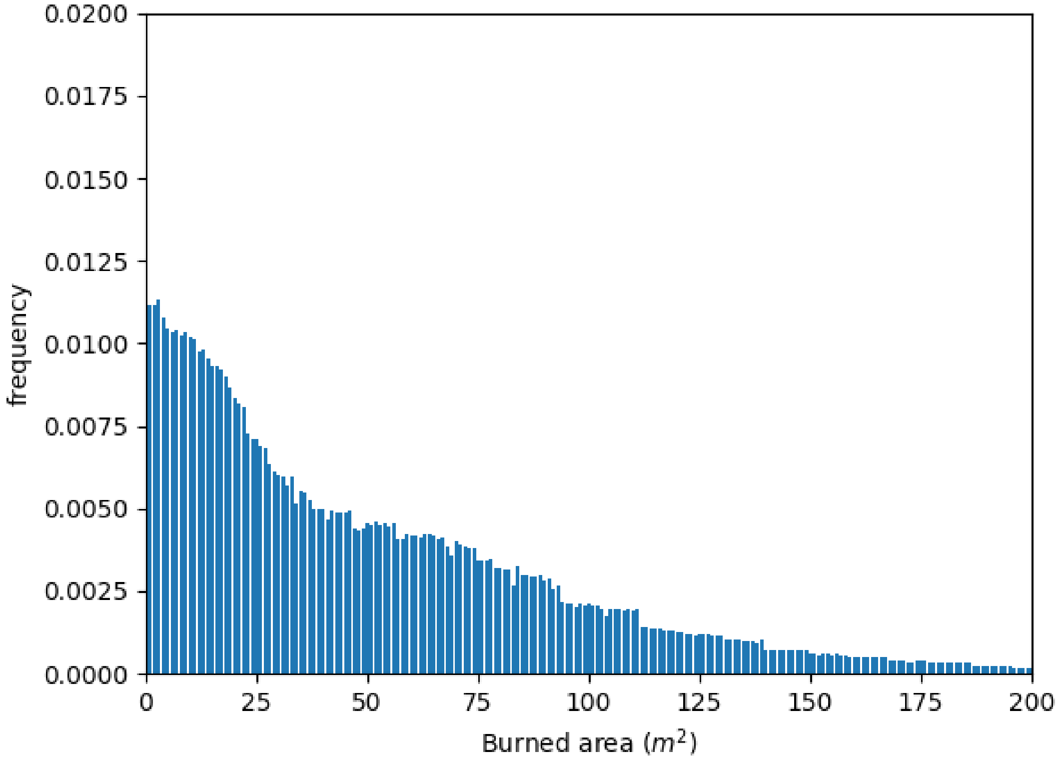


Fig. 9 The distribution of burned areas for all available 1-2 family dwellings with 1-2 stories with reported floor areas between 10 and 450 m^2. The distribution is the result of both incident to incident variance and also uncertainty that arises from the binning of burned areas

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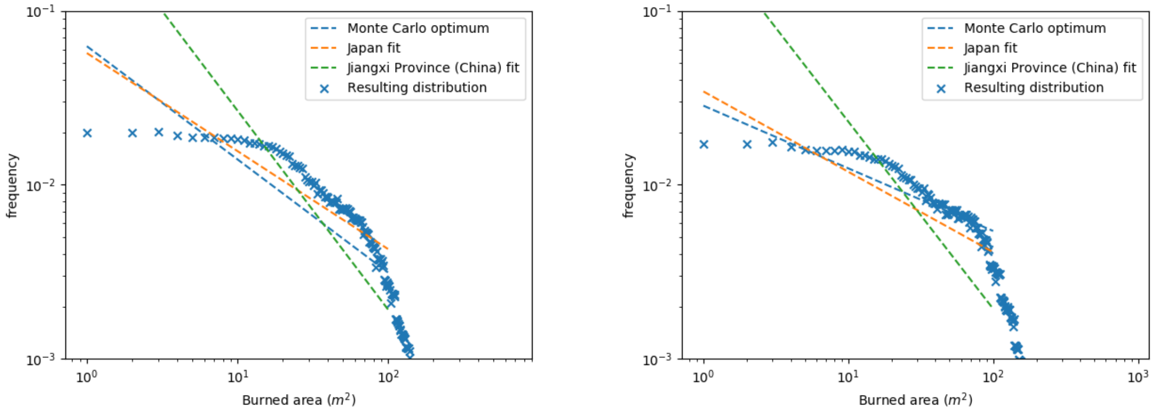
areas. In the example case, a burned area of 1 m^2 would be far more likely than a burned area of 24 m^2 given the report.

To mitigate this shortcoming, a Monte-Carlo method was developed to identify the power law distribution over the region 1-100 m^2 of burned area that is most consistient with the NFIRS reports. In order to do this, all relevant one-story fire incidents with one damaged story were queried from NFIRS. By limiting the query to one story incidents, all reports have either one story of minimal damage, one story of signficiant damage, one story of heavy damage, or one story of extreme damage with all other fields marked as zeros per Figure 6. For incidents with a response times of 2 minutes, 48% of the incidents were classified as minimal damage, 20% were classified as signficant damage, 15% were classified as heavy damage, and 16% were classified as extreme damage. For incidents with response times of 7 minutes, 38% were classified as minimal damage, 23% were classified as significant damage, 15% were classified as heavy damage, and 23% were classified as extreme damage. Then for both response times, the total relative frequency of incidents with burned areas exceeding 100 m^2 was calculated; for example, for incidents with a response time of 7 minutes, roughly 10% of the generated distribution's probablity mass is above 100 m^2. Therefore, the Monte-Carlo simulation should draw directly from the distribution in this region with probability of 0.1 to generate the burned area. In other cases, it draws from a power-law distribution with parameters A and B (see equation 3). Also, a floor area is randomly drawn from all relevant 1-2 family residential fire incidents in one story structures. It is important to note that the main floor area is the same as the total structure area because these structures only have one floor. The distribution of floor areas used in this draw is depicted by the histogram in Figure 11.

Once the Monte-Carlo simulation draws a burned area and a floor area, it calculates the fraction of the floor that was burned according to equation 4.

$$f = \frac{A_b}{A_f} \tag{4}$$

Then the binning of the simulated incident can be deteremined based on the categories shown in Figure 6. The steps of the Monte-Carlo simulation are summarized in the flow chart shown in Figure 12.



(a) 2 minute response time

(b) 7 minute response time

Fig. 10 The burned area distributions for 1-2 family resisidential fires with response times of 2 minutes (a) and 7 minutes (b). Also shown is the fit lines from the data from fire incidents in Japan and China for burned areas less than 100 m^2 as reported by Lu et al. [7]. The "Monte Carlo optimum" is the power law distrubution that gives the closest distribution of damage reports for one story buildings.

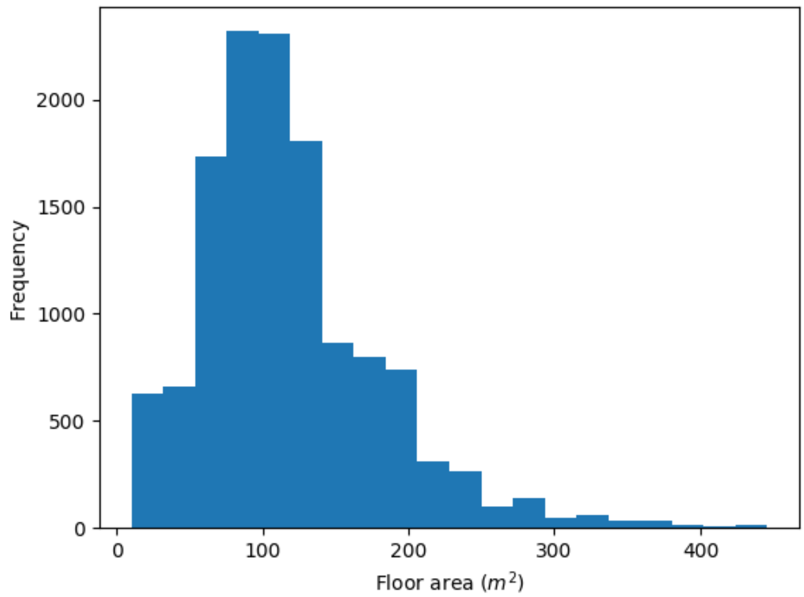


Fig. 11 A histogram of reported main floor areas for relevant incidents with reported response times of 7 minutes.

The Monte-Carlo simulation is then run for 20,000 iterations, which was verified to produce convergent results. The result is a set of fractions that indicates the fraction of fires that were classified as minimum, signficant, heavy, and extreme damage. The error associated with the result can be calculated according to equation 5,

$$error = \sqrt{(f_{sim,min} - f_{min})^2 + (f_{sim,sig} - f_{sig})^2 + (f_{hvy,min} - f_{hvy})^2 + (f_{sim,xtr} - f_{xtr})^2} \quad (5)$$

where $f_{sim,min}$, $f_{sim,sig}$, $f_{sim,hvy}$, $f_{sim,xtr}$ are the fractions of fires classified as minimal, significant, heavy, and significant damage by the Monte-Carlo simulation, respectively, and f_{min}, f_{sig}, f_{hvy}, f_{xtf} are the actual fractions of fires classified as minimal, significant, heavy, and extreme, respectively.

Then, the "optimal" power law distribution is determined as the one that minimized the error defined in equation 5. This is done by running the Monte Carlo simulation for every value of b between 0 and -1, with resolution 0.01 (e.g. -0.01, -0.02, etc.), and calculating a for each b such that the total probability bounded under the power law curve over the interval 1-100 m^2 is equal to the total probabliity over the same interval as determined by the aforementioned methodology of assigning uniform distributions to each reported story damaged. This optimization procedure is summarized in the flow chart below, Figure 13

The values of b that correspond to the lowest error are the power law fits are labeled as the “Monte-Carlo optimum” lines in Figure 10. The optimal power law paramers were found to be a=0.625 and b=-0.65 for response times with of 2 minutes 6.3% error and a=0.0285 and b=-0.36 with 2.6% error for response times of 7 minutes. It is important to note that the Monte Carlo approach assumed independence between the burned area and the floor area, which is discussed in more detail in the next section. Also, the distributions were generated for a very specific type of fire incidents- namely unsprinklerd fires that were extinguished by fire service personel in 1-2 family residential dwellings. For both response times of 2 minutes and 7 minutes, the optimal power law fits have similar slopes to the regions of the generated distributions just below 100 m^2, which is consistient with the hypothesis that the generated distribution would be prone to errors arising from the uniform uncertainity distributions for small burned areas, but because the region above 100 m^2 is expected to deviate from a power law, the region below this tail is perhaps most reliable. This analysis does not necessarly support the hypothesis that the true distribution of fire incidents follows a power law distribution, but it does provide a framework for how it could be estimated if there is strong enough reason to believe it is the underlying distribution based on data from other countries that report burned areas directly.

7.3 Independence of burned area and floor area

Although Lu et Al. [7] conclude that the distribution of burned areas for urban fires follows a power law distribution over the interval of 1-100 m^2, it is not clear what the effects of building size are in generating this distribution. For example, does the same power law distribution apply to all building sizes, except the part of the distribution where the burned area exceeds the total building area? On the other hand, are larger buildings more likely to incur more area of damage? In order to answer this question, an analysis was conducted involving fires in 1-2 family residential dwellings with one story in total, subject to the same querying restrictions mentioned in the “Methods” section. For these fires, if burned area is independent of the building area, then larger buildings should have more incidents that are classified as minimum damage and fewer that are classified as heavy damage than smaller buildings. As an example, if the same burned area distribution applies to all sufficiently large buildings, regardless of size, then a fire that is 20 m^2 is equally likely in a one story building that is 50 m^2 or 100 m^2. However, in the larger building, the incident would be classified as minimal damage, but in the smaller building, the incident would be classifed as signficiant damage. As a result, it would be expected that larger one story buildings have fewer incidents that are classified above minimal damage. Figure 14 shows the fraction of fires classified as each damage type as a function of floor area.

Figure 14 shows that the fraction of each damage classification is relatively constant over floor area. Based on the definitions of the damage categories, this implies that the fraction of the structure burned is relatively independent of the size of the building, which also indicates that larger buildings are more likely to incur larger burned areas during fire incidents.

8 Effect of NFPA 1710 compliance

NFPA 1710 provides performance standards for both the turnout time and the travel time. These times represent the time from the point at which the department recieves notficiation of the incident to when the first unit leaves the station and the time from when the first unit leaves the station to when it arrives to the scene of the fire, respectively. This standard [2] states that “90% of all emergency responses to fire calls must turnout within 80 seconds or less” and “The fire department’s fire suppression resources shall be deployed to provide for the arrival of an engine company within a 240-second travel time to 90 percent of the incidents.” Because the response time metric defined earlier in this paper represents the completion of both turnout and travel, the distribution of these times can provide insight into whether or not individual departments are meeting the NFPA 1710 standard. Given the wording of the standards, a department that meets both standards has a 90% chance of completing the turnout task in less than 80 seconds, and a 90% chance of completing the travel task in less than 240 seconds. If these two tasks are taken as independent, then a department that meets the standard has a 81% (0.9 x 0.9) chance of completing both tasks in the less than the specified 90% times. This means that the 81st percentile of a departments’ response time distribution cannot exceed the sum of the standard turnout and travel times, which is 320 seconds. Therefore, by determining the response time at the 81st percentile for an individual department, one can conclude that a department fails to meet at least one of the standards. It is important to note that if the 81st percentile is below 320 seconds, one cannot conlude that the department meets both standards because they can compensate a failure to meet one standard by performing above the other standard. It is worth noting that Upson et al. conducted a similiar approach by combining the alarm handling time and turnout time into one metric called "mobilization time" [11]. However, for this analysis, we exclude alarm handling time because it is under the control of the dispatcher and occurs before the department receives notification of the alarm.

Given that an individual department's 81st percentile response time implies its compliance with NFPA 1710, an analysis was conducted to examine the relationship between departments' 81st percentile response time and the tendency for severe fire events in their respective communities. Again, only 1-2 family residential fires with reported floor areas between 25 and 450 m^2 were considered and the fires must have been extinguished by fire service personel. Also, sprinklered fires were excluded. In order to ensure statistically meaningful results, only departments with 50 or more relevant incidents were considered and the 81st percentile response time was evaluated using only these incidents. Also, the departments were classified based on the size of their populations protected when possible. The scatterplots in Figure 15 show the relationship between the 81st percentile response time of an individual department and the tendency for severe fires in its community.

Figure 15(a) shows a moderate relationship between the fraction of fires in a community that are reported as doing significant damage and the 81st percentile response time of the respective department. It is interesting that the correlation becomes stronger when the analysis is limited only to fires that do extreme damage (Figure 15(b)), even though the two plots consist of data from the same 180 departments. Also, any fire that contributes to the fraction of extreme damage incidents in Figure 15(b) will also contribute to the fraction shown in 15(a). The fact that the correlation is strengthened when limiting the analysis only to the most severe fires further supports the notion that the department's primary effect is to reduce the risk of the most damaging fire incidents; however the department's performance is less of a factor in preventing lower thresholds of damage. Figure 15(c) shows a more modest correlation between the fraction of fires that spread beyond the room of origin and the department's 81st percentile response time. Figure 15(d) shows no correlation between the average monetary losses from fire incidents in a community and the 81st percentile of the respective department. This is likely due to the large amount of variance in property values between communities, shown in Figure 15(e). When dividing the property losses by the property value as previously shown, a correlation becomes apparent, shown in Figure 15(f). The correlation coefficients denoted as r indicate moderate positive correlations in Figure 15(a) and 15(c), moderate to high positive correlations in 15(b) and 15(f), and negligible correlations in 15(d) and 15(e) [12].

9 Evaluating data quality and consistency

Data quality is a common concern with the use of reports from NFIRS. In this section, methods are presented that give insight into the data quality assoicated with various parameters and identify trends in departments' reports that could indicate satisficing or data unreliability.

The "stories damaged" entry (see Figure 6) indicates the fraction of a story burned by the fire and for one-story buildings, this paramter gives incidation of the fraction of the structure burned by the flame. Also, the fraction of the property value lost (see 4) gives insight into the fraction of the structure that was damaged by flame, smoke, or overhaul. As a result, it is reasonable that the lower limit of the story damage classification (e.g. 25% for signficant damage) would be the lower limit of the fraction of the property value lost. In other words, if a one story building incurs significant damage, then at least 25% of the structure was damaged by flame; therefore it is expected that in most cases, at least 25% of the value of the structure was lost. If this is not the case, then the value of the struture must not be uniformly distributed over its area, but given that the "property loss" entry does not consider the contents of the structure, it would not be skewed by the fire damaging a room that held high value items. Also, it is reasonable that the fraciton of the property value lost would exceed the upper limit of the damage category (e.g. 49% for "significant damage") because the reported property losses include damage done by smoke, water, and overhaul, which are all neglected in the "stories damaged" entry. The distribution of the fraction of the property value lost for each damage classification is shown in Figure 16.

Figure 16 shows that there is a lot of scatter associated with each damage classification, with the exception of the "extreme" damage classification, which indicates losses that are equal to the property value in over 75% of incidents. The median values for all four damage classifications fall within their defined flame damage intervals, but the fact that a significant number of incidents classified as significant and heavy damage fall below 25% and 50% of the property value lost could indicate inconsistent reports.

It is also expected that the overwhelming majority of fires that do extreme damage to a story of a residential structure would spread beyond the room of origin. Given that a fire that does extreme damage must burn at least 75% of a story, the only way these fires could also be classified as confined to the room of origin is if one room consists of more than 75% of the story, which is unlikely. In Figure 17, the fraction of fires that spread beyond the room of origin is plotted against the fraction of fires that do extreme damage to at least one story.

As expected, the overwhelming majority of departments fall above the red line in 17. The departments that fall below this line report more fires that do extreme damage to at least one story of structure than fires that spread beyond the room of origin, which likely indicates inconsitient reporting.

As shown in Figure 16, fires that are reported as doing extreme damage generally cause monetary property losses that exceed 75% of the property value. Therefore, it would be expected that communities that have a large fraction of fires that do extreme damage would on average have a larger average fraction of property value lost. Figure 18 shows a scatter plot of the average fraction of the property value lost vs. the fraction of fire relevant incidents that do extreme damage to at least one story.

Figure 18 shows that the average fraction of property value lost is moderately correlated with the fraction of fires that do extreme damage in a community.

10 Conclusions

The analyses conducted in this paper show the relationship between several measures of fire severity and response time for unsprinklered 1-2 family residential fire incidents reported in the National Fire Incident Reporing System (NFIRS). It was shown that a log-normal distribution provides a reasonable approximation for the distribution of response times reported in NFIRS; however the log-normal distribution has a heavier tail than the empirical distribution, which could potentially lead to the overestimation of the frequency of response times in excess of 20 minutes.

An analysis was conducted of the relationship between the reported NFIRS fire spread category and the response time, which shows that longer response times are linked to an increased frequency of fires reported as “confined to building” and a decreased frequency of fires reported as “confined to room” over the interval of 4-11 minutes. This trend may be due to the fact that longer response times increase the probability of the room of origin reaching flashover conditions, at which point the fire is more likely to spread to the rest of the builidng. By comparison, the other three spread categories remain relatively constant over the range of response times from 1-20 minutes. This is perhaps in part due to the fact that the distinction between “confined to floor of origin” and “confined to building of origin” does not necessarily reflect fire size and the fact that a residential fire spreading beyond the building of origin is a fairly improbable event, regardless of response time.

It was also shown that on average, increasing response times are linked to increasing monetary losses; however due to the large amount of scatter in the dataset, an analysis was conducted to describe how the loss distributions evolve with increasing response time. It was found that the main effect of increasing response time is to add weight to the right tail of the distributions rather than to shift them upward. For example, the probablity of a fire incuring more than $5,000 of property losses is nearly the same between fires with a 3 minute and 12 minute response time, but the probability of a fire with a 12 minute response time incurring more than $50,000 of property losses is nearly double that of a fire with a 3 minute response time.

Increasing response times were also shown to increase the probability an incident report describing “extreme” damage by flame to one story residiences over the interval of 4-14 minutes with a corresponding decrease in the probability of the report describing only “minimal” damage. The findings indicate that the risk of a fire damaging more than 75% of the residence is more than 30% higher for response times exceeding 14 minutes compared to response times of 4 minutes.

Given that other countries have described the effect of response time in terms of the evolution of a power law distribution of the area burned, a method was presented to infer the burned area from reported NFIRS parameters. Due to the large amount of uncertainty inherent to this approach, it is not clear whether the U.S. data supports the notion that the burned areas in resiediental fires follows a power law; however a Monte-Carlo approach was able to use draws from a power-law to simulate the NFIRS reports with relatively small amounts of error.

It was found that the probability of a fire burning more than 75% of a one-story residence does not depend strongly on the area of the structure. This finding could indicate that larger residences are more likely to experience larger fires.

A framework was presented for inferring whether individual departments comply with the NFPA 1710 standard, which is based on the 81st percentile of their response time distributions. It was found that the quantities most strongly correlated with the 81st percentile response time of individual departments are the fraction of fires that incur extreme damage to at least one story and the average fraction of the property value lost in their respective communities.

Finally, several methods are presented for evaluting the data consistency of NFIRS by identifying contradictory reports. For example, some departments report a greater number of fires that incur extreme damage than fires that spread beyond the room of origin. These methods could be used to filter unreliable reports in NFIRS.

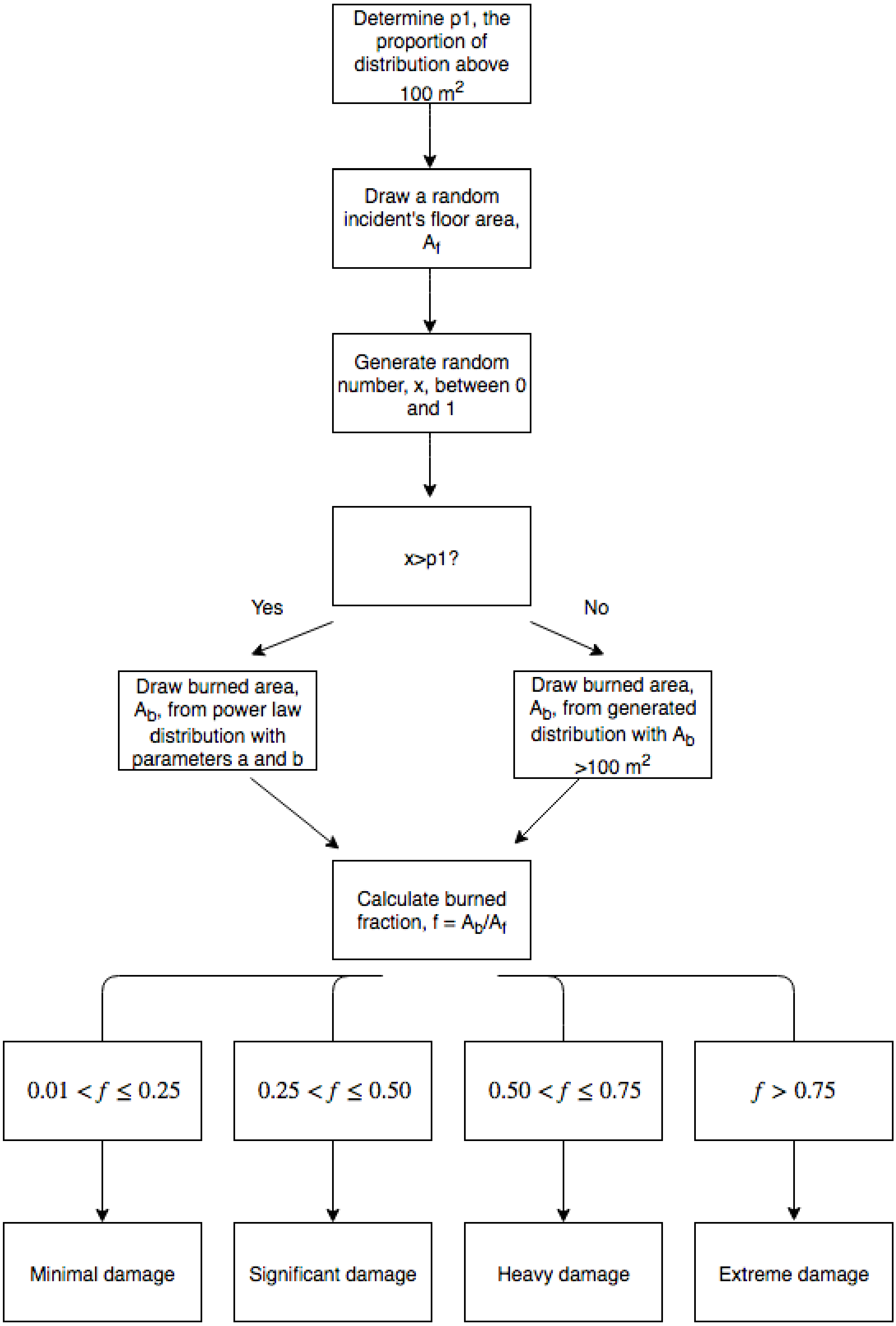


Fig. 12 A flow chart summarizing the steps in the Monte-Carlo simulation process

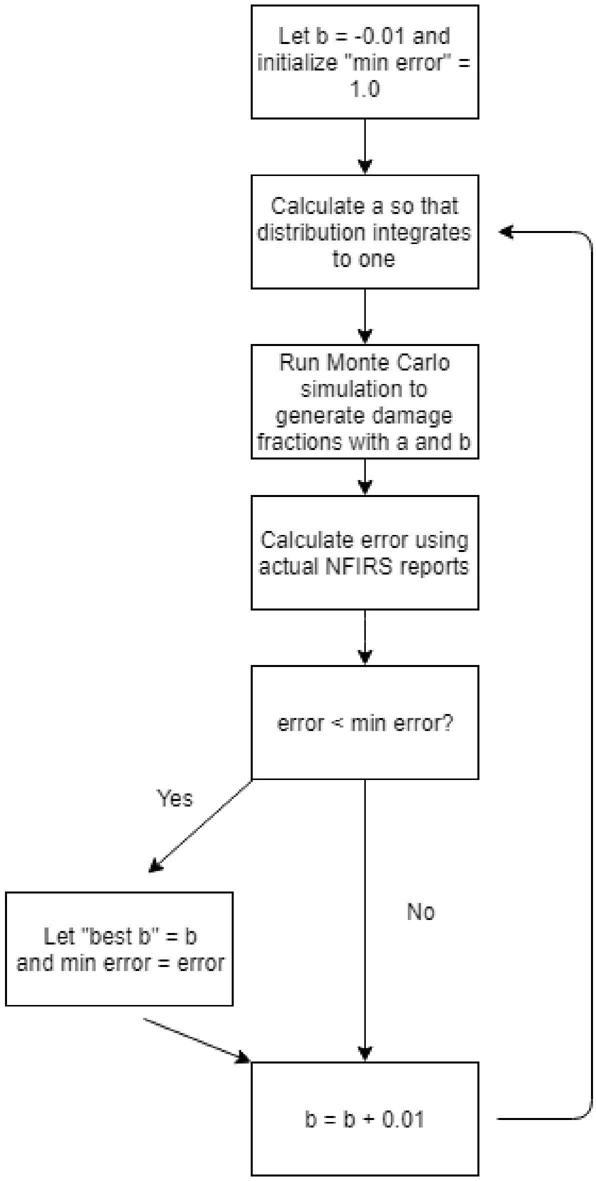


Fig. 13 A flow chart summarizing the steps in the optimization process

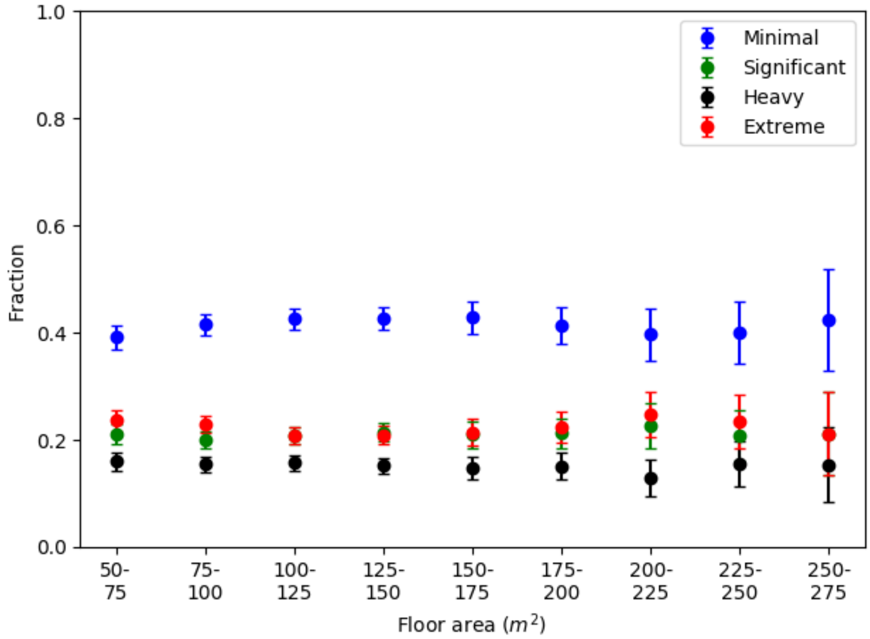
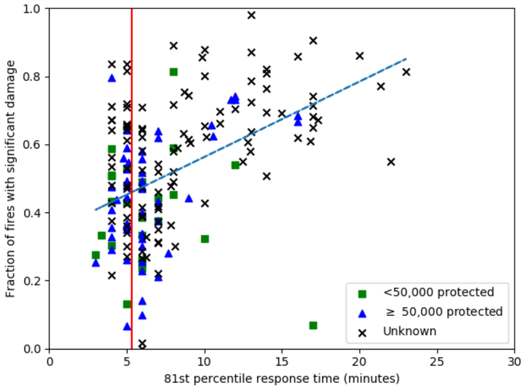
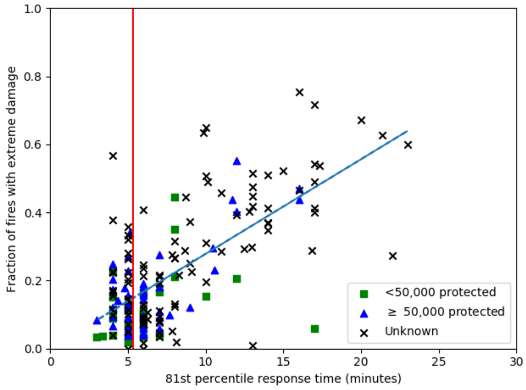


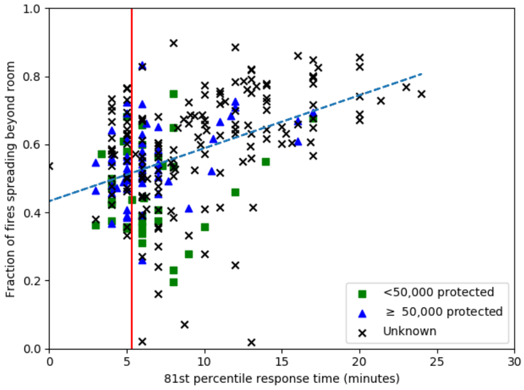
Fig. 14 The fraction of one story 1-2 family residential fires classified as each damage category as a function of floor area. Because floor area is a continuous variable, incidents were binned in intervals of 25 m^2 Note, because the structures are only one story, the floor area is the same as the building area.



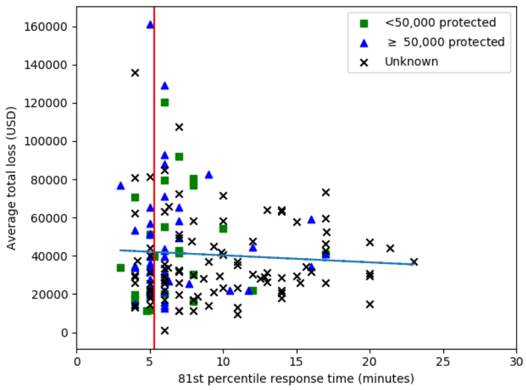
(a) n=180 departments,y=0.022x+0.34, r=0.47



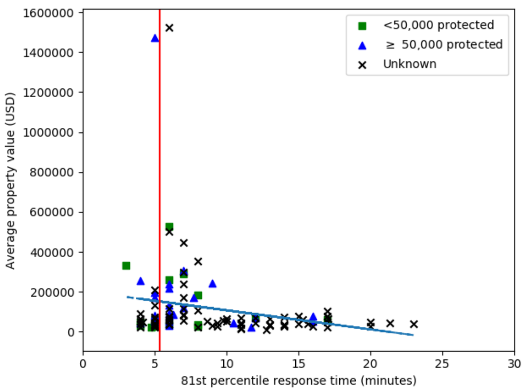
(b) n = 180 departments,y = 0.028x+0.00, r=0.69



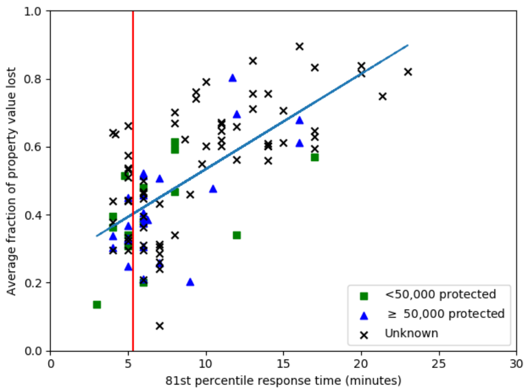
(c) n=255 departments, y=0.016x+0.433, r=0.44



(d) n=161 departments, y=-367.54x+43955, r=-0.06



(e) n=116 departments, y=-9575x+203183, r=-0.21



(f) n=107 departments, y=0.028x+0.25, r=0.69

Fig. 15 The fraction of fires with at least significant damage (a), fraction of fires with extreme damage (b), fraction of fires that spread beyond the room of origin (c), the average total losses (d), the average property value of residences where incidents occur (e), and the average fraction of the property value lost (e) for various departments plotted against the 81st percentile of their response time to 1-2 family residential fires. The vertical red lines indicate the implied NFPA 1710 standard of 320 seconds.

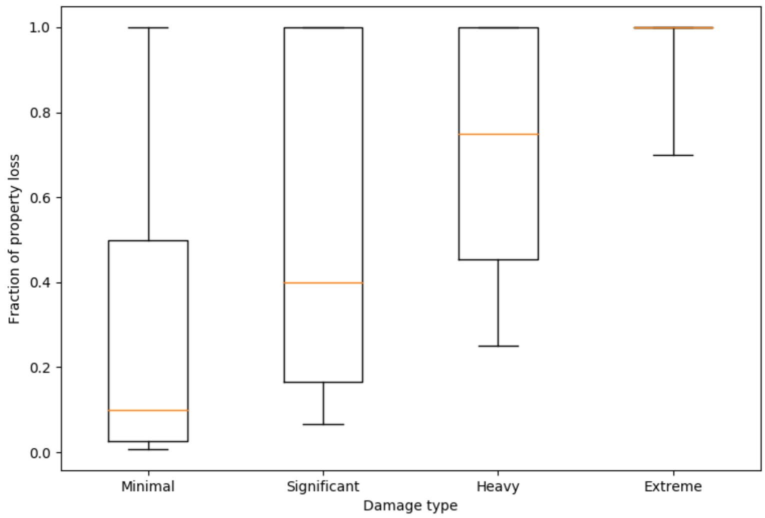


Fig. 16 Boxplots showing the distribution of the fraction of property value lost for each damage classification. The horizontal orange lines represent the median, the edges of the boxes represent the 25th and 75th percentiles, and the whiskers represent the 10th and 90th percentiles. Only one-story 1-2 family residential incidents with reported floor areas of 10-450 m^2 are considered.

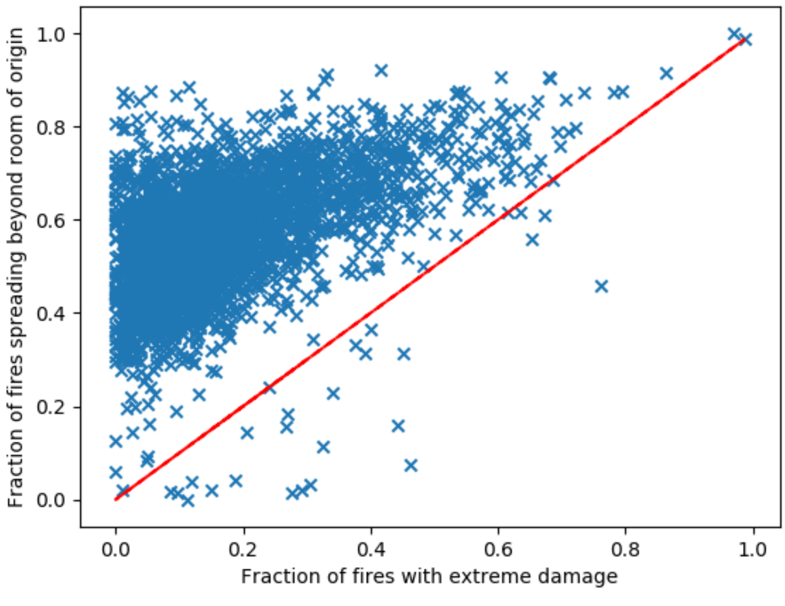


Fig. 17 Scatterplot of fraction of fires that spread beyond the room of origin vs. fraction of fires that do extreme damage in a community. Each point represents a single department. Departments below the red line have a higher fraction of fires that do extreme damage than spread beyond the room of origin. Only departments with 50 or more relevant incidents that report each parameter are considered.

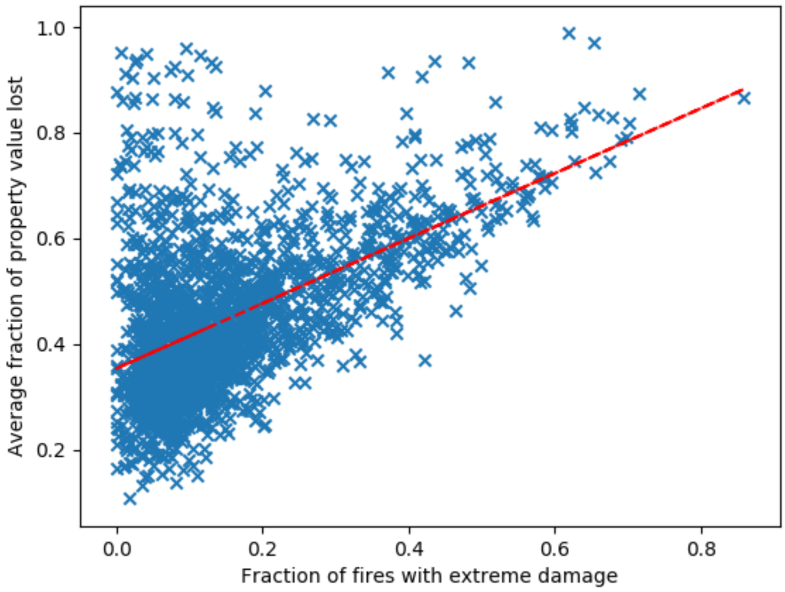


Fig. 18 Scatterplot of the average fraction of the property value lost vs. fraction of fires that do extreme damage in a community. Each point represents a single department. The red line represents a linear regression fit with equation y=0.615x+0.354 and r=0.528. Only departments with 50 or more relevant incidents that report each parameter are considered.

References

1. Jennifer D Flynn. *Fire service performance measures.* National Fire Protection Association, Fire Analysis and Research Division, 2009.
2. National Fire Protection Association et al. *NFPA 1710, standard for the organization and deployment of fire suppression operations, emergency medical operations, and special operations to the public by career fire departments.* NFPA, 2010.
3. National Fire Protection Association et al. *NFPA 1221, Standard for the Installation, Maintenance, and Use of Emergency Services Communication Systems.* National Fire Protection Association, 2010.
4. Stefan Särdqvist and Göran Holmstedt. Correlation between firefighting operation and fire area: analysis of statistics. *Fire technology*, 36(2):109–130, 2000.
5. PG Holborn, PF Nolan, and J Golt. An analysis of fire sizes, fire growth rates and times between events using data from fire investigations. *Fire Safety Journal*, 39(6):481–524, 2004.
6. Neil Challands. The relationships between fire service response time and fire outcomes. *Fire technology*, 46(3):665–676, 2010.
7. Lu Lu, Chen Peng, Jiping Zhu, Kohyu Satoh, Deyong Wang, and Yunlong Wang. Correlation between fire attendance time and burned area based on fire statistical data of japan and china. *Fire Technology*, 50(4):851–872, 2014.
8. PENG Chen, ZHU Ji-ping, and Bing-hua LI Kohyu SATOH. Frequency distribution of the first response time of firefighting. *Fire Saf Sci*, 19(1):33–37, 2010.
9. U.S. Fire Administration. Nfirsgram: calculating fire loss, 2016. URL `https://www.usfa.fema.gov/data/nfirs/support/nfirsgrams/nfirsgram_calculating_-fireloss.html`.
10. Geza Schay. *Introduction to probability with statistical applications.* Birkhäuser, 2016.
11. Robert Upson and Kathy A Notarianni. *Quantitative evaluation of fire and EMS mobilization times.* Springer Science & Business Media, 2012.
12. Mavuto M Mukaka. A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal*, 24(3):69–71, 2012.