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Data-Driven Probabilistic Post-Earthquake Fire Ignition Model for a Community

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ABSTRACT

Fire following earthquake (FFE), a cascading multi-hazard event, can cause major social and economical losses in a community. In this paper, two existing post-earthquake fire ignition models that are implemented in Geographic Information System (GIS) based platforms, Hazus and MAEViz/Ergo, are reviewed. The two platforms and their FFE modules have been studied for suitability in community resiliency evaluations. Based on the shortcomings in the existing literature, a new post-earthquake fire ignition model is proposed using historical FFE data and a probabilistic formulation. The procedure to create the database for the model using GIS-based tools is explained. The proposed model provides the probability of ignition at both census tract scale and individual buildings, and can be used to identify areas of a community with high risk of fire ignitions after an earthquake. The model also provides a breakdown of ignitions in different building types. Finally, the model is implemented in MAEViz/Ergo to demonstrate its application in a GIS-based software.

Keywords Fire following earthquake; ignition; probabilistic; community; MAEViz/Ergo; Hazus

1. INTRODUCTION

Our built environment and communities have been developed towards an interconnected social and economic network. Such interconnectivity between different aspects of a system leads to cascading effects. In many cases, an extreme hazard causes direct infrastructure and asset losses, while subsequent losses due to disruptions in operations and functions can exceed the direct damage [1]. If a city has to stay functional after a hazard and recover from the event, then the performance of individual elements, connectivity of critical infrastructure elements in the

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system, and cascading effects on the system should be incorporated in the design of the community.

This paper focuses on the problem of post-earthquake fires at the community scale. A study of 20 previous earthquakes from seven countries, where 15 of which occurred between 1971 and 2014, shows that fire events that followed the earthquakes caused considerable damage [2]. The likelihood of a fire event is typically amplified following seismic events due to an increase and/or introduction of available fuel and ignitions sources, such as ruptured utility lines or toppled appliances. On the other hand, active fire protection systems, such as sprinklers, may be ineffective due to ruptured water lines, loss of water pressure, or inadequate water supply due to widespread firefighting efforts for multiple neighboring fires. Passive fire protection systems, such as spray-applied materials or compartmentation partitions, can also be damaged in case of an earthquake and/or compromised by seismic shocks.

The methodology to evaluate community resiliency for post-earthquake fires involves four main steps: (a) identifying areas of the community that may experience ignitions, (b) modeling spread of fire, from the burning area to the neighboring buildings, (c) modeling active suppression efforts by firefighters, which also affect the rate of fire spread, and (d) quantifying damage and performance of the buildings which experienced fire in the areas affected by ignition and spread. Within this context, ignition is defined as a structurally significant fire, which requires firefighter intervention. The fire spread quantifies the affected geographic area given the initial fire ignitions, while suppression is related to the work of extinguishing a fire, starting with the discovery time through the complete control of the fire by the firefighters. A holistic methodology has to consider the four steps mentioned above, in order to capture the performance of a community. The authors of this paper are working towards developing such a holistic approach considering different aspects of post-earthquake fires at individual buildings and at the community level. For example, in previous studies, the authors have adopted the concept of fragility function for quantifying fire damage in a building at system level [3,4]. Meanwhile, the authors are working towards developing a spread and suppression model that explicitly incorporates the available water for suppression efforts, given the earthquake damage to the water network [5]. As part of the holistic methodology, this paper focuses on modeling post-earthquake fire ignitions in a community.

The proposed model in this paper is based on empirical data from historical events in California to build a data-driven probabilistic model for predicting ignitions in a community. The empirical data are mainly obtained from firefighter reports, and are categorized as structurally significant fires, i.e. fires which ignited and grew to the point where a firefighter intervention was required. When a fire is developed in a building, the response not only depends on the structural behavior of elements, but also on the non-structural fire safety design of the building, such as the firefighting measures (e.g. sprinklers) or provision of compartments to prevent fire spread. When using the historical ignition data (structurally significant fires), it is implied that if active fire protection measures (e.g. sprinklers) were present, their probability of successful operation is inherently encompassed in the data. Therefore, the outcome of the proposed model provides recommendation to firefighters for allocation of their resources to areas with high risk of ignitions, and to some extent helps them plan their resources (e.g. number of fire houses and fire engines) based on the number of ignitions.

In recent years, a number of fire ignition models have been developed to simulate post-earthquake ignitions [6]. Lee et al. [6] list and compare the existing ignition models and conclude that "[FFE] data include a great deal of uncertainty, only some of which is captured in reported statistics." Among the existing models, two have been implemented in computer programs, Hazus [7] and MAEViz/Ergo [8]. Both computer programs are Geographical Information System (GIS) based platforms developed to estimate potential losses from hazards on communities. The U.S. Geological Survey recently led a group of over 300 scientists and engineers to study the consequences of a potential earthquake in California, which resulted in "the Shakeout Scenario" [9]. The Hazus-based study found that a hypothetical 7.8 magnitude earthquake on the southern San Andreas Fault could cause approximately 1600 fire ignitions, out of which 1200 would spread over large areas, and a few would grow into conflagrations [9]. Another example is the Hazard Mitigation Plan (HMP) released for the New York City in 2014 [10], which included a study [11] showing that a moderate earthquake could result in an estimated 1100-1200 deaths, and ignite up to 900 fires simultaneously in the NY-NJ-CT area. The study used Hazus, and compiled comprehensive soil information for the region, and a complete building inventory of Manhattan.

This paper starts with an overview of Hazus and MAEViz/Ergo platforms. A discussion on the current FFE modules implemented in Hazus and MAEViz/Ergo is provided, and the shortcomings of the available FFE ignition modules are discussed. The original contribution of this paper is a new probabilistic post-earthquake fire ignition model that is proposed based on historical FFE events. The proposed model can be used to estimate the number of ignitions in a region after an earthquake. One of the objectives in developing the FFE ignition model is to have a model that can be implemented in GIS based programs for community resilience assessment. Therefore, the new ignition model is implemented in MAEViz/Ergo to show the application.

2. GIS-BASED TOOLS FOR HAZARD RISK MANAGEMENT

A general comparison of Hazus [7] vs. MAEViz/Ergo [8] is given in Table 1. Hazus, a GIS based platform, estimates potential losses from earthquakes, floods, or hurricanes based on the performance of buildings, essential facilities, transportation, or utilities, and can be obtained from the Federal Emergency Management Agency (FEMA) website. Hazus is a tool designed to provide local, state and regional officials with information for emergency response, recovery, and mitigation planning to reduce risk of disaster damage [7]. The program provides an inventory of data for the United States based on census tract areas. Hazus comprises an earthquake module with a fire following earthquake model embedded. The Hazus manual states that there are areas that the available research is limited, such as the fire following earthquake area. The potential losses due to fire are not based on rigorous calculations, and therefore the program does not include the potential loss due to fire in estimating the total economic loss, casualties or loss of shelter. The fire following earthquake module is discussed further in Section 3.1.

Table 1: Comparison of Hazus and MAEViz/Ergo

		Hazus	MAEViz/Ergo
General	**Type of hazard**	Earthquake, floods, hurricanes	Earthquake
	Accessibility	Free but requires ArcGIS (not free)	Free
	Source code	Not available	Available to user (open source)
	Inventory	Includes default inventory data for U.S.A.	Limited inventory data available
	Scale of analysis	Census tract, county or state*	Individual buildings
FFE	**Model**	Empirical	Analytical
	Components	Ignition, spread, suppression	Ignition
	Output	No. of ignitions	Probability of ignition for each building and no. of ignitions

* Hazus has recently introduced an “Advanced Engineering Building Module” that performs analysis at the building level, but the user needs to provide the inventory data.

MAEViz/Ergo is an open source platform for earthquake hazard risk management [8, 12] developed in association with the MAE Center (Multi-hazard Approach to Engineering) at the University of Illinois, Urbana Champaign. This is a tool designed to model earthquake events, evaluate risk and potential losses, and develop mitigation strategies. MAEViz/Ergo provides an extension to a post-earthquake fire plug-in that was developed by Turkish researchers [13]. Similar to Hazus, the accuracy of results greatly depends on the accuracy of the inventory data. MAEViz/Ergo does not provide a default inventory dataset, and it is up to the user to input the most recent and available detailed inventory for the analysis. The data for inventory should be collected and is available from a number of sources including the United States Census Bureau, the Bureau of Labor Statistics, the Department of Education, the Department of Agriculture, and the Federal Communications Commission.

3. EXISTING FIRE FOLLOWING EARTHQUAKE IGNITION MODELS

Table 1 provides a comparison of the Fire Following Earthquake (FFE) models available in Hazus and MAEViz/Ergo. The fire ignition models are discussed further in this section.

3.1 Ignition Model in Hazus

The FFE module in Hazus consists of three different components: (1) ignition, (2) spread, and (3) suppression [7]. The module requires, as inputs, general building stock inventory (i.e. square footage), essential facility inventory (i.e. fire stations and their available resources), and the Peak Ground Acceleration (PGA). In addition, the user should provide the wind condition, and simulation properties such as the maximum simulation time. The module outputs the number of ignitions, total burned areas, population exposed to fire, and the building value consumed by the fire.

The ignition model calculates the number of fires that are expected to occur after the earthquake in a region of interest [14]. In this model, ignition implies a fire that requires the fire department response to suppress. The ignition is provided in terms of ignition rate, or in other words the frequency of ignitions per million square feet of total building floor area per district under consideration. The model is empirical and is based on seven historical FFE events in the United States post 1970s. The historical events and their corresponding number of ignitions are shown in Table 2.

Table 2: Historical FFE events for the ignition model in Hazus

Earthquake	No. of ignitions in dataset
1971 San Fernando	91
1983 Coalinga	3
1984 Morgan Hill	6
1986 N. Palm Spring	1
1987 Whittier Narrows	20
1989 Loma Prieta	36
1994 Northridge	81
Total Number of ignitions	**238**

The ignition model was developed by selecting, for each FFE historical event, census tracts with PGA values larger than 0.13g and a population density of larger than 3000 persons per sq. km (7772 persons per sq. mile). The two criteria were selected as previous analysis showed that (1) ignition rates are negligible at MMI VI or less (on a Mercalli intensity scale), and (2) fire following earthquake is a problem in dense urban areas. The value of 3000 persons per sq.km (7772 persons per sq. mile) was selected based on the population density in large urban areas in California (such as Los Angeles and San Francisco). The selection included census tracts in the areas that did or did not experience ignition. A total of 1435 census tracts for the seven earthquakes were selected, with 155 of them experiencing ignition (some tracts have more than one ignition), and 1380 of them are zero-ignition points. A number of influencing factors on ignition (such as total floor area, population and etc.) were studied, and eventually an ignition model that uses a polynomial form to relate ignition rate (ignition per total floor area: Ign/TFA) to peak ground acceleration (PGA) was proposed, as shown in Eq. 1. All 1435 data points and the ignition model are shown in Fig. 1, with the fit having an R^2 value of 0.084.

$$\mathrm{Ign/TFA} = 0.581895(\mathrm{PGA})^2 - 0.029444(\mathrm{PGA}) \quad (1)$$

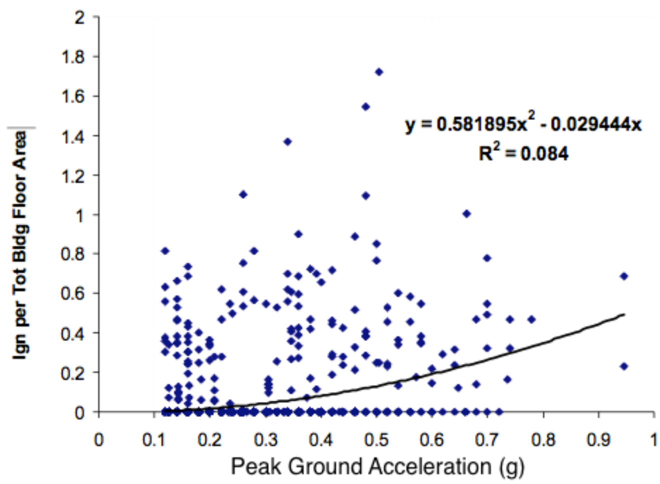

Figure 1: Historical ignition data and the ignition model in Hazus (figure taken from [14])

The procedure to use Eq. 1 and to provide an estimate for the number of ignitions in a census tract in Hazus includes the following two steps:

1. Given a PGA, Eq. 1 is used to calculate the mean ignition rate. Because of uncertainty and considerable variation in data (Fig. 1), the mean ignition rate is adjusted based on the standard deviation of the residuals (a process to incorporate the model error).
2. The mean ignition rate is multiplied by the total building floor area of the census tract to get the mean number of ignitions. A Poisson process is then used, with the obtained mean number of ignitions, to estimate the probability of different number of ignitions. At this point, a table is constructed that contains the CDF for a range of potential number of ignitions. A random number is generated to represent the Poisson CDF that leads the program to choose the corresponding number of ignitions.

Since both steps involve random number generations, the process has to be repeated several times to achieve more realistic results (Hazus technical manual recommends 10 times). The temporal distribution of ignitions (the time of ignitions) are also determined based on randomly generated numbers.

3.2 Turkish Ignition Model in MAEViz/Ergo

The FFE model in MAEViz/Ergo is based on the work of Turkish scholars, Yildiz and Karaman [13], and will be referred to as the "Turkish FFE model" in this work. The Turkish FFE model provides a probabilistic post-earthquake ignition model that considers the damage level in buildings' internal gas and electric systems and overturning of appliances [13]. Compared to the empirical ignition model in Hazus, the Turkish ignition model in MAEViz/Ergo is built upon an analytical approach. The model consists of three main components: utility systems (gas and electric systems), hazardous appliances and contents (industrial products, flammable material, cooking stove, portable heater, water heater), and the less hazardous appliances and contents (lighting fixtures, refrigerator, computers, television, microwave). The ignition model provides the probability of ignition for every building in the region of interest. The calculated probability for every building is compared to a defined threshold to determine if the building will experience ignition or not. The defined thresholds change for different building occupancy types.

The relationship between damage to gas pipelines and wiring systems, and ignition due to gas leakage and electrical sparks are formulated based on the works of Peyghaleh [15] and Zolfaghari et al. [16]. The dataset for formulating the ignitions due to utility systems come from non-U.S. sources [15].

Ignitions due to overturning of appliances and contents are modeled using the motion of appliances due to acceleration, and the formulation is based on the work of Reinoso et al. [17]. The overall ignition model incorporates the importance of the three components by assigning a weight to each component, having more weight on the ignitions due to utilities, compared to ignitions due to hazardous and less hazardous appliances. The weights are based on questionnaires given to scientists. The methodology to have a different level of significance (weights) in each component and subcomponent of the model is based on an Analytical Hierarchy Process.

The implemented Turkish ignition model in MAEViz/Ergo is applied to a case study to evaluate FFE ignitions in a region in Turkey [13]. The results from Yildiz and Karaman's study [13] provide the probability of ignition for every building, ranging from 0.15 to 0.46. Such values can be used to compare probability of ignition for different buildings in the region; however, the predicted total number of ignitions in the region is not realistic. The probability of ignition for individual buildings in a community with thousands of buildings is expected to be in the order of 10^{-5} or 10^{-6}. Therefore, the model is suitable for comparative purposes (sensitivity studies) but not for predicting loss estimations from an FFE event.

4. PROPOSED FFE MODEL

The two FFE models discussed in Section 3.0 use different approaches to quantify ignitions after an earthquake. The model in Hazus is comprehensive in a sense that it includes the three phases namely ignition, spread, and suppression of fire. However, the ignition model in relation to data (Fig. 1) can be improved by introducing additional parameters and probabilistic factors into the model to capture the uncertainty and the spread in the data. Meanwhile, the Turkish probabilistic model in MAEViz/Ergo can be used to calculate the probability of ignition in individual buildings and compare their performance, but the model is not validated against historical FFE events, and the total number of ignitions in the region is unrealistic. Also, some of the datasets in developing the models came from non-U.S. sources. This section proposes a new probabilistic ignition model to address the above shortcomings. Fig. 2 provides an overview of the four main steps required to develop the new model in conjunction with Sections 4.1 to 4.4.

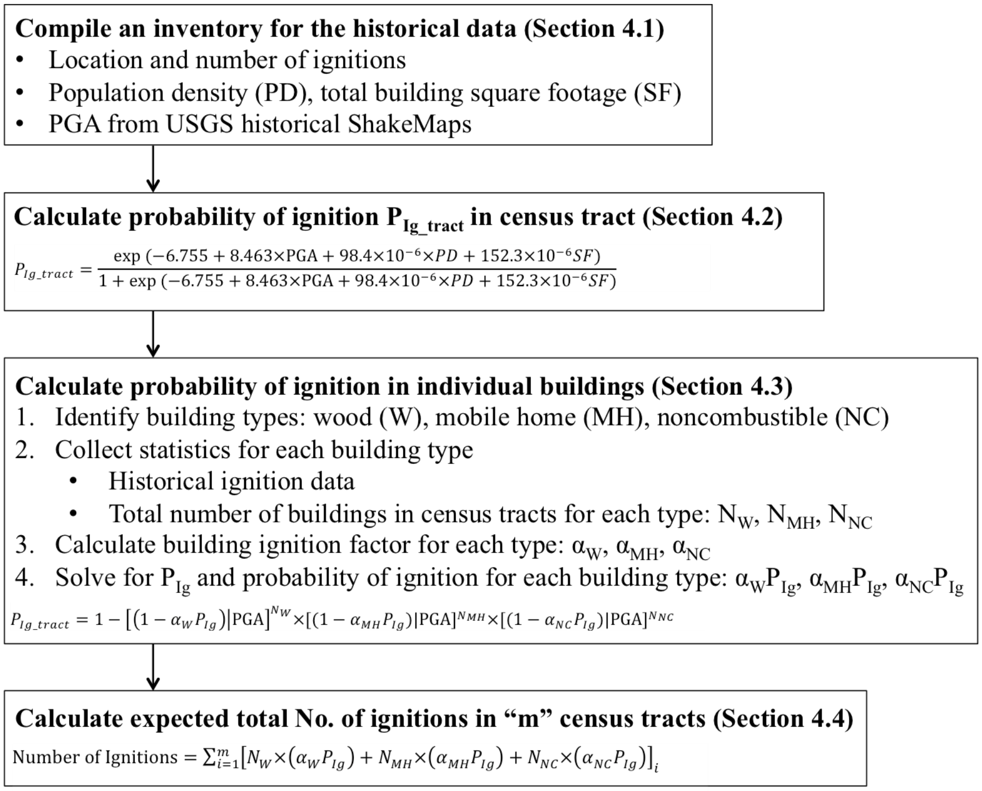

Figure 2: Overview of the proposed FFE ignition model

4.1 Inventory of Historical Data

The proposed probabilistic model is derived based on FFE historical data. Analytical models, such as the one implemented in MAEViz/Ergo, generally use event trees that are based on logical occurrence of events after an earthquake and certainly have a significant value. However, the type of data that is needed to derive the components of such analytical models is not easily available. Therefore, a probabilistic ignition model is proposed based on seven historical FFE events, all of which occurred in the U.S. and after 1983. Similar to Hazus, only U.S. data are included as the construction types, safety and building standards, and the built environment is different in the U.S. compared to other countries such as Japan that has experienced FFE. In addition, older data are excluded since building standards, appliances, and the nature of urban environment have changed such that older events (going back as far as 1906 San Francisco FFE) may not be valid any longer. The selected events include Coalinga (1983), Morgan Hill (1983), North Palm Spring (1986), Whittier Narrows (1987), Loma Prieta (1989), Northridge (1994), and the recent earthquake in South Napa (August 2014). A listing of the earthquakes and a summary of compiled dataset used in this study is provided in Table 3.

Table 3: Summary of the compiled dataset for the proposed ignition model

Earthquake	Counties with ignition	No. of census tracts w/ PGA>0.08	No. of census tracts w/ ignition	Total No. of ignitions
1983 Coalinga	Fresno	63	1	3
1984 Morgan Hill	Santa Clara	472	6	6
1986 N. Palm Spring	Riverside	344	1	1
1987 Whittier Narrows	Los Angeles	2196	20	20
1989 Loma Prieta	San Francisco, Alameda, Santa Cruz	1578	31	36
1994 Northridge	Los Angeles, Orange	2944	68	82*
2014 Napa	Napa	80	4	6
	Total	7677	131	154

* The dataset includes one additional ignition, based on the work of Davidson [18], compared to the 81 ignitions in Hazus dataset.

Six of the earthquakes chosen in this study are the same as those from Hazus (Table 2 in Section 3.1). The only earthquake, that is included in the Hazus study, but not in this work is the 1971 San Fernando earthquake. The detailed data for all the other six earthquakes are found and compiled for this work, except the San Fernando earthquake, for which the Hazus study states that the data is based on unpublished sources. As the unpublished data is not available, the San Fernando earthquake was excluded from the compiled database in this study. In addition, nowadays the communities will most likely have a different response compared to an event back in 1971. Finally, a recent earthquake that occurred on August 24, 2014 in Napa (California) and was the source of six fire incidents is added to the collection [19].

It should be noted that although the proposed ignition model will be implemented in MAEViz/Ergo as will be discussed in Section 5.0, Hazus and ArcGIS are used to collect and compile the data to develop the ignition model. This includes three main steps (3 layers of data in ArcGIS), as illustrated in Fig. 3:

1. Information on the ignition incidents was compiled. In order to collect the required information for the ignition points, the location of ignition in the form of street address, geographical longitude/latitude, or the corresponding census tract at which the ignition point occurred was required.

2. Hazus inventory was used to compile geographic and demographic information grouped based on census tracts for regions that experienced the earthquake events. ArcGIS was employed to combine the Hazus inventory with the ignition data (from the previous step). Every ignition point, based on its location, was located at a census tract, for which Hazus inventory provided square footage, population density, and building counts.

3. As a final step, an additional map layer was added in ArcGIS, which included the recorded PGA values for historical earthquakes in the region of study. ShakeMap archives are available on the USGS website in a "shape file" format that is readable to ArcGIS. The PGA map layer was overlaid on the Hazus inventory, to extract PGA values for every census tract. The ShakeMaps provide contours of PGA values. In this study, the mean value of PGA in every census tract was selected as the PGA corresponding to that census tract. This way, PGA was related to the census tracts, and consequently to the ignition data as well as characteristics of the tracts.

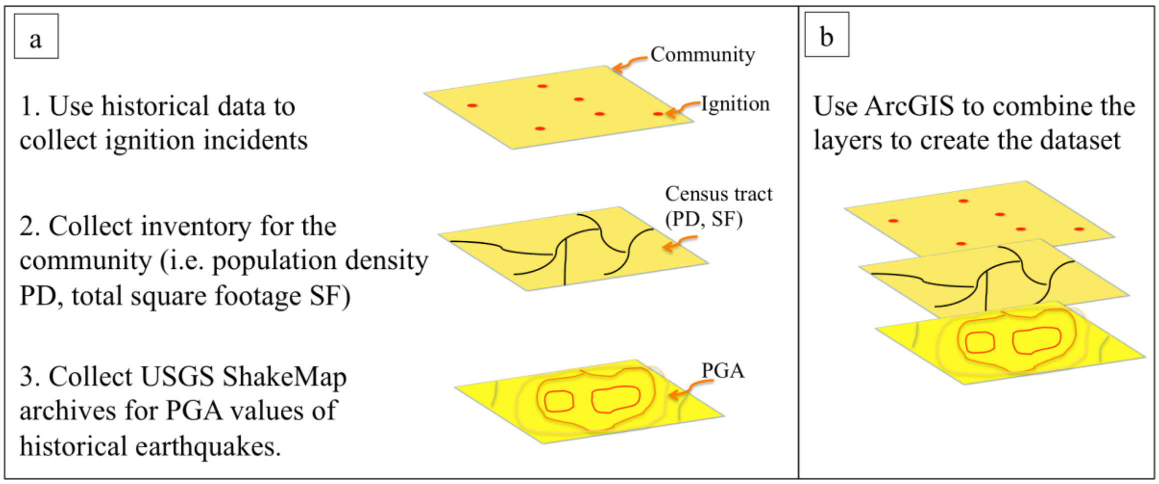

Figure 3: Process to compile dataset for ignition model (a) required layers, (b) combined

With the exception of the Napa earthquake, the ignition data are obtained from the work of Davidson [18]. In her work, ignition data from earthquake-specific reconnaissance reports were compiled. After Davidson's study, Scawthorn [14] led a study to improve the ignition model in Hazus that used the same historical earthquake events as Davidson's (with the addition of San Fernando in Hazus). It should be noted that in both studies, the datasets include only those ignitions that: (1) became structural fires, (2) required fire department help to extinguish, (3) occurred within 10 days of the earthquake, and (4) were identified as earthquake-related [18]. This paper uses Davidson's data for six of the historical events between 1983 and 1994, while the ignition data for the 2014 Napa earthquake are based on the reconnaissance report prepared in September 2014 [19].

The ignition data reported by reconnaissance studies, and the inventory in Hazus are based on different census tracts (Hazus is based on the year 2000 census tracts, while the reported ignition data are based on the year 1990 census tracts). There were a few ignition points that had to be re-mapped; therefore, the street address of the ignition point, provided by Davidson [18], was used to locate and map the ignitions in the corresponding census tracts in Hazus.

The compiled dataset for every historical earthquake includes census tract, population density, total building square footage, building counts and their type, and PGA. The minimum PGA in a census tract with an ignition is 0.08g; therefore, census tracts with PGA of smaller than 0.08g are excluded. As shown in Table 3, with the seven considered earthquakes, a total of 7677 census tracts are selected, 131 of which experienced at least one ignition. The total number of recorded ignitions is 154, implying that some tracts have more than one ignition. Overall, 7546 (7677-131=7546) tracts have zero ignitions.

The zero-ignition census tracts are included in the dataset to properly capture probability of ignition; as such tracts experience no ignition while having a reasonable PGA (larger than 0.08g). Table 3 summarizes the counties with ignitions, number of census tracts, and ignition statistics for the seven considered earthquakes. It should be noted that the counties provided in Table 3 are only those that experienced ignition; however, census tracts from other counties that experienced PGA larger than 0.08 are included in the dataset as well. The proposed approach for collecting the inventory data is similar to that of Davidson [18]. Davidson was the first to incorporate 'zero' ignition data in a thorough process, and she compiled two sets of data with different filters: Dataset "A" had about 3,200 data points and dataset "B" included many lower intensity data, totaling almost 8,000 points. The second dataset (B) is in line with the process used for this work.

4.2 Probability of Ignition in Census Tract

The Hazus ignition model relates ignition rate to PGA and total building floor area in a census tract, and Davidson's study includes five covariates in her ignition model (earthquake intensity; land area that is commercial, industrial, or transportation; total building square footage; building area that is unreinforced masonry; and population density). It should be noted that Davidson proposes alternative models that considers additional covariates such as land area that is high intensity residential and the median year built over all housing units. This paper proposes a probabilistic ignition model that predicts probability of ignition in a census tract based on three covariates: PGA, total building square footage, and population density of the census tract. The correlation coefficient between total building square footage and population density, for the collected data including zero-ignition points, is calculated to be -0.264. Although, it was expected that the total building area and population density would be closely correlated, the correlation coefficient of -0.264 indicates the proper inclusion of both covariates in the model. This probabilistic independence between the two parameters at the census tract level, for the considered region, was confirmed in Davidson's study [18], where the correlation coefficient for her collected dataset was calculated as -0.22.

In order to develop the model, the compiled dataset is treated as a binary data, where a value of "one" represents an ignition in a census tract, and value of "zero" represents no-ignition. The census tracts that have more than one ignition are repeated for the number of ignitions in the tract (meaning a census tract with two ignitions represents two "ones"), if the ignitions are independent. The ignition locations in census tracts that experience more than one ignition are individually examined. The investigation shows that all ignition cases that occur in the same census tract are located far enough from each other (in the order of miles) that they can be considered to be independent ignitions. The locations for which the source and time of the ignition are available further confirm that these ignitions are independent. The only exception is the case of two ignitions in the Napa earthquake that are correlated (same ignition source and nearby locations), for which the two ignitions are represented as one.

With the binary data and the covariates selected as PGA, population density (PD), and square footage (SF), the logistic function is used to develop the model for probability of ignition in a census tract (P_{Ig_tract}), as shown qualitatively in Fig. 4. There is a cluster of "one" data at larger PGA, PD, and SF values, and a cluster of "zero" data at smaller PGA, PD, and SF. The model has a general form of Eq. 2, where it always has a value between zero and one (suited to model probability). The program "R" [20] is used to estimate the unknown parameters in Eq. 2 based on the collected dataset.

$$P_{Ig\_tract} = \frac{\exp(\theta_1 + \theta_2 \times \mathrm{PGA} + \theta_3 \times PD + \theta_4 \times SF)}{1 + \exp(\theta_1 + \theta_2 \times \mathrm{PGA} + \theta_3 \times PD + \theta_4 \times SF)} \tag{2}$$

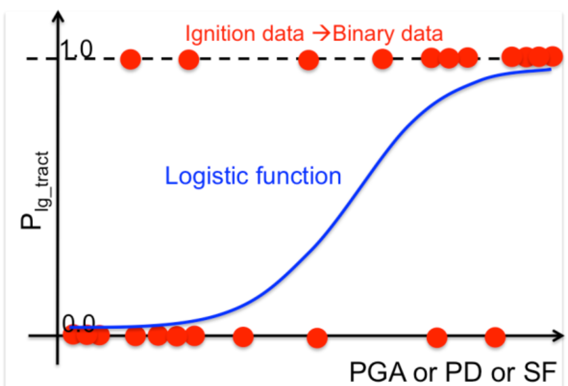

Figure 4: Qualitative representation of binary ignition data and logistic function

Table 4 shows the outputs of the program "R" for each unknown parameter in Eq. 2. The outputs of "significance test" in program "R" showed that there is a significant relationship between probability of ignition and each considered covariate. The final form of the ignition model is presented in Eq. 3, where PGA is in units of *g*, *PD* is the population density in population per square km area of the census tract, and *SF* is the total building area in thousands of square feet. All units are consistent with the inventory in Hazus.

$$P_{Ig\_tract} = \frac{\exp(-6.755 + 8.463 \times \mathrm{PGA} + 98.4 \times 10^{-6} \times PD + 152.3 \times 10^{-6} SF)}{1 + \exp(-6.755 + 8.463 \times \mathrm{PGA} + 98.4 \times 10^{-6} \times PD + 152.3 \times 10^{-6} SF)} \tag{3}$$

Table 4: The R output for parameters of the ignition model

Variable	Parameter	Estimate	Std. Error
Constant	θ_1	-6.755	0.252
PGA	θ_2	8.463	0.561
PD	θ_3	98.4e-06	14.00e-06
SF	θ_4	152.3e-06	29.12e-06

The range of data for the input parameters to the model is investigated to identify appropriate lower and upper bounds for the inputs, and to characterize where the model is more robust. In general, the minimum PGA in a census tract with an ignition is recorded to be 0.08g, while the historical data include census tracts experiencing ignition with a maximum PGA of 0.655. At small PGA values, ignition is more probable for tracts with larger population density and/or square footage. The upper bound values for population density and square footage in the historical data are approximately 37000 people per sq.km (95800 people per sq. mile) and 22000 thousands of ft^2 (2044 thousands of m^2) respectively. On the other hand, at larger PGA values, the probability of ignition becomes higher and less dependent on population density and square footage. The lower bound for population density and square footage, at larger PGA values, are approximately 653 people per sq.km (1690 people per sq. mile) and 1360 thousands of ft^2 (126 thousands of m^2).

Table 5 provides a breakdown of the ignition data and the range of values for the observed population density and building square footage given a PGA range. It can be seen that the number of ignitions are significant in relation to the total number of census tracts when PGA is larger than 0.6 (4 ignitions in 19 census tracts where the maximum population density and square footage are smaller than those for lower PGA brackets).

Table 5: Breakdown of ignition data given the input parameters

PGA	Total no. of census tracts	No. of ignitions	PD for census tracts with ignition (people per sq.km)		SF for census tracts with ignition (thousands of ft^2)	
			Min	Max	Min	Max
PGA<=0.20	5809	53	411	37026	1424	21998
0.20<PGA<=0.40	1625	59	80	18237	810	11686
0.40<PGA<=0.60	224	38	441	10400	1361	7735
PGA>0.60	19	4	653	1538	3214	6835

Fig. 5 shows the probability of ignition (Eq. 3) for a range of population density [0 to 40,000 people per sq. km (103,627 people per sq. mile)] and total building square footage [0 to 15,000 thousands of ft^2 (1395 thousands of m^2)] in a census tract for different PGA values. The range of values for population density and square footage that is used in Fig. 5 is based on census data from cities in California, including San Francisco and Los Angeles. It is shown that at very low

PGA (0.08g), the probability of ignition is small, whereas at a high PGA (0.655g), the probability may reach to values close to 1.0. Meanwhile, for intermediate intensity earthquakes with PGAs in the range of 0.2 and 0.4, the effect of PD and SF on the chance of fire ignition is more significant than for extreme values of PGA. Larger building square footage increases the chance of having an ignition in the area, while for two census tracts with the same square footage but different population density, a larger population density implies a higher chance of ignition due to presence of more ignition sources such as appliances.

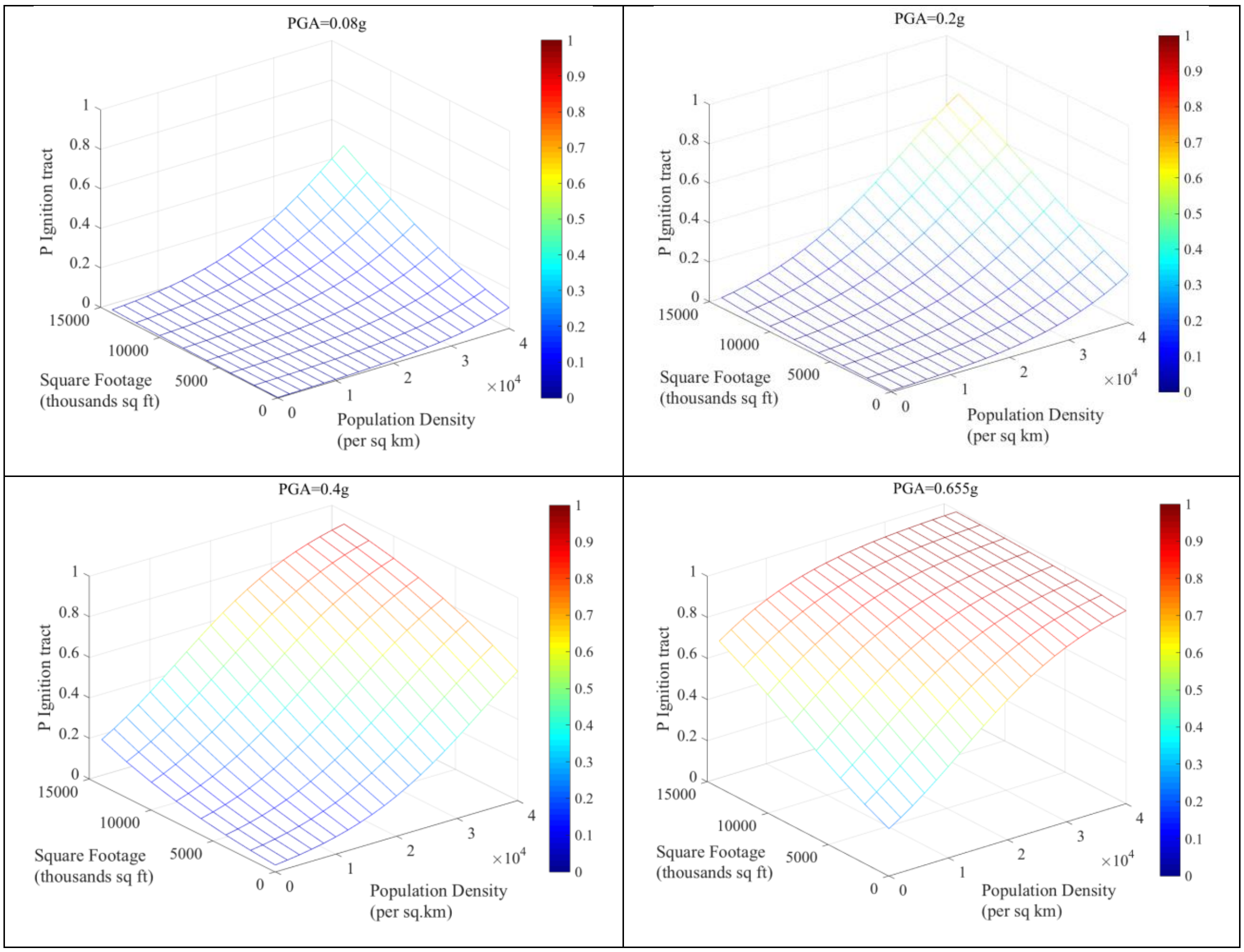

Figure 5: Probability of ignition for a census tract based on Eq. 3

Eq. 3 can also be used to find probability of ignition of any region under study (not necessarily a census tract); however, the model is derived based on a dataset at the level of census tracts. As the region of study becomes considerably larger than a census tract, the level of accuracy of the ignition model may be affected.

4.3 Probability of Ignition in Individual Buildings

The discussion so far has been focusing on post-earthquake fire ignitions at the level of a census tract. The next step in advancing the ignition model further is to estimate the probability of ignition for individual buildings in a region. This would provide officials with the distribution of ignitions within a census tract and help identify vulnerable parts of the region. One parameter that affects the probability of ignition for individual buildings is the general building construction type (concrete, steel, masonry, wood, and or mobile homes). In this work, buildings will be grouped into three categories according to their construction type: wood (W), mobile homes (MH), and noncombustible (NC) such as concrete, steel, and masonry buildings.

It is assumed that probabilities of ignition for the three building types are related as given in Eq. 4a, with P_{Ig} as a common factor and α_{W}, α_{MH}, and α_{NC} as the ignition factors for each building type. Note that P_{Ig} itself is physically meaningless unless multiplied by the ignition factors to obtain the probability of ignition in each building type, as shown in Eq. 4b, where P_{Ig_W}, P_{Ig_MH}, and P_{Ig_NC} are the probability of ignition in a wood building, a mobile home, and a noncombustible building, respectively.

$$\frac{P_{Ig\_W}}{\alpha_W} = \frac{P_{Ig\_MH}}{\alpha_{MH}} = \frac{P_{Ig\_NC}}{\alpha_{NC}} = P_{Ig} \tag{4a}$$

$$P_{Ig\_W} = \alpha_W P_{Ig} \, , P_{Ig\_MH} = \alpha_{MH} P_{Ig} \, , P_{Ig\_NC} = \alpha_{NC} P_{Ig} \tag{4b}$$

The building construction type for individual ignition data points is available for part of the dataset that was compiled to develop the ignition model (explained in Section 4.1). Table 6 provides the number of buildings and their construction type that experienced ignition in four historical FFE events based on [19, 21, 22, 23]. Table 6 also shows the total number of buildings for each construction type from the census tracts in Table 3 (statistics are obtained from the inventory in Hazus). The building ignition factors (α_{W}, α_{MH}, and α_{NC}) are calculated by (a) first taking the ratio of the number of buildings that experience ignition to the total number of buildings for each category of building construction type, and (b) then normalizing the three ratios (for the three categories) with respect to the largest value (that corresponds to the ratio for mobile homes). The process and the building ignition factors are shown in Table 7.

Table 7 shows that mobile homes have the largest ignition factor (i.e. frequency of ignition), followed by wood and noncombustible buildings. It is expected and logical to have the lowest ignition factor for the noncombustible buildings. Wood buildings have, by far, the largest number of ignitions, but as the total number of wood buildings is significantly larger than the two other categories, the ignition factor for wood construction is comparable with the noncombustible buildings. Meanwhile, the higher propensity of mobile homes to experience post-earthquake ignitions could be attributed to the fire safety strategies associated to this particular type of construction such as construction materials (higher flammability), absence of active fire protection measures, or a more vulnerable gas and electric connections.

Table 6: Statistics of building types for historical events: with ignition and total count

Earthquake	Historical ignition data					Total no. of Buildings in census tracts[1]			
	W	MH	NC	NA	Total	W	MH	NC	Total
Coalinga	2	0	1	0	3	251742	15144	27420	294306
Morgan Hill	2	2	0	2	6	644264	32728	69773	746766
Northridge	67	0	6	9	82	3316841	120704	387628	3825173
Napa	2	4	0	0	6	127247	6757	13016	147019
Total	**73**	**6**	**7**	11	97	**4340094**	**175333**	**497837**	5013264

Note (1): No. of buildings in all census tracts from Table 3.

Table 7: Building ignition factors

	α_1 (wood)	α_2 (mobile home)	α_3 (noncombustible)
Absolute value	73/4340076=16x10^{-6}	6/175333=34 x10^{-6}	7/497837=14 x10^{-6}
Normalized value	16/34=0.471	34/34=1.0	14/34=0.411

Having defined building ignition factors and Eqs. 4(a) and (b), probability of ignition in a census tract can now be related to probability of ignition in each building. The probability of ignition in a census tract is the complement of having no ignition in that tract (Eq. 5). The probability of no ignition in *one* wood building is $(1-P_{Ig\_W})$, while the probability of no ignition in N_{W} wood buildings in a tract is $[(1-P_{Ig\_W})|PGA]^{N_w}$, assuming ignitions in buildings of the same type are independent, conditional on the PGA. The same formulation holds for mobile homes and noncombustible buildings with a total of N_{MH} and N_{NC} mobile home buildings and noncombustible buildings in a tract respectively. Eq. 5 can be rewritten as Eq. 6 based on the probability of no ignition in each building type. Eq. 6 relates the probability of ignition at a census tract to probability of ignition for individual buildings considering their construction type. Combining Eqs. 6 and 4b with building ignition factors from Table 7, result in Eq. 7 where the only unknown is P_{Ig}. P_{Ig_tract} is known through Eq. 3, N_{W}, N_{MH} and N_{NC} are obtained from the inventory for the region of interest (Section 4.1).

$$P_{Ig\_tract} = 1 - P_{No\ ignition} \tag{5}$$

$$P_{Ig\_tract} = 1 - [(1-P_{Ig\_W})|\mathrm{PGA}]^{N_W} \times [(1-P_{Ig\_MH})|\mathrm{PGA}]^{N_{MH}} \times [(1-P_{Ig\_NC})|\mathrm{PGA}]^{N_{NC}} \tag{6}$$

$$P_{Ig\_tract} = 1 - [(1-0.471P_{Ig})|\mathrm{PGA}]^{N_W} \times [(1-1.0P_{Ig})|\mathrm{PGA}]^{N_{MH}} \times [(1-0.411P_{Ig})|\mathrm{PGA}]^{N_{NC}} \tag{7}$$

Eqs. 3 and 7 are the final form of the proposed ignition model. Eq. 7 cannot be rearranged to explicitly solve for P_{Ig}, meaning that if the probability of ignition in a census tract (P_{Ig_tract}) is known, the probability of ignition for buildings should be calculated using a numerical procedure, such as Bisection Method or trial and error. Once P_{Ig} is obtained from Eq. 7, the probability of ignition in individual buildings is calculated from Eq. 4b as a function of the building type.

Finally, the available data for individual building construction type is further analyzed for the occupancy type. The following table provides a breakdown of the occupancy type, based on three categories of residential (Res), commercial (Comm), and other (including educational facilities). Out of 87 available data points, a total of 75 ignitions were recorded in residential category, 9 ignitions in commercial category, and 2 ignitions in others. The results show that, given an ignition in wood or mobile home categories, it is more likely that the fire occurs in a residential building. On the other hand, given a structurally significant fire in a noncombustible category, it is less likely that the building is residential. Therefore, it appears that there is a strong correlation between general building construction type and occupancy, for the analyzed events. Besides, the data about occupancy is only partially available. For these reasons, it was decided not to include occupancy as a factor for the probability of ignition at the building level.

Table 8: Statistics of building and occupancy types for historical events

Earthquake	Wood			Mobile Home			Noncombustible			Not Available
	Res	Comm	Other	Res	Comm	Other	Res	Comm	Other	
Coalinga	2	0	0	0	0	0	0	1	0	0
Morgan Hill	1	1	0	2	0	0	0	0	0	2
Northridge	62	5	0	0	0	0	2	2	2	9
Napa	2	0	0	4	0	0	0	0	0	0
Total	**67**	**6**	**0**	**6**	**0**	**0**	**2**	**3**	**2**	**11**

It should be noted that the problem of fire following earthquake is a function of many parameters, including soil type, types of structural system, degree of seismic damage, etc. However, in order to create a model that captures all those parameters, reliable validation data from previous events are needed, which is not readily available. Meanwhile, when applying such models, the user needs to collect the information for the input parameters. Based on the experience of the authors, particular information about individual buildings, their structural system, retrofits over time, etc. is not available and require extensive effort and time to collect the information, if possible at all. Therefore, for practicality, a model to predict the number of ignitions following an earthquake cannot include all these parameters at this time.

4.4 Expected Total Number of Ignitions

The process to estimate the number of ignitions for any region, using the proposed ignition model, is shown in a flowchart in Fig. 6 and can be described as the following:

1. Compile an inventory of census tracts for the region of study. The inventory should include:
   (a) Population density (PD),
   (b) Total building square footage (SF),

(c) Number of wood buildings (N_W), number of mobile homes (N_{MH}), and number of noncombustible buildings (N_{NC}).
PD and SF are used in Eq. 3, while N_W, N_{MH}, and N_{NC} are used in Eq. 7.

2. Select an earthquake scenario. For the selected ground motion, the PGA values for every census tract should be calculated. PGA is an input to Eq. 3.
3. Using Eq. 3, calculate the probability of ignition in a census tract. This calculation is performed for "m" number of census tracts in the region of study.
4. Given the probability of ignition in each census tract (Step 3), and the number of each building type, calculate probability of ignition for each individual building using Eq. 7.

The expected number of ignitions in each census tract equals to the sum of probabilities of ignitions for all buildings in that census tract. The number of ignitions in the region of study is the sum of ignitions in all census tracts, shown in Eqs. 8(a) and (b):

$$\text{Number of Ignitions} = \sum_{i=1}^{m}\left[N_w \times P_{Ig\_W} + N_{MH} \times P_{Ig\_MH} + N_{NC} \times P_{Ig\_NC}\right]_i \quad (8a)$$

$$\text{Number of Ignitions} = \sum_{i=1}^{m}\left[N_w \times \left(0.471P_{Ig}\right) + N_{MH} \times \left(1.0P_{Ig}\right) + N_{NC} \times \left(0.411P_{Ig}\right)\right]_i \quad (8b)$$

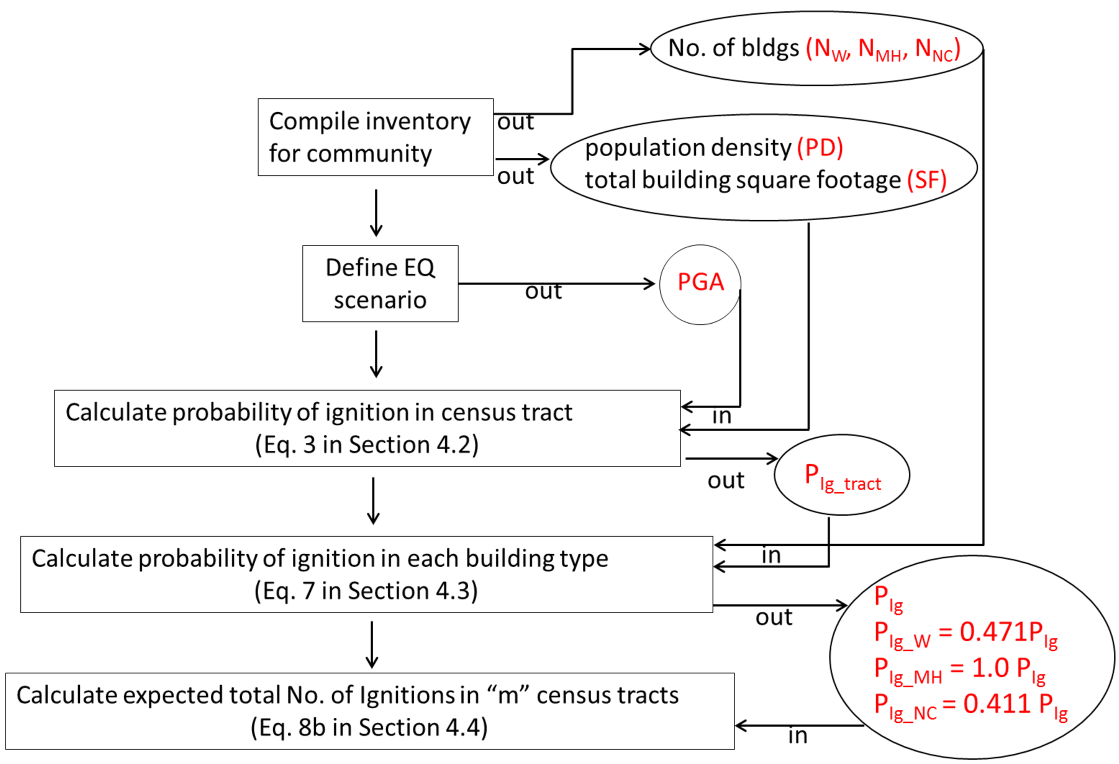

Figure 6: Flowchart for using the proposed ignition model

At the building level, the model can also be used to perform a sensitivity analysis and compare probability of ignitions between buildings in an area, given the properties of the region and the type of the buildings. The model is suitable for implementation in a GIS-based platform, to visually present the distribution of ignitions in the area of study. In addition, the model can be employed to estimate the total number of expected ignitions after an earthquake (Eq. 8b), providing an overall performance of the region in case of an FFE event.

In order to validate the model, Eqs. 3, 7, and 8b are used to estimate the number of ignitions after the available FFE historical events. The same historical events that were collected to develop the model are used as part of the validation study since no other real event is available. Hazus had previously used the same approach for validating the FFE ignition model in the program. Fig. 7 illustrates the results at an intermediate step in the validation study. The figure shows the breakdown of census tracts for different range of P_{Ig_tract}, which is a step before calculating the probability of ignition in individual buildings. The total number of tracts for each event is the number of census tracts where a PGA higher than 0.08g was observed.

The number of ignitions from the proposed model is calculated for all seven considered earthquakes and given in Table 9, where it is compared with the actual reported number of ignitions. Table 9 also gives the number of ignitions calculated using Eq. 1 from Hazus, and the number given in a validation study by Hazus that followed the procedure explained in Section 3.1. If only Eq. 1 is used to obtain the number of ignitions in census tracts with PGA larger than 0.13 and population density larger than 3000 per sq km, and given the total building square footage, the total number of ignition for all the historical earthquakes are considerably different from the actual number of ignitions recorded in the events. When Eq.1 is adjusted as discussed in Section 3.1, Hazus provides a range for the number of ignitions as the program suggests running the analysis a number of times to capture uncertainties in the process. This again reflects the complications in incorporating uncertainties in the Hazus model, while the proposed model inherently incorporates a probabilistic approach and is robust. Note that the Hazus validation study goes back to a study that was completed in 2001 [24], while the fire ignition model in Hazus was updated in 2009. It is therefore possible that the Hazus predictions have been improved compared to the predictions provided in Table 9. Overall, the proposed probabilistic model in this work captures the number of fire events after an earthquake reasonably well, given the level of uncertainty that exists in the problem. In addition, the proposed model has the advantage of providing the breakdown in the number of ignitions for different considered building types.

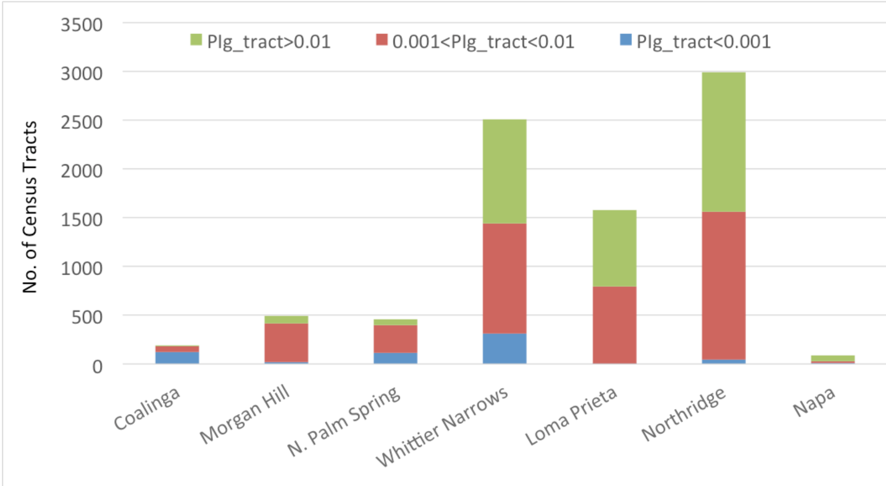

Figure 7: Statistics of obtained probability values at the census track level (P_{Ig_tract}) using the proposed model

Table 9: Validation study for the ignition model, and in comparison with Hazus

Earthquake	Number of Ignitions						
	Actual	Hazus (Eq. 1)	Hazus (Complete process)	Proposed Model			
				Total	W	MH	NC
1983 Coalinga	3	0	1	0.5	0.5	0	0
1984 Morgan Hill	6	1	N/A	4	4	0	0
1986 N. Palm Spring	1	0	N/A	3	2	1	0
1987 Whittier Narrows	20	40	33-43	32	27	1	4
1989 Loma Prieta	36	23	14-38	27	22	2	3
1994 Northridge	82	98	72-101	90	75	3	12
2014 Napa	6	1	N/A	3	3	0	0
TOTAL	154	163	N/A	**160**	**134**	**7**	**19**

The proposed model is valid for areas in the U.S. other than California, as long as the safety and building standards, appliances, and the nature of urban environment is similar. The input parameters for the model at the census tract level (PGA, population density, and square footage) directly influence the probability of ignition, regardless of the location. At the building level, the construction type and building standards are to be similar to those in California in order for the model to be valid.

Similarity in the source of ignition is another parameter to be investigated when validating the model for different regions. Therefore, the source of 154 ignitions in California were investigated, and it was deduced that 41 ignitions happened due to gas leaks, 65 ignitions occurred due to electric arcing, and 48 ignitions due to other reasons such as chemical spills, building damage, and etc. Table 10 provides the breakdown of ignition source for each historical event. It should be noted the source of ignition for some of the data points are not recorded, those point are counted in the "others" category. It is evident that electricity and gas leaks are the primary reasons for the post-earthquake ignitions.

Table 10: Source of ignition in historical events

Earthquake	Ignition source		
	Gas	Electric	Others
1983 Coalinga	0	2	1
1984 Morgan Hill	2	2	2
1986 N. Palm Spring	0	1	0
1987 Whittier Narrows	8	11	1
1989 Loma Prieta	13	14	9
1994 Northridge	16	34	32
2014 Napa	2	1	3
Total	**41**	**65**	**48**

5. IMPLEMENTATION OF FIRE IGNITION MODEL IN MAEVIZ/ERGO

One of the objectives in developing the proposed FFE ignition model was to have a model that can be implemented in GIS-based platforms. Therefore, as an example of application, the new proposed fire ignition model is implemented in MAEViz/Ergo. The existing fire ignition plug-in in MAEViz/Ergo, discussed in section 3.2, is adopted for the implementation of the proposed model. The main parts of the code that are modified in the fire ignition plug-in, aside from adding required descriptions and defining public variables, include (1) BuildingFireIgnition.java, (2) gisMetadata, (3) gisSchemas. Eclipse Luna, with the programming language Java was used for the implementation.

Eqs. 3 and 7 are coded in BuildingFireIgnition.java. Eq. 3 is used for PGA values larger than 0.08, since previous historical data showed that ignitions at low PGA values can be ignored (discussed in Section 4.1). With the global probability of ignition calculated from Eq. 3 and as an input to Eq. 7, the "Bisection Method" is used to solve for the probability of ignition in individual buildings. The bisection method is a root-finding method that repeatedly bisects an interval and then selects a subinterval in which a root must lie for further processing. The acceptable threshold for the error in solving for the probability of ignition in individual buildings (P_{Ig_W}, P_{Ig_MH}, and P_{Ig_NC}) is set to be 10^{-12}.

The required inputs for Eqs. 3 and 7 include population density, total building square footage, number of different building types, and the PGA at the census tract level. The framework is coded such that the user is asked to provide a dataset that includes all the relevant parameters for census tracts in the area of the study. In order to allow the user to input a new dataset, the gisSchemas is extended and a new xml-based schema description file is added (this is the standard procedure to add any new dataset to MAEViz/Ergo). The description file includes the variables, and the data attributes (e.g. integer or double for storing numerical values). The user can obtain the required dataset for the analysis from Hazus, given that the required dataset is at the census tract level.

Every building in the inventory dataset of MAEViz/Ergo should have a corresponding census tract number. The ignition model is coded such that the census tract ID is used to map the input data by the user (at the census tract level) to individual buildings. The output is the probability of ignition at the tract level (Eq. 3) and for every building (from Eq. 7).

The above setup is based on PGA values that are input by the user for every census tract, i.e. all of the buildings in a census tract have the same PGA value. One advantage of the above setup is that existing shakemaps from historical earthquakes can be used to obtain the actual PGA values for the area of interest, rather than using simulated values. However, the ultimate goal is to have the user define an earthquake scenario and allow MAEViz/Ergo to perform the earthquake simulation to obtain PGA. In that case, the earthquake analysis is performed before running the fire ignition module and the output PGA values from the earthquake analysis is an input to the fire ignition module. Both options for providing PGA to the fire ignition module (by user or from running earthquake simulations) can be programmed in MAEViz/Ergo. Overall, the accuracy of results is dependent on the accuracy of the provided dataset by the user, as well as the inventory data. Gathering accurate data is one of the most important and critical steps in evaluating and predicting performance of a community during and after an earthquake.

Fig. 8 shows the flow of analysis when using the fire following earthquake plug-in in MAEViz/Ergo. The required inputs including building damage, appliance existence probabilities, and ignition threshold are the default inputs for the Turkish ignition model (Section 3.2). The required input for the proposed ignition model is at the census tract level circled in red in Fig. 8. Fig. 9 shows a sample of results based on the new fire ignition model. Fig. 9 shows the census tract ID (column *loc3*) for every building that is identified with an ID (column *parid*). The output from the ignition model includes probability of ignition for the census tract where the building is located (P_{Ig_tract} in Eq. 3 shown in the column labeled as p_ig_tr in Fig. 9), and the probability of ignition for individual buildings (P_{Ig_W}, P_{Ig_MH}, or P_{Ig_NC}, shown in the column labeled as p_ig_bldg in Fig. 9). MAEViz/Ergo provides a statistical tool for the tabulated data; the tool can be used to obtain the sum of the probability values for individual buildings that represents the expected number of ignitions in the region of interest.

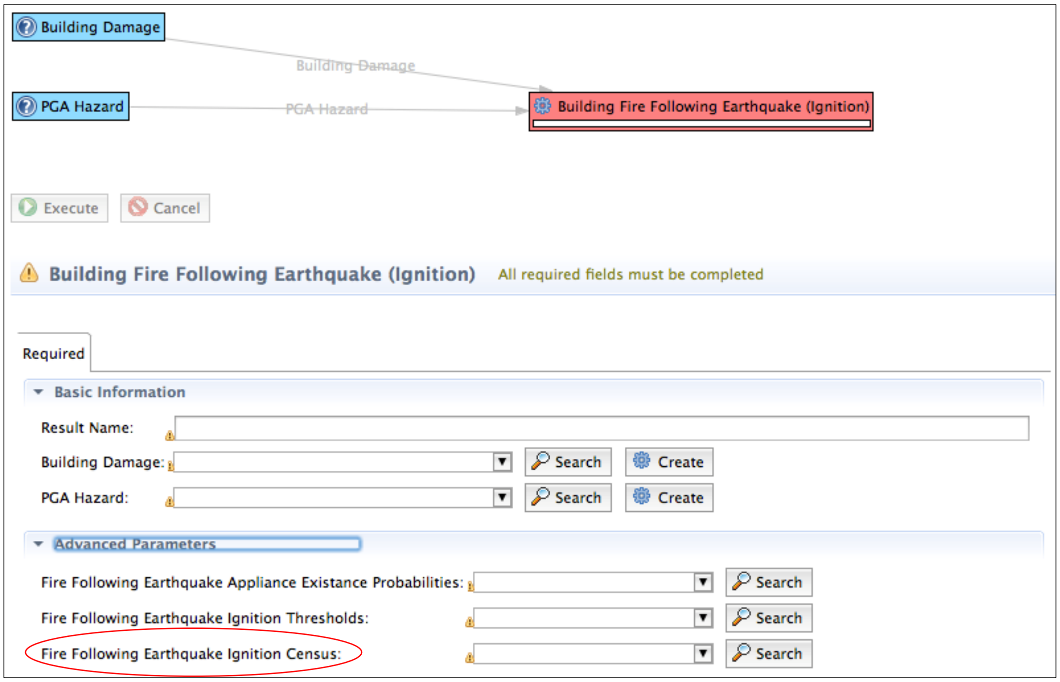

Figure 8: Flow of analysis for fire following earthquake in MAEViz/Ergo

parid	loc3	p_ig_tr (0–1)	p_ig_bldg (0–1)
06087120400CA3IND6HMCMH	06087120400	0.05	0.0000391562
06087122203CA3IND6HHCMH	06087122203	0.06	0.0000749781
06087120900CA3IND6HHCMH	06087120900	0.16	0.0001056916
06087120700CA3COM1CMCC2L	06087120700	0.08	0.0000297054
06087120400CA3IND6HHCMH	06087120400	0.05	0.0000391562
06087120900CA3AGR1HMCMH	06087120900	0.16	0.0001056916
06087123100CA3GOV1CMCC2L	06087123100	0.04	0.0000291738
06087121300CA3AGR1HMCMH	06087121300	0.11	0.0001657781
06087120301CA3IND6HHCMH	06087120301	0.08	0.0000591684

Figure 9: Sample results from the implemented proposed ignition model in MAEViz/Ergo

6. SUMMARY AND CONCLUSIONS

This paper started with an overview of the existing Fire Following Earthquake (FFE) models to evaluate the number of fire ignitions after an earthquake in a community. Two such models exist: Hazus and a plug-in for MAEViz/Ergo based on the work of Turkish researchers. The ignition model in the FFE module of Hazus is an empirical one that was developed based on historical FFE events. The model provides the number of ignitions in a census tract; however, the formulation includes random number generation and the setup requires the user to run the analysis a number of times (10 times is recommended) to capture the uncertainties in the process. The model fit to the ignition data in Hazus has an R^2 value of 0.084 so that the model can be improved considerably in relation to the historical data. On the other hand, a FFE plug-in is incorporated in MAEViz/Ergo, which relates fire ignitions to potential ignition sources such as utilities and appliances based on analytical procedure. The ignition model provides probability of ignition in individual buildings in a community, but the outcome can be used for comparative purposes rather than for realistic estimate of the total number of ignitions within a community. Also, parts of the ignition model were developed using non-U.S. sources and should be adjusted for U.S. application.

The paper proposed a novel ignition model based on historical FFE data. The model relates probability of ignition in a census tract to PGA, population density, and total building square footage in a census tract. The probability of ignition in a census tract is then related to probability of ignition of individual buildings in the census tract based on the building construction type (wood, mobile home, and noncombustible). The formulation can be used to obtain the total number of ignitions in a region of interest, as well as the breakdown of ignitions in the considered building types. The model was validated against historical FFE events and showed good agreement with the historical data.

The proposed fire ignition model was implemented in MAEViz/Ergo to demonstrate its application in a GIS-based platform. The ignition model can be used together with a GIS-based platform to evaluate the expected number of fire ignitions after an earthquake and identify areas of a community with high risk of fire ignitions. This way, resources in a community can be properly allocated and appropriate mitigation techniques can be implemented. As part of future research, inventory data will be collected for an earthquake prone community and a case study will be conducted using the proposed post-earthquake fire ignition model in MAEViz/Ergo. In future, the ignition model will be integrated with fire spread and suppression models that could be used by firefighters for mitigation planning and allocation of resources.

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