Toward Probabilistic Risk Assessment of Wildland–Urban Interface Communities for Wildfires

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Abstract. The number of wildfire incidents affecting communities in Wildland–Urban Interface (WUI) areas has been rapidly increasing. Understanding the fire spread between structures and evaluation of the response of the communities to the possible wildfire scenarios are crucial for proper risk management in the existing and future communities. This paper discusses a stochastic methodology to evaluate the community's response to potential wildfire scenarios. The methodology has three primary features: (1) it is based on stochastic modeling of fire spread; (2) it breaks the wildfire incident into two consecutive segments: spread inside the wildland and spread inside the community; (3) it integrates the two spread models in the form of a conditional probability. The paper focuses on fire spread inside the community and applies the proposed methodology to two case studies in California, US. The two case studies demonstrate variations in fire spread within the communities for the given fire scenarios approaching from the wildland. The performance of communities is characterized using cumulative distribution functions of the number of ignited buildings over time.

1. Introduction

The economic and social impacts of wildfires have been rising in recent years and the wildfire hazard represents a global concern now [1–4]. The frequency and intensity of wildfires are expected to increase due to changing weather patterns and human suppression activities of the past century [5–8]. Destructive fires will continue to pose risks to communities, especially those built in the wildland-urban interface. Records show that 8 out of the 10 most destructive fires in California, US, in terms of insured losses, happened since 2017; also 6 out of the 10 most destructive fires, in terms of structure losses happened since 2017 [9, 10]. Meanwhile, expansion of major wildfires is found beyond the Western US, such as the

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2016 Gatlinburg fire in the Southeast US [11], the 2017 fires in Portugal, and the 2018 Mati fire in Greece [12].

The current approach to manage the fire hazard within wildland–urban interface (WUI) communities is neither sufficient nor sustainable. Here, WUI is defined as a geographic boundary that human developments and flammable vegetation merge in a wildfire-prone environment [13]. Large losses from wildfires have led to the development of educational programs and recommendations for mitigation actions to reduce the vulnerability of structures in WUI communities [14–16]. However, only a few of these recommendations have been validated [17, 18]. For example, no data could be found to support that the clear distance between homes can be reduced from 30 ft to 15 ft if in-home sprinkler systems are installed, a recommendation by NFPA 1141 [18]. Thus, science-based guidelines on WUI communities, such as home spacing, width of the roadways, effectiveness of fuel breaks, and defensible spaces, are needed to understand how the community responds to a wildfire under different scenarios.

A workshop on "Preparing for Disaster: Advancing WUI Resilience" was held in 2020, wherein the knowledge gaps on wildfire risk assessment and WUI disaster resilience were identified and the required steps to establish solutions were discussed [19]. The workshop outcomes indicated the need to go beyond single structures and establish community-based approaches to WUI resilience. Also, quantifying the risk and developing validated models for fire spread in WUIs and in transition from wildland to WUI were introduced as some of the knowledge gaps and research needs [19]. Having a structured methodology to conduct risk assessment on communities helps with the mitigation, planning for suppression and evacuation, and response [20]. The rest of this section provides a brief background on wildfire modeling and risk assessment in the wildland and communities.

1.1. Background

Performing risk assessment of WUI communities that are exposed to wildfires and quantifying the potential damage requires an understanding of both the wildfire hazard in the wildland and the vulnerability of communities. In another word, the probability of ignition and fire scenarios in the wildland should be combined with the associated response of the communities to quantify risk. For example, Haas et al. [21] introduced and discussed a methodology to account for WUI fire risk by combining a wildfire hazard map and a WUI map of the population, but raised the need for the fire simulation inside/around populated areas for a better estimation of the risk. In another study on structures affected by historic wildfires, the location and arrangement of structures were found to be strong contributing factors to the fire risk [22]. In general, the risk assessment can be conducted using analysis of historic events, simulation of fire scenarios, or a combination of both. One issue with relying on past events is that sufficient data on extreme scenarios may not be available. Hence, validated models could be employed to simulate potential scenarios based on their likelihood of occurrence and to conduct stochastic studies considering uncertainties in the process. It is preferred for the

models to be computationally efficient and flexible enough to accommodate the simulation of several hundred to thousand scenarios.

Significant research has been conducted to understand wildfire behavior in the wildland, where land is mainly covered with vegetation [23–26]. One of the widely-used models in the US to simulate wildfire in the wildland is the Rothermel model [27], which combines data on fuel (i.e., vegetation), weather, and topography to calculate the rate of spread (ROS) of fire. Other models, such as Cheney's or McArthur's have been developed to predict wildfire spread in the Australian Grasslands [28, 29]. Several tools are available to simulate fire spread in the wildland. For example, the Fire Area Simulator (FARSITE) is a common tool in the US for operational purposes. FARSITE calculates fire growth, mainly in the wildland, using deterministic approaches [30] and is widely used by the California Department of Forestry and Fire Protection and the US Forest Service [31]. WFDSS-FSPro is another tool used in the US to calculate the probability of fire spread in the wildland for risk measurements [32].

There has also been significant research on fire dynamics inside buildings and the response of individual structural components to fire (e.g., roofing material) [33–35]. However, research on large outdoor fires within communities (e.g., due to wildfires), and the connection between mitigation actions at the household level and the wildfire response at the community level lag behind [36]. Meanwhile, not much data on large-scale building fires is available for the validation of simulations. WUI Fire Dynamic Simulator (WFDS) is a physics-based model, which is an extension of the Fire Dynamic Simulator (FDS), developed by NIST to simulate WUI fires [37]. FDS was mainly established for application to structural and stationary fires and WFDS was expanded to include vegetative fuel to the platform [38–40]. Meanwhile, due to the challenges in capturing the physics of the fire spread and the required input data, cellular automata and probabilistic methods have become popular. For example, Jiang et al. [41] developed a model based on cellular automata with applicability to both wildland and WUI fires. Such models usually include simplifying assumptions on the physics of the process but are significantly faster than those using computational fluid dynamics and detailed physics-driven models. Khakzad [42] developed a methodology for modeling fire spread in wildland-industry interface (WII), a similar problem as discussed in this paper, with the assumptions tailored toward the industrial plants. The method is based on the most probable path of fire and is developed using a Dynamic Bayesian Network [42]. Cicione et al. [43] developed and applied a semi-probabilistic fire model to simulate fire spread in informal settlements.

One important aspect in understanding wildfires is the spatiotemporal scales of interest when it comes to resolving the fire spread outside and inside the community. Progression of a fire line over a few feet (in the space domain) and a few minutes (in the time domain) is typically not recorded when an intense fire is burning across hundreds to thousands of acres in the wildland. However, similar distance and time intervals can make a difference when the fire spreads between buildings. Thus, fire spread within the wildland and a community is typically studied using different spatiotemporal scales and platforms. Given that WUI communities are most often threatened by fires that start in the wildland and spread far

enough to reach the community, two platforms might be needed to properly capture the behavior of fire across the two domains. If two platforms are used to simulate fire spread, the boundary information from one platform to the other should be transferred properly.

In summary, limited options are available to study fire spread in WUI and response of communities, when comparing the modeling techniques and tools for wildland fires and structural fires. Thus, there is a need for additional research to better understand the fire spread between structures and the associated risks within WUIs. There is typically a mixture of both structures and vegetation in WUIs. Structures and vegetation have different heat release rates, duration of burning, and different responses to external triggers such as flame and firebrands (e.g., time to ignition). Moreover, the required resolution of analysis (in both space and time) is higher for the inputs when analyzing wildfire in communities.

1.2. Objectives

The objectives of this paper are to (1) discuss the steps to integrate stochastic modeling of wildfires in WUI communities within a holistic probabilistic risk assessment framework, and (2) introduce a stochastic methodology to simulate fire spread in WUI communities and characterize the community performance.

- Section 2 of the paper discusses assumptions and components of a probabilistic risk assessment framework, including: (1) wildfire model: capturing the likelihood of the wildfire hazard and the potential exposure of the WUI community by simulating various scenarios of fire spread in the wildland, (2) transitioning the fire hazard from the wildland to the WUI community with quantifiable parameters that can be used as input for the community model, and (3) community model: characterizing the response of communities to wildfire scenarios considering individual building features as well as their aggregated behavior.
- Section 3 of the paper proposes a stochastic "community model" to capture uncertainties in fire spread within WUI. The methodology is applied to two WUI communities for pre-defined fire scenarios, i.e., the "wildfire model" and the "transition to the community" are not simulated. The Streamlined Wildland Urban Interface Fire Tracing (SWUIFT) model [44] is used as the basis to introduce uncertainties in the fire spread model and characterize the performance of communities using measurable metrics.

2. Probabilistic Risk Assessment Framework

This section discusses a methodology to enable risk assessment of WUI communities, relying on stochastic-based models to capture the progression of fire within the wildland, from the wildland to the community, and within the community. Such methodology can be used to establish working protection plans and mitigation strategies for a community considering various potential fire scenarios and the features of the community (e.g., layout and construction materials) that could

affect the vulnerability of the community subjected to a wildfire. Given the large number of variables involved, their high degree of uncertainty, the level of complexity and interactions between parameters, and their effects on the fire behavior, a stochastic approach is needed.

The framework comprises of five components: (1) inputs, (2) a platform to simulate wildfire ignition and spread in the wildland (hereinafter ''wildfire model''), (3) a platform to simulate fire spread inside the community (hereinafter ''community model''), (4) a link bridging the two platforms, and (5) outputs. The outputs represent the consequences of various wildfire scenarios and can be defined to communicate the wildfire risk for the community. The framework is demonstrated in Figure 1. The rest of this section introduces the five components and describes the structure of the risk assessment framework.

2.1. Components of the Framework

Input: Several well-established variables affecting wildfire behavior have been widely incorporated in simulation platforms. Topography (mainly slope), land cover (mainly type and density of vegetation, the corresponding amount and release rate of energy, and moisture content), and weather parameters (e.g., wind speed and direction, temperature, and humidity) are the most frequently used inputs. There are also anthropogenic factors, such as human-caused ignitions and suppression activities, that have a significant influence on the number of fire occurrences and the final size of burned areas. The characteristics of the community is another important input; details such as the layout and configuration of the community components (buildings, roadways, vegetation areas) and the type of construction material for structures should be defined in the model. This information in particular distinguishes the risk outcome for the community of interest.

Wildfire model: The wildfire model consists of two parts: (1) a stochastic ignition model defining location and time of the ignition(s) within the domain of the analysis, and (2) a spread model which can work either probabilistically (e.g., cellular automata models) or deterministically (e.g., WRF-Fire [45]) given the ignition(s). The spread model should characterize the behavior of the fire using quantifiable variables such as the ROS, fire perimeter, and fire intensity.

Community model: The community model should capture the fire spread properly; thus, the model should include: (1) high spatial and temporal resolutions; (2) timber structures as combustible fuel versus steel or concrete structures and the natural and man-made fire breaks, such as roadways, parking lots, and ponds; and (3) the uncertainties in the behavior of fire (e.g. spot fires). It is preferred for the model to have a fast processing time to enable a large number of simulations for capturing the uncertainties.

The link between the wildfire and community models: The link between the two models should translate the output of the wildfire model to a quantified input for the community model. In other terms, the community model requires initial ignition(s) as an input, which is adopted from the result of the wildfire model. A community can be attacked by a fire line approaching from the wildland and/or by fire spotting before the fire front reaches the community. Different platforms
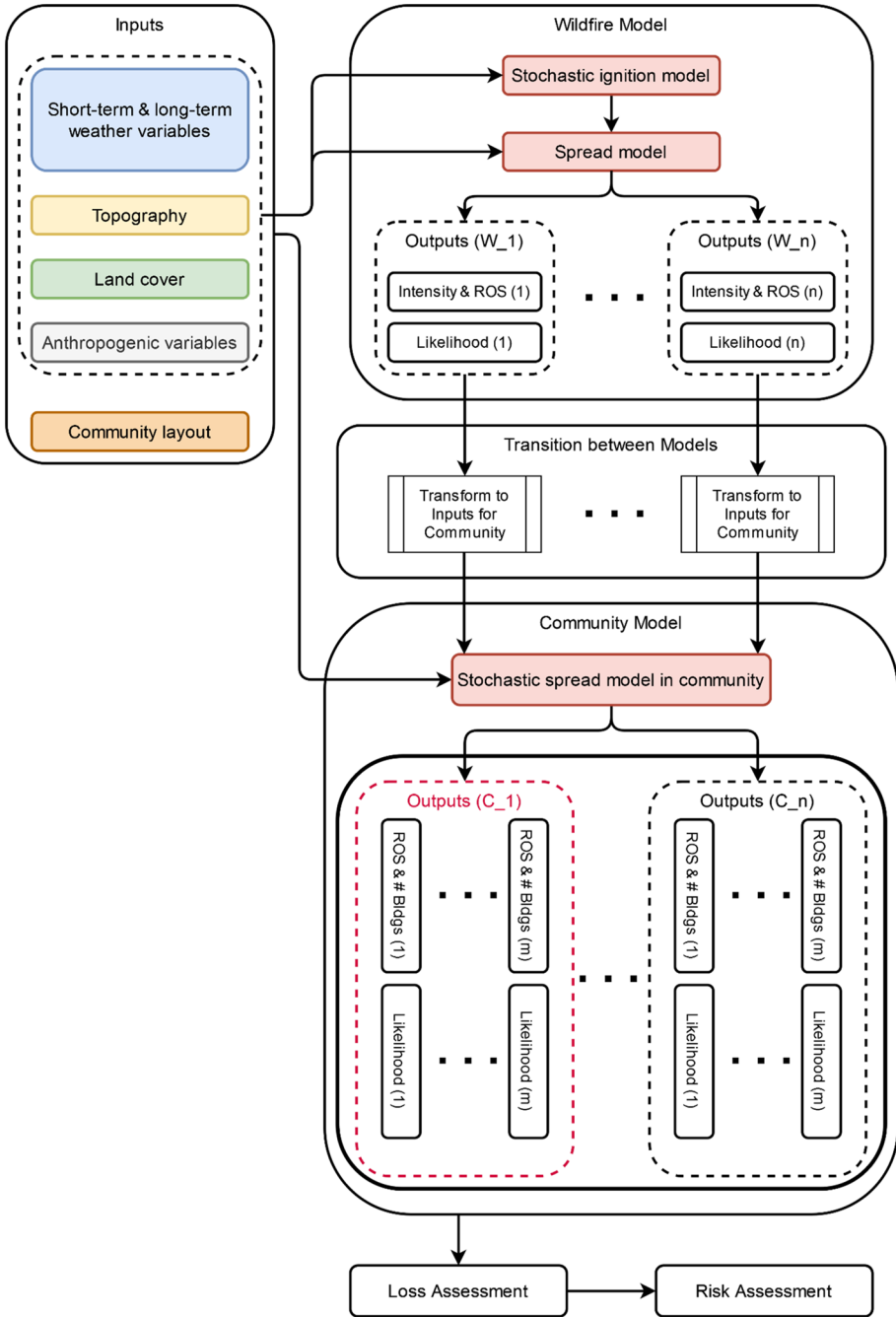
Figure 1. Stochastic-based methodology for risk assessment of WUIs for wildfire (Color figure online).

might be used for the wildfire and community models based on the interest of users. Hence, introducing a link between the wildfire and community components is necessary for the completeness of the framework. There is a need to systematically define and distinguish between potential scenarios for the community. The considered domain within which the community is defined and the decision on when to switch from the wildfire model to the community model depend on the models in use and the standardized definitions to be researched and agreed upon.

Output: The output of the community model, which is used for communicating the risk, should be tangible, and more importantly, comparable across communities. Hence, quantities that are introduced as outputs should be established in coordination with community partners. This paper discusses three potential outputs to be considered individually or in combination to communicate the consequences of a wildfire in a community: (1) the expected total number of ignited structures; (2) the cumulative probability distributions of the number of ignited structures over time; this parameter is also a proxy for the rate of fire spread inside the community, (3) triggers of conflagration, when a large number of structures are ignited during a short time frame, and the corresponding time at which conflagration occurs. It is not intended to report the statistics of outputs only (e.g., median and standard deviation). Such static measures do not necessarily reflect the evolution of fire events within a community; for example, there could be an area within the community that is vulnerable and fire tends to spread quickly, leading to conflagration. Thus, the results could be characterized based on the distribution of potential outcomes but should provide the flexibility to assess various scenarios in detail.

2.2. Description of the Framework

The framework combines the responses in both wildland and WUI communities, providing the ability to estimate the probability of loss in a community conditioned on the probability of wildfire scenarios (real or simulated). The choice of modeling tools depends on the user's preferences and the specific features/capabilities of such platforms. The methodology is generalized enough for application to any community as long as the stochastic simulations are conducted properly and the outputs capture the consequences in WUI communities.

The stochastic procedure starts with sampling from all relevant input variables. A random fire ignition spreads following the chosen wildfire model. Ignition, in particular, might be based on statistical analyses of historical events. Here, the term ignition carries the concepts of time and space. Given the importance of fire spotting, its influence on the advancement of a wildfire, and the high level of uncertainty associated with this fire spread mechanism, it is recommended for the wildfire model to account for fire spotting. The output to characterize the wildfire behavior should, at the minimum, include the perimeter/frontline of the wildfire, the ROS (i.e., how fast the fire advances), and whether or not the fire reaches a community. Repeating this process for a large number of cases yields an ensemble of wildfires (e.g., W_1 to W_n in Figure 1) that are ignited at different locations and have various ROS. The information can be used to define the likelihood of

the hazard as a joint probability of the time that it takes for the wildfire to reach the community from the location of ignition and its corresponding intensity when reaching the community. Wildfire scenarios can be categorized into multiple classes in terms of intensity and with assigned probabilities.

The ROS and location and direction of the fire front are sufficient information to initiate the spread in the community model. Simulation of fires in WUI communities should reflect the performance of individual structures as a function of construction materials as well as the communality configuration (e.g., layout and distance between buildings, type and density of vegetation). The model should simulate fire spread with a relatively high spatiotemporal resolution considering the layout of structures. Moreover, the model should incorporate fire spotting as it plays a significant role in WUI fire spreads [17, 46].

The community model should keep track of the fire advancement with respect to the location of buildings to record ROS and the number of ignited structures. It is assumed that the available, or yet to be created, models have a time component included, which provides the ability to track the evolution of fire inside the community, allowing to follow the progression of fire and ignited structures over time. Depending on the level of sophistication of the model, different levels of structural damage can be defined. Until further research is conducted, a simple and more conservative method may take a binary approach and consider an ignited structure as completely lost. Once the fire is initiated in the community model, random sampling of the input variables and model parameters should be conducted to simulate the fire spread inside the WUI community. By repeating the procedure, an ensemble of simulated fire spreads inside the community is created for *each* of the given wildfire scenarios (e.g., C_1 to C_m in Figure 1). Thus, the likelihood of outputs from the community model can be conditioned on a certain wildfire scenario. Repeating the analysis for all simulated wildfires and aggregating the results will lead to the probability of loss for the community.

3. Stochastic Spread Model in the Community

This section discusses simulation of fire spread in WUI communities including uncertainties in the process, that is the focus is on the "community model" indicated by the red box in Figure 1. The methodology is applied to two case studies: (1) the Trails community close to San Diego, CA, which was hit by the 2007 Witch and Guejito fires, and (2) the Fountain Grove community in Santa Rosa, CA, which was hit by the 2017 Tubbs fire, the second most destructive fire in the modern history of California as of 2022. The performance of the two communities is evaluated for the historic 2007 Witch and Guejito fires and the 2017 Tubbs fire and the results of the stochastic simulations are compared with observations in reality. Each of the wildfire scenarios can be considered as one of the several simulations in the ensemble of wildfires (i.e., the output of the wildfire model).

The case studies are selected for two main reasons:

(1) The two communities have different features and layouts, including the distance between structures, and the density of vegetation inside and around the community.
(2) The communities were hit by fires with completely different behaviors. In the Trails community, the first few structural ignitions were reported as early as one hour before the fire front reaches the community. These ignitions were due to firebrands flying ahead of the fire. In this case, the fire was controlled and suppressed inside the community. On the other hand, the Fountain Grove was completely burned out by the Tubbs fire, where the fire line swept through the community.

Details about the two case studies are available in Maranghides and Mell [47] and Watkins et al. [48].

The Streamlined Wildland–Urban Interface Fire Tracing (SWUIFT) model is used to establish the stochastic fire spread simulations inside the communities [44]. The SWUIFT model discretizes the community into grid cells of 10 m × 10 m resolution and captures the fire spread in 5-min time steps. The current version includes three types of land cover, namely, vegetation, structure, and non-combustible (roadways, water bodies, and parking lots).

SWUIFT accounts for short-range and long-range fire spread mechanisms, and simulates fire spread due to radiation and fire spotting. A *burnable* cell (i.e., vegetation and structure cells) can experience three ordered stages if affected by fire: ignition, fully developed with contribution to spread, and burnt. Structure cells can ignite if they receive a certain threshold of radiant energy or accumulated mass of firebrands. The considered value for the critical ignition flux for radiation is 14 kW/m^2, which is slightly larger than reported values in existing experiments [49, 50] to account for tiling and finishing. Following experiments in the literature [51], the ignition condition due to firebrands is determined as the accumulation of 24 g of firebrands landed on a circle with a diameter of 10 cm. A contributing structure cell to fire spread generates firebrands as a function of wind speed following an empirical relationship by Waterman [49, 52]. A vegetation cell ignites due to spotting if 224 g of firebrands land on the cell. When ignited, a vegetation cell is assumed to generate 4923 g of firebrands in a timestep, following a study by Wickramasinghe [53]. The generated firebrands are transported downwind following a lognormal distribution as a function of wind speed and dispersed sidewind following a normal distribution.

For this study, the SWUIFT model is selected as it is designed to have a manageable computational cost, i.e., in the order of minutes for each simulation, to conduct probabilistic analysis. Monte Carlo simulations with Latin hypercube sampling are set up to capture uncertainties in fire spotting, ignition criteria, wind speed, etc. More details about SWUIFT and the input raster for the two case studies can be found in Masoudvaziri et al. [44]. It should be noted that the proposed framework in Section 2.0 is generalized enough that can be used with other spread simulation tools. The rest of this section will focus on the definition of random variables and the corresponding distributions to be included in SWUIFT, and the quantification of damage in the two listed communities.

3.1. *Random Variables*

The uncertainty in the SWUIFT's input parameters should be characterized to conduct stochastic analysis. Table 1 summarizes the parameters, their default values in SWUIFT, and the proposed distributions. A brief description of the model parameters is provided, followed by a sensitivity analysis to identify the influencing parameters.

Heat radiation is one of the fire spread mechanisms implemented in SWUIFT, which is assumed to be generated by and causes ignition in structure cells. Research on spontaneous ignition of wood shows that the critical radiant heat flux across bare wood grains is 12 kW/m^2 [49, 50]. The threshold is taken as 14 kw/m^2 in SWUIFT to account for tiling and finishing. Hence, for the sensitivity analysis, a uniform distribution between 12 kW/m and 16 kW/m^2 is considered for the parameter "Radiation_threshold" as listed in Table 1.

Fire spotting is another fire spread mechanism in SWUIFT, which is a function of a number of parameters. Due to the high level of uncertainty involved in fire spotting, probability distributions are typically defined to model the process. Firebrand generation for vegetation is a function of the mass of firebrands, as determined by experiments and vegetation type. Firebrand generation for structures is a function of the mass of firebrands and wind speed. The transport of firebrands depends on wind speed and direction.

Table 1
Random Variables in SWUIFT and the Corresponding Distributions

Parameter	Description	Point value	Distribution
Radiation_threshold	The threshold for a structure grid cell to ignite due to radiation	14,000 [W/m^2]	Uniform (12,000, 16,000)
Fb_wind_coef	The coefficient for longitudinal distribution of firebrands along the wind direction. The coefficient is used to determine the mean value of the distribution	30 [–]	Uniform (20, 40)
Fb_wind_sd	The standard deviation for the longitudinal distribution of firebrands along the wind direction	0.3 [m]	Uniform (0.25, 0.4)
Fb_wind_sd_transverse	The standard deviation for the transverse distribution of firebrands (perpendicular to the wind direction)	4.85 [m]	Uniform (3, 9)
Fb_mass	Mass of generated firebrands	0.5 [g]	Beta (2, 7, 0.05, 1)
Fb_dist_mu	Mean value for the distribution of firebrand dispersion on a structure grid cell, when landed	0.01 [m]	Uniform (0.001, 0.2)
Fb_dist_sd	The standard deviation for the distribution of firebrand dispersion on a structure grid cell, when landed	0.5 [m]	Uniform (0.01, 1)
Wind_speed	Average wind speed over each time step	Varies with time step [m/s]	Weibull (14, 8)

Transport of the firebrands from structures and vegetation is typically modeled by two independent distributions: (1) a log-normal distribution along the wind direction (longitudinal), and (2) a normal distribution perpendicular to the wind direction (transverse). Each of the two distributions is characterized by two parameters, the mean and the standard deviation. Equation 1 shows that the mean of the distribution in the longitudinal direction (μ_x) is a function of wind speed. As part of the transport model, three random variables are defined: (1) the coefficient "Fb_wind_coef" when defining the mean of the distribution in the longitudinal direction, (2) the standard deviation for the distribution in the longitudinal direction "Fb_wind_sd", and (3) the standard deviation for the distribution in the transverse direction "Fb_wind_sd_transverse". The mean for the transverse distribution is set equal to zero to avoid an inclination of firebrands to one side when considering the direction perpendicular to the wind.

$$\mu_x = \ln(Fb\_wind\_coef \times windspeed) \tag{1}$$

Given that more in-depth studies are required for proper quantification of the parameters of firebrand distributions and understanding the phenomenon, in general, uniform distributions are assigned to the parameters, as listed in Table 1.

The mass of firebrands is an important factor in all stages of fire spotting. In SWUIFT, the mass of firebrands affects the generation and ignition criteria. Studies show that the mass distribution of firebrands is highly skewed with most of the sample population being very light [54–56]. To account for variation in the observed data, a Beta distribution is considered for the mass of firebrands "Fb_-mass". Note that to keep the computations manageable, all firebrands for a given simulation in SWUIFT have the same mass; the defined Beta distribution is used to randomly generate the mass of firebrands between simulations.

The final stage in fire spotting is the ignition due to firebrands landing on unburned fuels. In the case of structures, SWUIFT assumes that ignition may occur if enough firebrands are accumulated toward the edges of the structure cells. SWUIFT tracks the source of generated firebrands and calculates the dispersion of firebrands as a cluster based on existing experiments on mass accumulation of firebrands [51, 57, 58]. The distribution for dispersion of the landing firebrands is assumed to be log-normal. The parameters of the lognormal distribution, "Fb_dist_mu" and "Fb_dist_sd" in Table 1, follow a uniform distribution.

A Weibull distribution can be assumed for wind speed following the literature and current practice [59, 60]. In SWUIFT, wind speed can vary over time, but as part of the sensitivity analysis to investigate the effect of wind speed, constant values are used in each simulation.

3.2. Sensitivity Analysis

A sensitivity analysis is completed on the input parameters to identify the critical random variables for which the SWUIFT model is sensitive and should be inclu-

Figure 2.   Results of the sensitivity analysis on the parameters of SWUIFT for (a) the Fountain Grove community and (b) the Trails community (note: labeled values in the figure represent mean, standard deviation, and coefficient of variation of the number of ignited structures, respectively) (Color figure online).

ded in the stochastic analysis. The results of the sensitivity analysis can be used to (1) reduce the number of random variables in the stochastic study and help with the required computational resources, (2) provide insight on the parameters with significant influence to be researched in the future and improve the model performance.

Random variables are generated using Monte Carlo simulations with Latin hypercube sampling following the distributions in Table 1. The random variables are considered independent. For the sensitivity analysis, batches of simulations were run, where one parameter was assigned as a random variable in each case, and all other parameters were set to their default values in SWUIFT (i.e., the point value in Table 1). In addition, a batch of simulations was run with all the parameters varied, note that the random variables are assumed to be independent. Based on the listed distribution in Table 1, the first and third quartiles of the wind speed are 7.32 and 8.19 m/s, respectively. Given the range for the transport parameters in the longitudinal direction (Fb_wind_coef and Fb_wind_sd in Table 1), the expected distance for firebrand transport ranges from 151 m to 317 m, and 169 m to 355 m for the first and third quartiles of the wind speed, respectively. The wind speed makes a notable difference in the right tail of the transport distribution (i.e., 317 vs. 355 m).

Figure 2 presents the mean, standard deviation, and coefficient of variation of the number of ignited structures for both communities with varying random variables. The results show that three random variables have the most influence on the outcome: (1) Wind_speed, (2) Fb_dist_sd, and (3) Fb_wind_coef (shown in red in Figure 2). The figure also includes the results for a case where the three critical parameters are taken as random variables (shown in green in Figure 2). Comparing the results for the case with three critical variables and the case with all parameters taken as random (shown in blue in Figure 2) indicates that the former provides more conservative results, capturing scenarios with a higher number of ignited buildings. Thus, the rest of this study will include the three identified parameters as random variables in the stochastic simulations with the rest of the parameters set to the default value in SWUIFT.

Convergence analysis is conducted on both case studies to confirm the required number of simulations for the stochastic study, where the above-mentioned three parameters are randomly generated. Batches of 200, 500, 1000, 2000, and 5000 simulations with Latin hypercube sampling are generated. For each batch, the mean, minimum, maximum, and standard deviation of the total number of ignited structures are reported, shown in Figures 3 and 4. The figures also include the breakdown of the number of ignitions due to fire spotting and radiation. Convergence is achieved when the change in the simulated number of ignited structures is
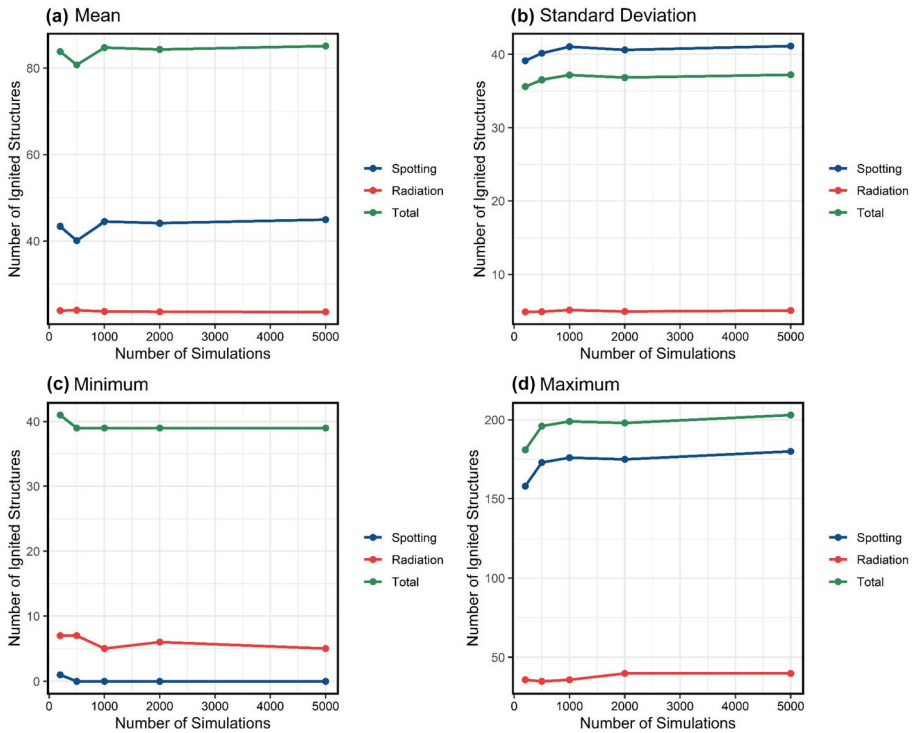
(a) Fountain Grove

(b) Trails
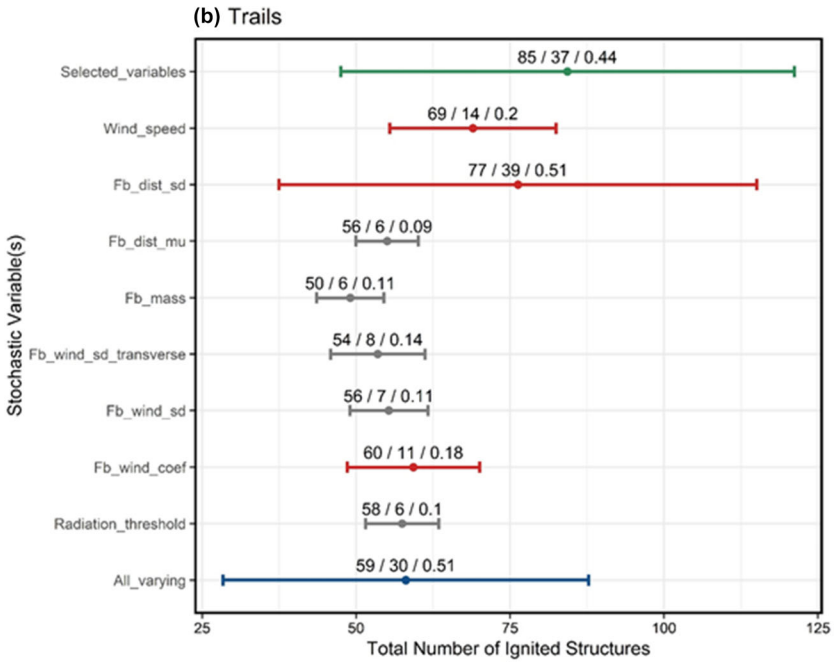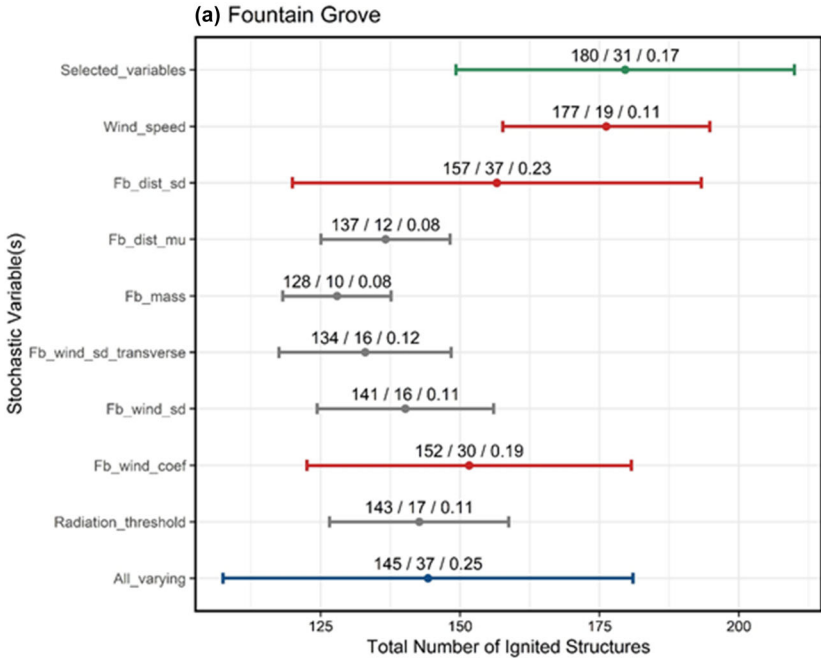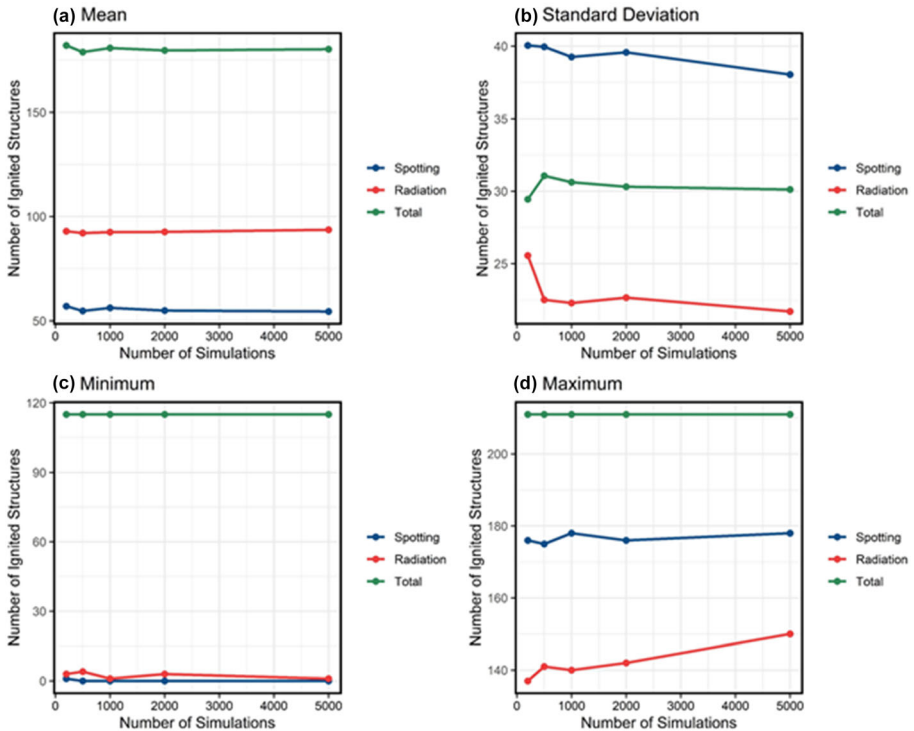
Figure 3. Convergence analysis for the Fountain Grove community. Mean, minimum, maximum, and standard deviation for the number of ignited structures are examined (Color figure online).

less than 10%. Based on the results, batches of 2000 simulations ensure convergence and increasing the number of simulations will not result in changes more than 10%; thus, simulations with 2000 random realizations will be used in the following sections. Note that for the minimum and maximum plots, the sum of ignitions due to radiation and fire spotting does not yield to the total number of ignitions. This is due to the fact that the plotted number of ignited structures as a function of ignition type does not map to the same simulation. For example, a minimum value of zero for fire spotting and radiation does not imply that both mechanisms produced zero ignition in the same scenario.

3.3. Quantification of Community Response

In this study, the response of the WUI community to the wildfire scenarios is characterized using the distributions of the number of ignited structures over time. The stochastic simulations include uncertainty in the selected SWUIFT parameters from Sect. 3.1 (Wind_speed, Fb_dist_sd, Fb_wind_coef) as well as randomness in the transport of firebrands following the defined longitudinal and transverse distributions, and landing of firebrands within structure cells [44]. Given that the two

Figure 4. Convergence analysis for the Trails community. Mean, minimum, maximum, and standard deviation for the number of ignited structures are examined (Color figure online).
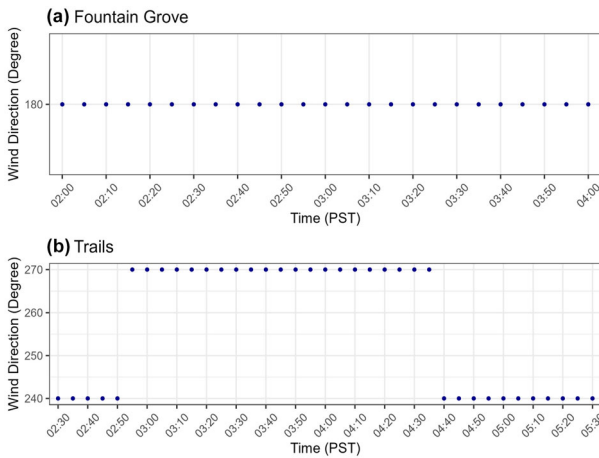
**Figure 5.** Wind direction used in simulations for each case study (Color figure online).

communities are being analyzed for real fire scenarios, the wind direction is modeled based on historical data. Figure 5 shows the wind directions used in each timestep for both cases. The geographical north is the reference for the provided values. In general, wind speed and direction should both be considered as random variables, when conducting risk assessment for a community.

The simulations are used to generate the cumulative distribution functions (CDF) of the number of ignited structures at 30-min time intervals, with the initial ignition inside the community as the reference time. The CDFs provide the probability of having "x number of ignited structures or less" at a given time. The information in the form of CDFs can be used to identify the potential for a sudden increase in the number of ignitions, as an indicator for conflagration or fast fire spread. The selected metric helps locate the vulnerable locations in a community and is practical for response and evacuation planning. The status of the individual structures can also be obtained from the implemented model. The probability of having a structure ignited, the cause of ignition (e.g., radiation or fire spotting), and the expected time of ignition can be tracked in the model. Such information can be used for mitigation at the building level and to strengthen structures against firebrands or radiation based on a quantified assessment of the community.

3.4. Results

Figures 6 and 7 illustrate the CDFs of the total number of ignited structures for the Fountain Grove and Trails communities, respectively. The CDFs are also
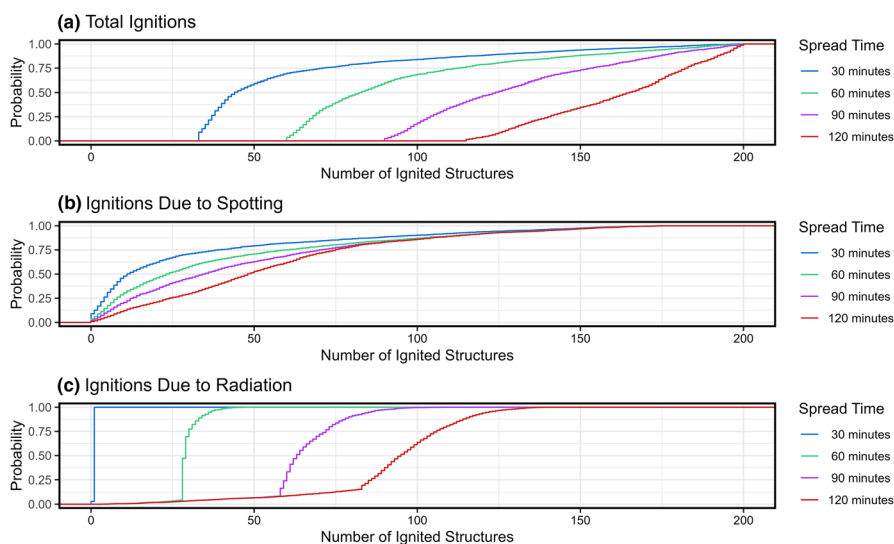
Figure 6. Result of the stochastic simulations of the community model (SWUIFT) for Fountain Grove (Color figure online).
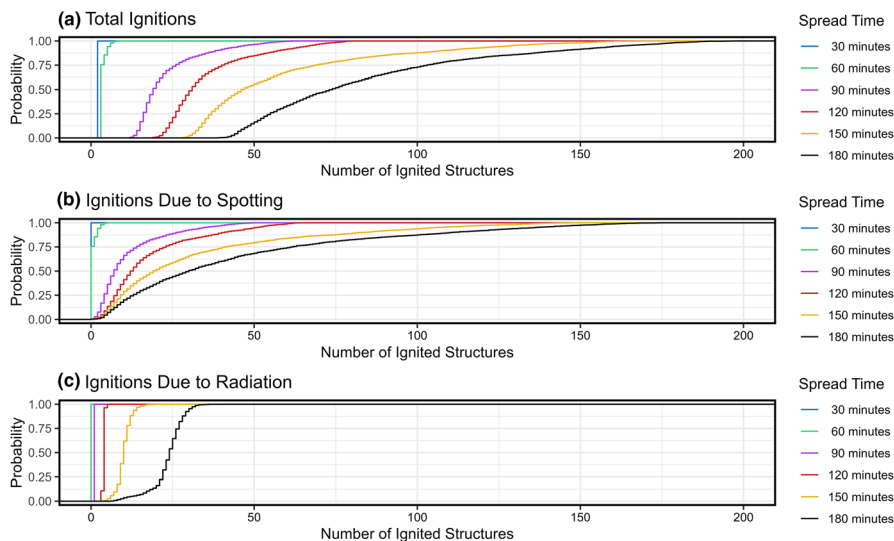
Figure 7. Result of the stochastic simulations of the community model (SWUIFT) for the Trails community (Color figure online).

plotted for ignitions due to radiation and due to fire spotting (i.e., the breakdown of total ignitions as a function of the spread mechanism).

The results show that both radiation and spotting play an important role in the Fountain Grove community, while in the Trails community, spotting is the main mechanism of fire spread. Two factors are the cause of this difference: (1) community layout: buildings are more distant in the Trails community compared to the Fountain Grove and vegetation coverage is lower inside the community; (2) initial ignitions: there are a few separated and distant ignitions in Trails before the fire front reaches the community, while in Fountain Grove, ignitions begin with the fire front. Hence, a larger area of vegetation and number of structure grid cells are ignited early in the simulation, which corresponds well with observations in reality.

The first result to investigate is the number of ignited structures at the end of the simulations. In the case of the Trails community, the number of ignited structures after 180 min range between 39 and 198, with a median of 74. In reality, 90 structures were affected 74 of which were destroyed [47]. In the case of Fountain Grove community, the value ranges from 115 to 211 after 120 min with a median of 185. In reality, almost all the structures in the community (208 inside the simulated area) were destroyed. Comparing the two cases, the distribution of ignitions for the Trails community is left-skewed whereas the CDF is right-skewed for the Fountain Grove community. This implies that most simulations in Fountain Grove experienced a large number of ignitions. Figures 8 and 9 showcase the spread in each community for the two scenarios of median and maximum number of ignited structures. Fire propagation in the median scenario for the Trails com-
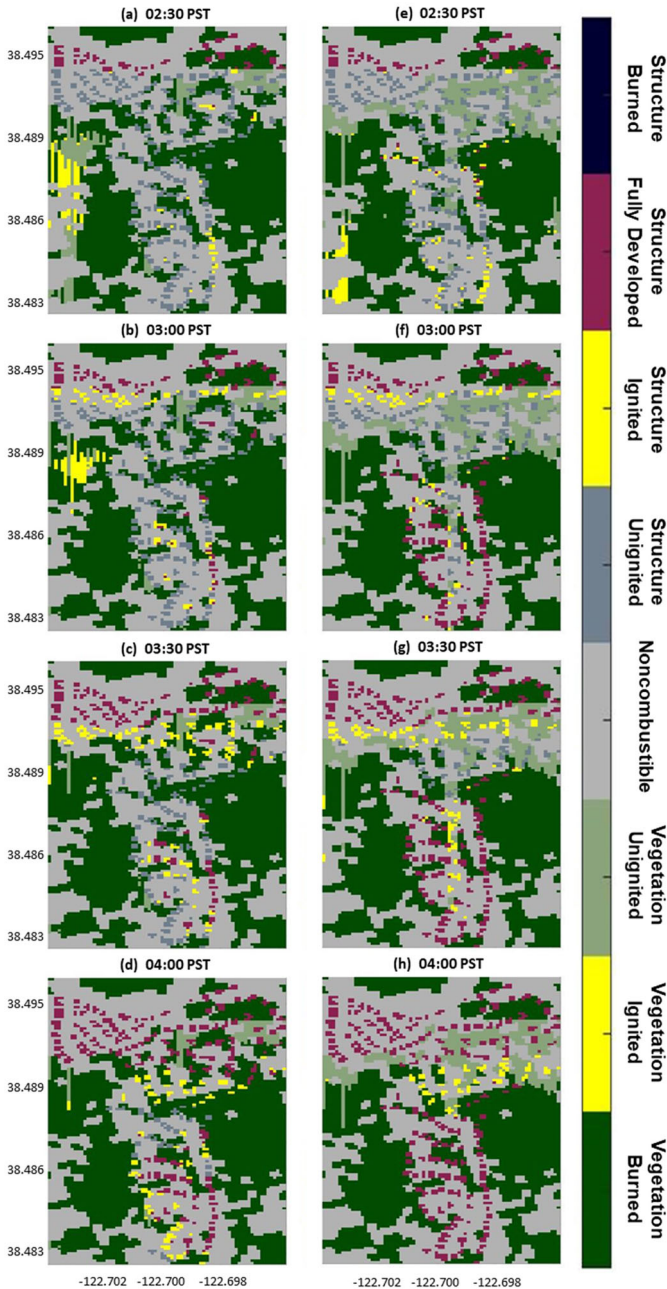
Figure 8. Fire spread in Fountain Grove: (a–d) showing a case representing a median scenario, and (e–h) showing a scenario with the maximum number of ignited structures (Color figure online).
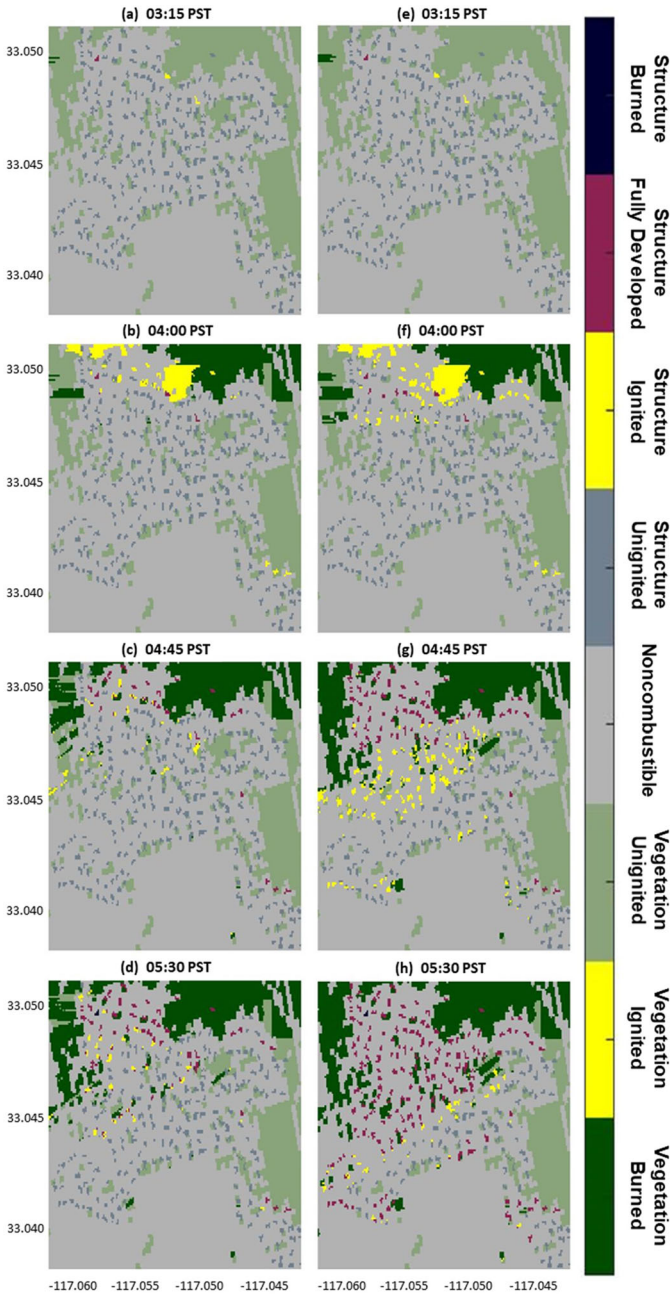
Figure 9. Fire spread in Trails: (a–d) showing a case representing a median scenario, and (e–h) showing a scenario with the maximum number of ignited structures (Color figure online).

munity is close to what happened in reality [47], whereas the maximum scenario for the Fountain Grove community is close to field observations [48].

The results indicate that 120 min after the wildfire reaches both communities, the *minimum* number of ignited structures in Fountain Grove is 115 whereas the *maximum* number of ignited structures in the Trails community equals 85 (i.e., lower than the minimum in Fountain Grove). Also, after 30 min, only a few ignitions are recorded in the Trails community whereas in some cases all structures are ignited in Fountain Grove. The median number of ignitions for the Fountain Grove community after 30 min is 12 structures, which is manageable to respond to, but the extreme cases indicate most of the structures on fire, which makes the fire hard to control in such a short time interval. The 2017 Tubbs fire affecting Fountain Grove was an example of one of the extreme simulated cases. Meanwhile, for the Trails community, no significant fire activity takes place before the first 60 min, and the number of ignited structures start to increase for some cases only at 90 min. This indicates a more manageable scenario for a community in terms of response and suppression.

Breakdown of ignitions due to radiation and spotting indicates that the number of ignitions is similar for both spread mechanisms in Fountain Grove (in the order of 150). In some cases, the two modes reinforce each other: a few sparse spot ignitions appear based on the locations and density of vegetation and structure cells, followed by further spread due to radiation and close proximity of structures. However, the same cannot be concluded for the Trails community. The number of ignitions due to fire spotting is significantly higher than radiation. Larger distances between structures and lower coverage of vegetation inside the community are the main reasons for slower spread and fire spotting as the main drive for fire spread.

Given the CDFs of the number of ignited structures, loss in terms of the monetary value of damaged buildings and the associated risk can be assessed when the results are conditioned on the probabilities of the fire scenarios obtained from the wildfire model (i.e., joint probability of spread direction and ROS). A binary criterion can be selected where an ignited structure is assumed to burn completely. Future research will expand to include different types of structures based on occupancy type and construction details, and different damage levels in response to fire. In addition, the loss assessment can go beyond monetary values to include social and environmental consequences.

4. Conclusion

The paper discussed a framework for risk assessment of WUI communities subjected to wildfires. The framework intends to integrate stochastic analyses of fire spread in WUI regions within available methodologies that capture probability of wildfire hazard in the wildland. The outcomes of the fire spread in WUI regions are conditioned on the outcomes of the wildfire scenarios in the wildland. The framework is flexible and can be used with different modeling tools.

The paper introduced a novel stochastic community model to capture uncertainties in fire spread within WUI. Random variables and the corresponding distributions were defined and a sensitivity analysis was conducted to identify the influencing parameters. The model was applied to two real wildfire events in California. The response of the communities against the corresponding wildfires was investigated and compared using cumulative distribution functions (CDFs) of the number of ignited structures over time and as a function of different fire spread mechanisms. It was demonstrated that the CDFs of the number of ignited structures can be used to evaluate the likelihood of how fast the fire spreads, whether or not the fire can be controlled, and the primary fire spread mechanism in the community.

The assigned distributions for some of the input parameters in the stochastic simulations of fire spread within a WUI community can be refined upon availability of more data from experiments or field observations. In general, the modeling capabilities can be enhanced as wildfire science advances, new methods of data collection are developed, and an improved understanding of fire dynamics and interactions of buildings and vegetation in WUI areas is established. Future studies will include a case study with the full application of the framework, incorporating probabilistic hazard assessment in conjunction with community response.

Finally, the proposed risk assessment framework for WUI communities can be used to guide mitigation actions within a community. Mitigation actions reduce the risk by preventing building ignition or spread of fire and are divided to those that can be applied to existing communities (e.g., use of fire-resistant construction material such as upgrading roofing material, provision of firebreaks across a community) and those for new land development (e.g., building layout and separations). Considering recent advances and evolving models in the field, the proposed framework can be used to investigate the influence of mitigation actions on the likelihood of the number of ignited structures during a certain period of time for a given fire scenario. The rate of increase in the number of ignited structures provides a measure for whether or not a successful suppression is possible (as was the case for the Trails community). The proposed approach will enable a quantified evaluation of the effects of individual structure and community features on the response of the community to a wildfire event.

Acknowledgements

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