Toward Simulating Dire Wildfire Scenarios

Thomas J. Cova[1]; Dapeng Li[2]; Laura K. Siebeneck[3]; and Frank A. Drews[4]

Abstract: Recent extreme wildfires are motivating unprecedented evacuation planning. A critical need is to consider *dire scenarios* that allow less time to clear an area than required. Although these scenarios often begin with an ignition near a community, any scenario can become dire due to weather conditions, human response, technology, cascading events, and community design. Although research has widely addressed scenarios with ample time and favorable conditions, protecting people in dire scenarios is much more challenging. We provide a framework for generating dire scenarios that includes difficult starting conditions, delayed decision-making, variable fire spread rates, limited warning technology, and random adverse events. The goal is to move beyond favorable scenarios and generate challenging ones that inspire novel protective planning. A key finding is that minimizing losses in dire scenarios may involve disaster response elements not represented in current simulation models, including improvisation and altruism. **DOI: 10.1061/(ASCE)NH.1527-6996.0000474.**

Introduction

The 2018 Camp Fire in Paradise, California, began as a scenario that most residents would consider common based on previous experience. The town had experienced 13 near miss fires in the last two decades, some that resulted in stressful evacuations, but none that resulted in any major losses. However, as the Camp Fire advanced toward Paradise at an unprecedented rate, officials planning for a 2–3 h evacuation were unaware that homes on the north edge of town would ignite in less than 90 min (Mooallem 2019). The result was a dire scenario that garnered worldwide attention and motivated a new era in wildfire evacuation planning, which has historically been very scarce (Kano et al. 2011).

Dire scenarios have not been a focus of previous study. Researchers and planners prefer favorable ones with ample time and positive outcomes to highlight model and plan efficacy. The accepted approach is to set ignition points far enough from a community to allow sufficient time for the residents to clear a study area. However, favorable scenarios do not challenge emergency managers to identify novel protective plans for the most difficult cases that arise in real wildfires. Furthermore, these dire cases are becoming more common as drought leads to larger, faster-moving wildfires (Thompson 2020). The goal of this paper is to propose a framework for generating dire scenarios, highlight their value in evacuation planning, and identify research challenges and opportunities.

[1]Professor, Center for Natural and Technological Hazards, Dept. of Geography, Univ. of Utah, Salt Lake City, UT 84108 (corresponding author). Email: cova@geog.utah.edu

[2]Assistant Professor, Dept. of Geography, South Dakota State Univ., Brookings, SD 57007.

[3]Associate Professor, Emergency Management and Disaster Science, Univ. of North Texas, Denton, TX 76203.

[4]Professor, Dept. of Psychology, Univ. of Utah, Salt Lake City, UT 84108.

Note. This manuscript was submitted on September 8, 2020; approved on January 20, 2021; published online on April 21, 2021. Discussion period open until September 21, 2021; separate discussions must be submitted for individual papers. This technical note is part of the ***Natural Hazards Review***, © ASCE, ISSN 1527-6988.

Dire Scenarios

We define a scenario as "dire" if the required time to clear an area is greater than the time available (i.e., lead time). Dire scenarios fall into the class of extreme events where important variables are located at the tail of their distribution (Tedim et al. 2018; Sanders 2005). *Evacuation time* and *lead time* are common metrics, where the former is the estimated time to clear an area of its population and the latter is the estimated time available to do so before hazard impact (Lindell et al. 2019). Here, we adopt a dynamic perspective and assume that both variables can be estimated at every point in time during a scenario. The estimate at time t represents the *remaining* lead time and evacuation time to move residents to safety. For example, if the estimated evacuation time is 1 h, and 20 min has transpired since it commenced, the remaining evacuation time is 40 min. We define a direness index that yields a score at time t across a scenario as

$$d_{ijt} = e_{ijt}/l_{ijt} - 1 \quad t = 0..T \tag{1}$$

where d_{ijt} = score for community i threatened by wildfire j at time t; e_{ijt} = time required to evacuate the remaining residents in community i from wildfire j at time t; and l_{ijt} = lead time at t before wildfire j impacts community i. This is a socioecological metric that integrates a human system variable (evacuation time) with a natural system one (lead time) (Moritz et al. 2017). Fig. 1 depicts a means to translate a score into a direness category ranging from "routine" to "extremely dire."

For example, assume that at 3:15 p.m. ($t = 0$), a community has 1 h to evacuate before a fire arrives at 4:15 p.m. ($l_{ijt} = 1.0$), and it will take 1.25 h to evacuate the residents ($e_{ijt} = 1.25$). Thus, the initial state of the scenario at time t is "dire" using Fig. 1 because evacuation time is 25% greater than lead time [$(1.25/1.0) - 1 = 0.25$]. Because this score is dynamic, a scenario can enter or exit a given dire category as events alter l_{ijt} and e_{ijt} (e.g., a blocked egress point at time t_1 that increases e_{ijt} or a change in wind direction at t_2 that increases or decreases l_{ijt}). In real wildfires, these variables are uncertain and so are a direness score and associated category. This means that a scenario that appears routine may turn out to be dire.

To provide an example, Fig. 2 depicts the anatomy of a routine scenario that turns dire due to a dramatic increase in a fire's

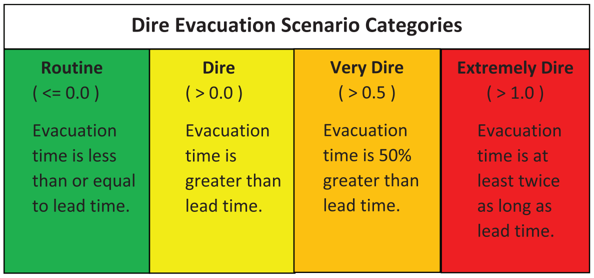

Fig. 1. (Color) Dire evacuation scenario categories based on a score.

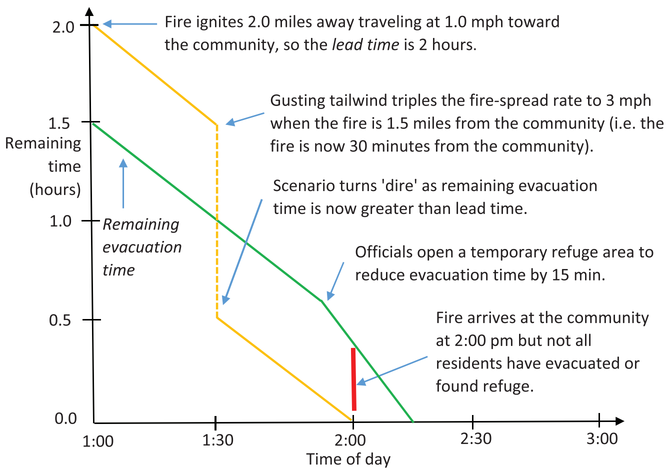

Fig. 2. (Color) Anatomy of a dire scenario due to a sudden increase in fire spread rate.

spread rate. At 1:00 p.m., a deputy reports a fire 2 mi from a community traveling 1 mph toward it, and officials estimate the initial lead time at 2 h. Evacuation time is estimated at 1.5 h, so the scenario is not initially dire ($1.5/2.0 - 1 = -0.25$). Officials warn the residents, and the plan is to have the area cleared by 2:30 p.m. At 1:30 p.m., a gusting tailwind triples the fire spread rate to 3 mph, and the lead time drops from 1.5 h to 0.5 h. Because the remaining evacuation time is 1 h, the scenario turns "very dire" ($1.0/0.5 - 1 = 1.0$). At 1:45 p.m., officials designate a temporary refuge area (TRA) to reduce the required time to protect the remaining residents by 15 min. Despite their best efforts, the fire enters the community at 2:00 p.m., but some residents have yet to clear the area or secure shelter, which could lead to casualties.

Dire Scenario Sources

Dire scenarios arise from a variety of sources. Foremost is a wildfire ignition point close to a community because this condition offers less time to respond than one further away. A second factor is detection time, which is usually brief because citizens rapidly report smoke plumes, but nighttime wildfires can go undetected longer when people are asleep. A third factor is official decision-making because emergency managers may delay the decision to alert or warn residents to avoid unnecessarily disrupting a community based on their threat assessment (Drews et al. 2014). This can lead to a dire scenario if officials subsequently issue a warning at the last minute (Cova et al. 2017). Notification systems can also affect a scenario if many residents do not receive an alert or warning in time (Lindell 2018; Doermann et al. 2021). Public response rates can affect scenario direness due to low-mobility households (e.g., age, disability, resources), a low warning compliance rate, or a tendency to adopt a wait-and-see approach (Dash and Gladwin 2007; McCaffrey et al. 2018; Edgeley and Paveglio 2019). Traffic factors can affect a scenario, as in the case where residents have difficulty finding a safe exit route (Brachman et al. 2019) or when many households depart at once and induce gridlock (Chen and Zhan 2008). Community design can affect a scenario if a road network cannot support rapid residential evacuation (e.g., many homes and few egress points).

There are many recent examples of dire wildfire scenarios. The 2018 Camp Fire is an iconic example because it includes many interacting factors. This case included a fast-moving fire that ignited near a low-egress community with many low-mobility residents. Furthermore, officials accustomed to prior near misses waited to assess the fire's direction and spread rate before ordering the first phased warning, and many residents did not receive a warning due to a low reverse-911 subscription rate (Todd et al. 2019). On the favorable side of the scenario, officials and residents were highly prepared and experienced with a state-of-the-art plan, and officials successfully reversed a lane on the main exit to increase the capacity of a key traffic bottleneck. Other examples of recent dire wildfire scenarios include the 2020 Almeda and Holiday Farm fires in Oregon, which both ignited close to a community and offered very little time to act. The 2017 Tubbs Fire in California was also dire given that it moved 12 mi in its first 3 h through populated areas on a Sunday night, and many residents reported not receiving a warning.

Modeling Dire Scenarios

To generate a dire scenario, a modeler can start with lead time less than evacuation time or design a scenario where the former falls below the latter at any point. Fig. 3 shows a scenario dashboard with factor categories (columns) to generate a dire scenario ranging from no impediment (green) to a minor impediment (yellow) to a major impediment (red). For example, Scenario 1 (row 1) includes minor impediments in the ignition location, fire spread rate, public response, and mobility. This scenario could be a proximal fire moving moderately fast toward households, some of whom voluntarily delay their decision to leave and others with low mobility. Scenario 3 has major impediments, including official decision-making, notification and warning, public response, and traffic congestion. In this scenario, the fire started far from the community, but delays and difficulties in warning residents ultimately led to a dire scenario with traffic congestion. Scenario 4 is the most challenging, with major impediments in all of the factor categories. Although Fig. 3 lists impedance categories in the columns, an analyst must provide the details for each category to create a realistic scenario.

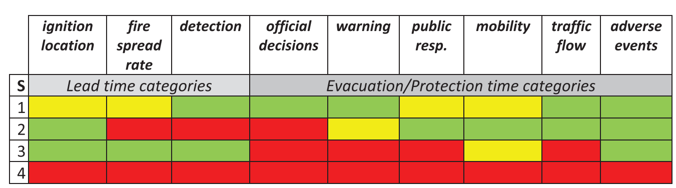

Fig. 3. (Color) Dire scenario dashboard where scenarios (rows) progress from routine to extremely dire (1–4) due to varying factor impediment levels (green, yellow, red).

In addition to combining factors to create a dire scenario, we need new metrics to compare outcomes that may not be successful. Wolshon and Marchive (2007) provide one example: the number of vehicles that do not clear a community in time when the lead time is short. This does not mean that the fire will trap the remaining residents because recent events reveal that many evacuees safely navigate burning corridors. Beloglazov et al. (2016) also developed a valuable dynamic metric to estimate the population threatened throughout a wildfire scenario called the *exposure count*, which may rise or fall as scenario direness changes.

Reducing Scenario Direness

Dire scenarios can become less so due to natural and human factors that increase lead time, decrease evacuation time, or both. Factors that may increase lead time by reducing a fire's spread rate include weather (natural), as well as fuel management and fire suppression (human). Although fuel management and fire suppression refer to an array of techniques, modelers do not generally include their effects in coupled fire-evacuation model scenarios because of a lack of data on local fuel management actions. There are also limits on including structural fuels in fire models, which reduces the predictive accuracy of fire spread rate estimates through communities (Kaufman and Roston 2020).

Many factors can decrease evacuation time before and during a scenario. Examples include phased warnings (Li et al. 2015), lane reversal (Xie et al. 2010), and traffic signal optimization (Ren et al. 2013). To broaden the purview, *protection time* is preferable because there are other options. Fire shelters and safety zones are alternatives that have multiple benefits (Amideo et al. 2019). First, they can protect people who cannot leave in time due to low mobility or egress issues, and second, they can reduce traffic delays for residents who decide to leave (i.e., shorter travel times). Households and communities can construct or assign areas of refuge, which can be public or private and permanent or temporary. In the 2018 Camp Fire, parking lots and community buildings were designated as temporary refuge areas (i.e., improvised fire shelter and safety zones), and designating and constructing places of refuge is a growing need. Steer et al. (2017) and Shahparvari et al. (2016) provide representative examples of optimal plans that combine evacuation and refuge shelters to protect people.

Many facets of human response in an actual wildfire can be challenging to model. One example not represented in current models is improvised protective actions. However, improvisation and flexible decision-making is often required in responding to dire disaster scenarios (Webb and Chevreau 2006). One recent example is the use of military transport helicopters to rescue campers trapped by the 2020 Creek Fire in California (Fuller and Mervosh 2020). Altruism is another neglected factor, particularly for many individuals caught in uniquely dire circumstances. Altruism refers to self-selected individuals who demonstrate a willingness to help others address a problem (Batson and Powell 2003). Altruistic examples in wildfires include (1) citizens providing rides for others, (2) citizens providing temporary refuge shelter, (3) citizens providing information via social media, (4) individuals clearing blocked traffic, and (5) citizens aiding in relocating vulnerable populations (e.g., medical facilities, retirement homes, childcare centers). Altruism relates to social capital because communities with greater social cohesion are more likely to have residents help one another (Aldrich and Meyer 2014). One example in the 2018 Camp Fire was Joe Kennedy, who single-handedly cleared abandoned cars that blocked traffic with a bulldozer (Mooallem 2019). Modelers may not have considered altruistic behavior because the need only arises in very dire scenarios, and it is difficult to predict how much might be displayed or where. However, altruistic acts can also lead to losses if people take excessive risks in helping others. Thus, it represents a challenging research frontier in creating more realistic agent-based wildfire evacuation simulations (i.e., agents helping or cooperating with other agents).

Conclusion

Although dire wildfire scenarios have not been a focus of study or modeling, they hold potential to help emergency planners and communities cooperate and consider novel protective actions. Key questions for further research include:

1. What can we learn from studying and modeling dire scenarios over favorable ones?
2. How does the direness of a scenario vary geographically across a threat area?
3. What factors serve to make a scenario more or less dire at different scales?
4. How can we incorporate protective behavior found in real wildfires into simulation models (e.g., improvisation, altruism)?
5. How many places of refuge do we need, where should they be located, and what capacity should they have to reduce likely scenarios from dire to routine?
6. What advanced technologies can help reduce the likelihood of dire scenarios before one occurs (e.g., artificial intelligence, wireless emergency alerts, automated fire detection, real-time decision support) (Zhao et al. 2021)?
7. What technology can aid in responding to a dire scenario (e.g., rescue robots, protective fire suits, temporary fire shelter)?
8. How can we visualize the dynamics of dire scenarios, as well as the beneficial and adverse events that affect lead and evacuation time, to improve situational awareness and decision-making?

Studying and modeling dire scenarios are important because they are challenging and increasing in frequency (Schoennagel et al. 2017). The benefit of simulating them is that it may lead to better planning and outcomes in cases where more things go wrong than right. Modeling wildfire evacuation as a coupled natural-human system is challenging (Ronchi et al 2019; Li et al. 2019), and there are limitations to the framework presented herein due to human behavior and uncertainty. Although the science of simulation continues to advance, we still have a long way to go toward incorporating many events that occur in real wildfires.

Data Availability Statement

No data, models, or code were generated or used during the study.

Notation

The following symbols are used in this paper:

d_{ijt} = direness score for community i threatened by wildfire j at time t;
e_{ijt} = time required to evacuate remaining residents in community i from wildfire j at time t;
i = index of communities;
j = index wildfires;
l_{ijt} = lead time at t before wildfire j impacts community i; and
t = index of time.

References

Aldrich, D. P., and M. A. Meyer. 2014. "Social capital and community resilience." *Am. Behav. Sci.* 59 (2): 254–269. https://doi.org/10.1177/0002764214550299.

Amideo, A. E., M. P. Scaparra, and K. Kotiadis. 2019. "Optimising shelter location and evacuation routing operations: The critical issues." *Eur. J. Oper. Res.* 279 (2): 279–295.

Batson, C. D., and A. A. Powell. 2003. "Altruism and prosocial behavior." In Vol. 5 of *Handbook of psychology: Personality and social psychology*, edited by T. Millon and M. J. Lerner, 463–484. New York: Wiley.

Beloglazov, A., M. Almashor, E. Abebe, J. Richter, and K. C. B. Steer. 2016. "Simulation of wildfire evacuation with dynamic factors and model composition." *Simul. Modell. Pract. Theory* 60 (Jan): 144–159. https://doi.org/10.1016/j.simpat.2015.10.002.

Brachman, M., R. L. Church, B. Adams, and D. Bassett. 2019. "Wayfinding during a wildfire evacuation." *Disaster Prev. Manage.* 29 (3): 249–265. https://doi.org/10.1108/DPM-07-2019-0216.

Chen, X., and F. B. Zhan. 2008. "Agent-based modelling and simulation of urban evacuation: Relative effectiveness of simultaneous and staged evacuations." *J. Oper. Res. Soc.* 59 (1): 25–33. https://doi.org/10.1057/palgrave.jors.2602321.

Cova, T. J., P. E. Dennison, F. A. Drews, L. K. Siebeneck, and M. K. Lindell. 2017. "Warning triggers in environmental hazards: Who should be warned to do what and when?" *Risk Anal.* 37 (4): 601–611. https://doi.org/10.1111/risa.12651.

Dash, N., and H. Gladwin. 2007. "Evacuation decision making and behavioral responses: Individual and household." *Nat. Hazard. Rev.* 8 (3): 69–77. https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(69).

Doermann, J. L., E. D. Kuligowski, and J. Milke. 2021. "From social science to engineering practice: Development of a short message creation tool for wildfire emergencies." *Fire Technol.* 57 (2): 815–837.

Drews, F. A., A. Musters, L. K. Siebeneck, and T. J. Cova. 2014. "Environmental factors that influence wildfire protective-action recommendations." *Int. J. Emergency Manage.* 10 (2): 153–168. https://doi.org/10.1504/IJEM.2014.066187.

Edgeley, C. M., and T. B. Paveglio. 2019. "Exploring influences on intended evacuation behaviors during wildfire: What roles for pre-fire actions and event-based cues?" *Int. J. Disaster Risk Reduct.* 37: 101182. https://doi.org/10.1016/j.ijdrr.2019.101182.

Fuller, T., and S. Mervosh. 2020. "You couldn't see anything': Harrowing helicopter rescues as California fires rage." *N.Y. Times*, September 8, 2020.

Kano, M., M. Kelley, and M. Hashemi. 2011. "Local emergency evacuation planning in California, USA: A comparison with the hurricane states." *Int. J. Emergency Manage.* 8 (1): 74–96. https://doi.org/10.1504/IJEM.2011.040400.

Kaufman, L., and E. Roston. 2020. "Wildfires are close to torching the insurance industry in California." *Bloomberg Businessweek*. November 10, 2020.

Li, D., T. J. Cova, and P. E. Dennison. 2015. "A household-level approach to staging wildfire evacuation warnings using trigger modeling." *Comput. Environ. Urban Syst.* 54 (Nov): 56–67. https://doi.org/10.1016/j.compenvurbsys.2015.05.008.

Li, D., T. J. Cova, and P. E. Dennison. 2019. "Setting wildfire evacuation triggers by coupling fire and traffic simulation models: A spatiotemporal GIS approach." *Fire Technol.* 55 (2): 617–642. https://doi.org/10.1007/s10694-018-0771-6.

Lindell, M. K. 2018. "Communicating imminent risk." In *Handbook of disaster research: Handbooks of sociology and social research*, edited by H. Rodríguez, W. Donner, and J. Trainor. Cham, Switzerland: Springer.

Lindell, M. K., P. Murray-Tuite, B. Wolshon, and E. J. Baker. 2019. *Large-scale evacuation: The analysis, modeling, and management of emergency relocation from hazardous areas*. Boca Raton, FL: CRC Press.

McCaffrey, S., R. Wilson, and A. Konar. 2018. "Should I stay or should I go now? Or should I wait and see? Influences on wildfire evacuation decisions." *Risk Anal.* 38 (7): 1390–1404. https://doi.org/10.1111/risa.12944.

Mooallem, J. 2019. "We have fire everywhere." *N.Y. Times Magazine*, July 31, 2019.

Moritz, M. A., E. Batllori, R. A. Bradstock, A. M. Gill, J. Handmer, P. F. Hessburg, J. Leonard, S. McCaffrey, D. C. Odion, and T. Schoennagel. 2017. "Learning to coexist with wildfire." *Nature* 515 (7525): 58–66. https://doi.org/10.1038/nature13946.

Ren, G., Z. Huang, Y. Cheng, X. Zhao, and Y. Zhang. 2013. "An integrated model for evacuation routing and traffic signal optimization with background demand uncertainty." *J. Adv. Transp.* 47: 4–27.

Ronchi, E., S. M. V. Gwynne, G. Rein, P. Intini, and R. Wadhwani. 2019. "An open multi-physics framework for modelling wildland-urban interface fire evacuations." *Saf. Sci.* 118 (Oct): 868–880. https://doi.org/10.1016/j.ssci.2019.06.009.

Sanders, D. E. A. 2005. "The modeling of extreme events." *Br. Actuarial J.* 11 (3): 519–557. https://doi.org/10.1017/S1357321700003251.

Schoennagel, T., et al. 2017. "Adapt to more wildfire in western North American forests as climate changes." *Proc. Nat. Acad. Sci.* 114 (18): 4582–4590. https://doi.org/10.1073/pnas.1617464114.

Shahparvari, S., P. Chhetri, B. Abbasi, and A. Abareshi. 2016. "Enhancing emergency evacuation response of late evacuees: Revisiting the case of Australian Black Saturday bushfire." *Transp. Res. Part E: Logist. Transp. Rev.* 93 (Sep): 148–176. https://doi.org/10.1016/j.tre.2016.05.010.

Steer, K. C. B., E. Abebe, M. Almashor, A. Beloglazov, and X. Zhong. 2017. "On the utility of shelter in wildfire evacuations." *Fire Saf. J.* 94 (Dec): 22–32. https://doi.org/10.1016/j.firesaf.2017.09.001.

Tedim, F., et al. 2018. "Defining extreme wildfire events: Difficulties, challenges, and impacts." *Fire* 1 (1): 9. https://doi.org/10.3390/fire1010009.

Thompson, D. 2020. "California wildfires growing bigger, moving faster than ever." Accessed September 10, 2020. https://apnews.com/article/wildfires-forests-holidays-fires-california-dc30bcead69e5b67004711b78bbda868.

Todd, Z., S. Trattner, and J. McMullen. 2019. "Ahead of camp fire anniversary, new details emerge of troubled evacuation." *PBS Frontline*, October 25, 2019.

Webb, G. R., and F. R. Chevreau. 2006. "Planning to improvise: The importance of creativity and flexibility in crisis response." *Int. J. Emergency Manage.* 3 (1): 66–72. https://doi.org/10.1504/IJEM.2006.010282.

Wolshon, B., and E. Marchive, III. 2007. "Emergency planning in the urban-wildland interface: Subdivision-level analysis of wildfire evacuations." *J. Urban Plann. Dev.* 133 (1): 73–81. https://doi.org/10.1061/(ASCE)0733-9488(2007)133:1(73).

Xie, C., D. Y. Lin, and S. T. Waller. 2010. "A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies." *Transp. Part E: Logist. Transp. Rev.* 46 (3): 295–316. https://doi.org/10.1016/j.tre.2009.11.004.

Zhao, X., R. Lovreglio, E. Kuligowski, and D. Nilsson. 2021. "Using artificial intelligence for safe and effective wildfire evacuations." *Fire Technol.* 57 (2): 1–13. https://doi.org/10.1007/s10694-020-00979-x.