Potential COVID-19 Outbreak in Fire Camp: Modeling Scenarios and Interventions

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Abstract: The global COVID-19 pandemic will pose unique challenges to the management of wildland fire in 2020. Fire camps may provide an ideal setting for the transmission of SARS-CoV-2, the virus that causes COVID-19. However, intervention strategies can help minimize disease spread and reduce the risk to the firefighting community. We developed a COVID-19 epidemic model to highlight the risks posed by the disease during wildland fire incidents. Our model accounts for the transient nature of the population on a wildland fire incident, which poses unique risks to the management of communicable diseases in fire camps. We used the model to assess the impact of two types of interventions: the screening of a firefighter arriving on an incident, and social distancing measures. Our results suggest that both interventions are important to mitigate the risks posed by the SARS-CoV-2 virus. However, screening is relatively more effective on short incidents, whereas social distancing is relatively more effective during extended campaigns. We conclude with a discussion of model limitations and potential extensions to the model.

1. Introduction

Fire personnel know all too well the occurrence and unpleasantness of "camp crud," a respiratory illness that is annually transmitted to many of these personnel while they spend time at fire camps [1]. COVID-19 is a dramatically different disease than camp crud. Furthermore, smoke exposure may complicate the risk of infection and the severity of the disease if contracted [2]. With fire season already underway in the U.S., there is an urgent need to understand how COVID-19 may impact wildfire incident management activities. In the absence of historical data, epidemiological simulation models can provide insights into the transmission of SARS-Cov-2 (the virus that causes COVID-19) and the potential impact of mitigation measures in fire camps.

Here, we developed an epidemiological simulation model of COVID-19 to analyze the impact of interventions on wildland firefighter health and workforce availability in the setting of a single large wildland fire camp. A wildland fire incident may pose unique challenges to avoiding the spread of SARS-Cov-2 among deployed firefighters. During an actively managed incident, hundreds to thousands of firefighters may be dispatched to the incident. These personnel come from around the country to help contain the fire [3]. Because many of these fires occur in remote areas, and the personnel are not local, there can be substantial logistical challenges with providing basic services for all the personnel. Historically, these logistics have been met by setting up fire camps. These fire camps are sites at which the personnel are provided with food, water, areas for sleeping, and sanitary services during

the time they are assigned to work on the fire [4]. While these camps do provide important services, they are also known to provide opportunities for viruses to spread among personnel [5]. The fire camp is not the only place that a virus might spread among personnel. For example, the incident command post, the location where the primary logistics functions of the fire are administered [4], may also provide opportunities for spread. Because the fire camp is the area often associated with disease spread, in this paper, we used the term "camp" generically to indicate the virus spreading throughout the personnel assigned to the fire.

We used our model to explore how the rates of infection and fatality vary with incident mobilization/demobilization dynamics, duration, and the number of assigned personnel, using real resource assignment data from three historical fires. We selected these three incidents because they captured a range of these characteristics (assignment timing, duration, personnel) thought to affect disease dynamics. Using a scenario analysis approach allows us to evaluate a range of parameters based on coarse assumptions about the efficacy of interventions. Specifically, we adjusted the model to explore the benefits of two risk mitigation measures that incident management teams may adopt: screening and social distancing measures.

Screening and social distancing measures may influence health and workforce outcomes in a variety of ways on a fire camp. Screening includes monitoring symptoms as firefighters enter camp and monitoring firefighter symptoms over time while in camp [6]. To address the initial screening of the firefighter arrival at the camp in our model, we assumed that screening reduces the number of infected personnel who arrive at a fire, but does not remove 100% of the potentially infectious personnel due to individuals who may be asymptomatic, pre-symptomatic, or misattributing symptoms as typical due to exertion and smoke exposure. Social distancing steps specific to the wildland fire environment include the use of remote briefings (rather than in-person briefings), reduced attendance at briefings, the expanded use of telecommunications, dispersed camping, the increased use of packaged meals that are delivered to the field, using the module as one concept so that crews are minimally interacting with people outside their crew, and wearing masks when appropriate. In our model, social distancing reduces the transmission parameter; thus, we are assuming that the mitigations reduce the average number of personnel that acquire the disease from a single infected person. In reality, disease transmission is a stochastic process. Random perturbations (i.e., a large spread event) early on in the incident may dramatically alter the trajectory of an outbreak in a fire camp. Our deterministic model abstracts from this real-world complication.

The wildland fire management community is developing guidance and planning modifications to wildland fire response strategies, operations, and logistics in order to mitigate the variety of risks posed by COVID-19 [6–8]. Furthermore, responders are the sharing lessons learned in the conduct of fire operations to better understand the considerations and consequences of putting COVID-19 mitigations into practice e.g., [9–15]. Notably, [15] summarizes some of the operational logistics and challenges associated with adapting to COVID-19 and implementing mitigation measures. As described above, one of the risks posed by SARS-CoV-2 is the rapid outbreak of infection in a traditional large fire camp, where high-density living and working conditions, limited hygiene, and a transient workforce can "create an ideal environment for the transmission of infectious diseases" [5]. The intent of this analysis is to help understand the risk of outbreak and to support risk-informed decision making.

2. Materials and Methods

2.1. Model Specification

We developed a compartmental epidemic simulation model [16] adapted to the context of a wildfire incident. Our model incorporated the movement of personnel to and from the incident, which have important implications for disease transmission. The model divided the population into four

health classes (susceptible, exposed, infectious, and removed, or SEIR). The outbreak evolved according to the following system of differential equations:

$$\dot{S} = -\frac{R_0}{D_I}\frac{S(t)\cdot I(t)}{N(t)} + (1-\gamma)A(t) - \frac{S(t)}{N(t)}X(t)$$

$$\dot{E} = \frac{R_0}{D_I}\frac{S(t)\cdot I(t)}{N(t)} - \frac{E(t)}{D_E} + \gamma A(t) - \frac{E(t)}{N(t)}X(t)$$

$$\dot{I} = \frac{E(t)}{D_E} - \frac{I(t)}{D_I} - \frac{I(t)}{N(t)}X(t)$$

$$\dot{R} = \frac{I(t)}{D_I}$$

$$\dot{N} = A(t) - X(t)$$

where R_0 is the basic reproduction number indicating the number of secondary infections caused by an index case over the duration of the infectious period D_I, N is the total population on the fire at time t, $A(t)$ is the number of new arrivals on the incident (all are assumed susceptible or exposed), $X(t)$ is the number of individuals exiting the incident, D_E is the exposed, or incubation, period (i.e., the period of time after an individual is exposed to the virus, prior to becoming infectious), and γ is the probability that new arrival personnel are infected.

The term $\frac{R_0}{D_I}\frac{S(t)\cdot I(t)}{N(t)}$ represents the number of new infections at time t. $\frac{R_0}{D_I}$ is the rate of transmission conditional on contact between susceptible and infectious individuals in the population. New infections enter the exposed class during which time they are not infectious, but most certainly will become infectious. Individuals in the exposed class enter the infectious class at a rate of $\frac{E(t)}{D_E}$.

Models of wildfire incidents need to reflect the dynamic population of fire fighters as there are individuals arriving and leaving due to reassignment or demobilization. New personnel arrive on the incident according to $A(t)$ and exit according to $X(t)$. Entering personnel were considered only to be either susceptible or infected; we discuss this in Section 2.2. However, the exits were proportional to the population in each class at time t. We estimated the number of personnel arriving and departing based on the empirical fire assignment data.

2.2. Model Assumptions

We parameterized the model based on the estimates from relevant literature (Table 1). Estimates of R_0 vary widely in the literature, but generally fall between 1.3 and 6.0 [17]. We used a baseline estimate of R_0 of 2.68 [16], and bound it by 1.34 (50% of 2.68) and 5.36 (200% of 2.68). While COVID-19 can affect individuals for several weeks [18], infected individuals with symptoms are likely to sequester themselves and be isolated from the susceptible population. Estimates from [18] suggest that the time from symptom onset to isolation is between two and five days. We assumed that an infectious individual was mixing in the population for three days. Estimates of the incubation period, D_E, are between four and six days [19]. We used five days in our models.

Table 1. Parameter values used in simulation.

Variable	Low	Medium	High	Extreme	Citation
R_0	1.34	2.68	5.36		[17]
D_I		3			[18]
D_E		5			[19]
Initial Infected		2			
Infection Fatality Rate	0.1%	0.3%	1%	2%	[20]
Infected Entry Rate	0.1%	1%	5%		

In order to propagate the disease's spread, the model required infectious personnel to enter the fire. This may occur through two pathways in our model; initial infectious personnel that arrive at the camp on the first day ("initial infected") and infectious entry throughout the course of the camp due to additional mobilizations ("infected entry"). We assumed that two infectious individuals entered each of the case study fires on the first day of the fire camp, which represents 1% of the peak personnel on the smallest of the three fires case study fires profiled. The value of the initial infected stayed constant for all the scenarios modeled. We considered various rates of infected individuals mobilizing to the incident. While these infected entry rates depended on the behavior of individuals while off duty, they also may be influenced by screening procedures. We considered 0.1%, 1%, and 5% to capture the range of general population disease prevalence and the potential effectiveness of screening procedures. The SEIR model assumed the continuous distribution of people, so the entry of infections may occur in non-integer numbers of personnel. We considered all non-infectious personnel to initially be susceptible.

Infection fatality rates vary widely in the literature because of demographic characteristics and variable testing. Early reports suggested that the case fatality rates may be as high as 6%; however, recent evidence suggests that it may be 2–3%, and much lower in younger healthy populations [20]. Furthermore, emerging evidence suggests that undocumented cases may imply actual cases were 45% to 90% higher than reported [21,22]. Therefore, we considered an infection fatality rate of 0.3%. We also considered a low bound of the infection fatality rate of 0.1%, which was comparable with the 2009 H1N1 pandemic [23], and high estimates of 1% and 2%.

2.3. Case Fires

We simulated COVID-19 outbreaks using three 2017 fires chosen to represent different incident archetypes: the Highline Fire, which burned for much of the summer but the personnel peaked early in the effort; the Lolo Peak Fire, which spanned July through September and had a relatively symmetric mobilization and demobilization phase; and the Tank Hollow Fire, which was shorter than the other two, and had fewer personnel throughout the incident. Figure 1 shows the mobilization/demobilization dynamics for the personnel expected to be at camp for the three fires we selected, providing perspective on when in the season they occurred, how long they lasted, and how many personnel were at the fire each day. Data for these fires were obtained from the Resource Ordering and Status System (ROSS) (see [3,24] for other peer-reviewed studies of suppression resource allocation and movement using ROSS). ROSS was queried to obtain the mobilization and demobilization dates for each person assigned to the fire, except those associated with aerial resources.
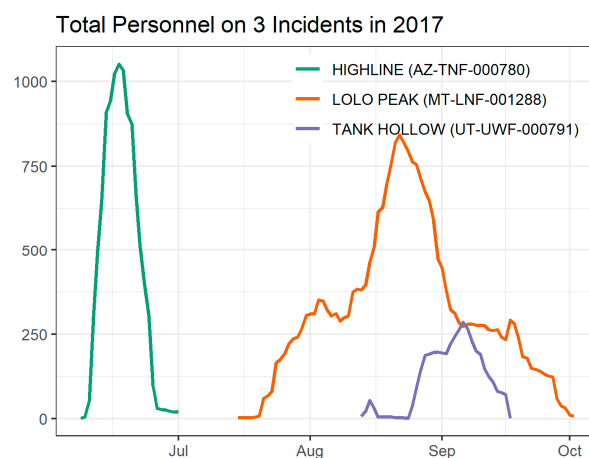
Figure 1. Total personnel assigned and expected to be at the fire camp (e.g., non-aerial resources) for three large incidents over time; data are from the Resource Ordering and Status System.

We fed these incident dynamics into the COVID-19 SEIR model to analyze the different scenarios. Table 2 shows the scenarios we analyzed regarding infection rates and the entry rates of infected personnel. These scenarios ranged from best to worst case, along with two risk mitigation options: comprehensive screening, and aggressive social distancing at camp (e.g., no catering, increased use of spike camps, remote briefings). The best-case scenario assumes that both mitigating measures are implemented jointly and effectively. The worst-case scenario assumes that either mitigation measures were not implemented, or they were implemented ineffectively. We also explored variable infection fatality rates, ranging from low (0.10%), medium (0.30%), high (1.00%), and extreme (2.00%). These fatality rates may differ from what was observed for the general population due to the responders' increased smoke exposure and fatigue, among other factors.

Table 2. Scenarios and corresponding model parameters. The infection rate parameter is drawn from [16]; medium is the baseline observed rate of 2.38, low is half of the baseline (1.34), and high is twice the baseline (5.36). The percentage of individuals arriving at the fire infected is varied from low (0.1%) to medium (1%) to high (5%); see Table 1.

| Scenario	Infection Rate (R0 Parameter)	Percent of Arriving Individuals that Are Infected
Best case	Low	Low
Worst case	High	High
Baseline	Medium	Medium
Enhanced screening	Medium	Low
Aggressive social distancing	Low	Medium

3. Results

Figure 2 shows the paths of infectious individuals and the total infections under the baseline assumptions for each fire over time. The total infections are defined as the individuals who became infected during the incident, whether they remained on the incident or left. Maximum daily infections generally peaked around the time of the peak assigned personnel. Despite the Highline Fire having a greater number of assigned personnel at the peak, the Lolo Peak Fire had by far the greatest number of infected persons due to the longer duration with substantial personnel assigned and the total number of personnel that worked on the fire. The Lolo Peak also had the highest number of modeled fatalities (Figure 3), which in the extreme case, could exceed ten fire personnel. At low to medium infection fatality rates, we would expect near-zero fatalities on the Highline and Tank Hollow fires.

We explored the impact of different infection rates of arriving personnel (Figure 4). This analysis has two interpretations: (1) different levels of disease prevalence in the general population, and (2) the relative effect of a screening protocol. Figure 4 displays the total cases under different infection rates of new arrivals. Under the first interpretation, these results highlight the impact of circumstances external to the firefighting community. In the Highline fire, the total cases are 247 when 5% of the arriving personnel are infected as opposed to 82 when 1% of the arriving personnel are infected.
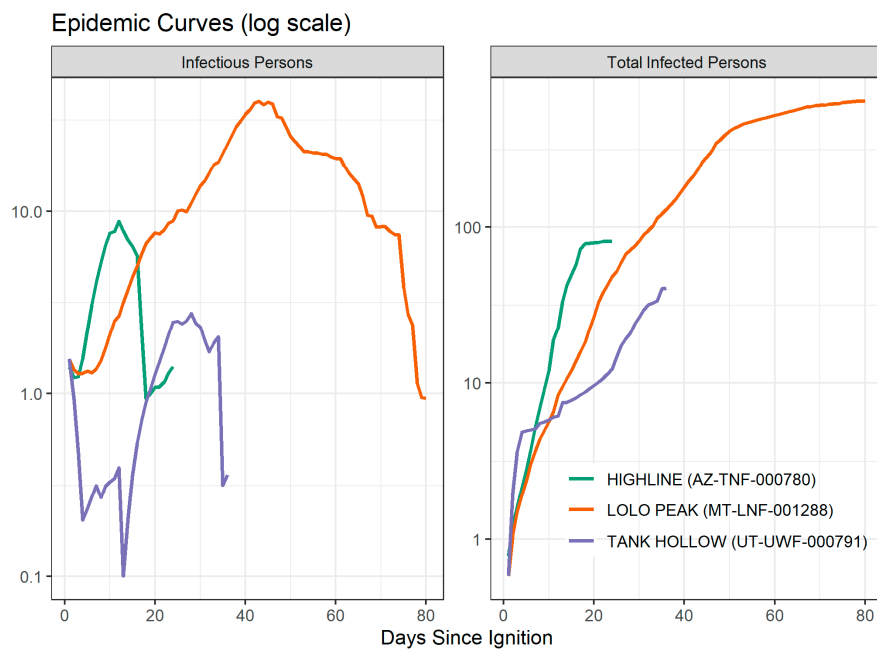
Figure 2. Infectious persons and total infected persons over the duration of each incident, under the baseline scenario. Note that the infectious status is temporary whereas the total number of infections is cumulative. Note that the vertical axis is log scaled.
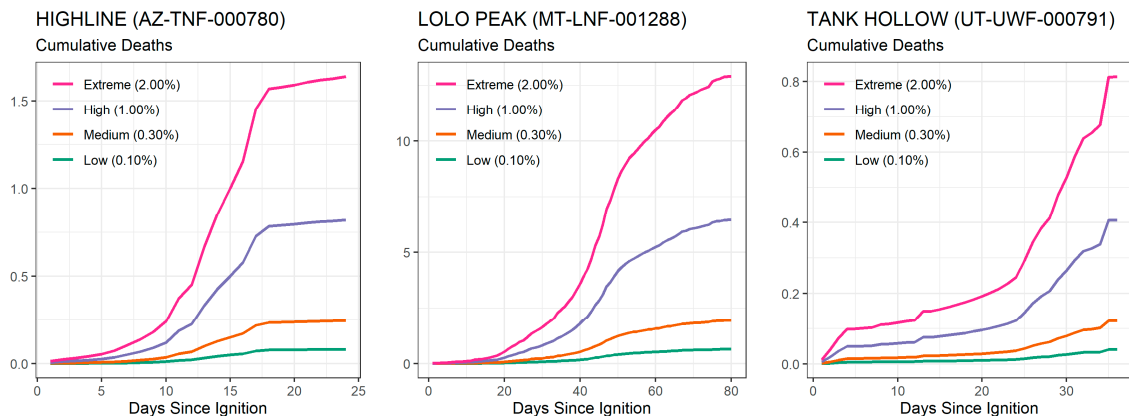

Figure 3. Cumulative deaths over time for the baseline scenario. Note that the vertical axis is not log scaled for this figure.

The second interpretation of this analysis is as the effect of screening arriving personnel, which in practice will be conditioned by the percentage of cases that are asymptomatic or pre-symptomatic. Assuming the disease prevalence in the population is approximately 1%, such that roughly 1% of new arrivals are infected (orange curve in Figure 4), if an effective screening protocol identified most of those infected individuals arriving on the fire and removed them from the population via quarantine, the infection rate of new arrivals could fall to 0.1% (green curve in Figure 4). On a fire like the Highline, this effective screening protocol would result in 45 fewer total cases representing 55% of the total cases incurred without screening. In contrast, the reduction of the same screening protocol on a fire like Lolo Peak reduces cases by 72, representing 11% of the total cases. The larger relative impact on a fire like the Highline is due to the relatively short duration and high population. In this type of incident, a relatively high share of new cases arises from the introduction of cases that originate outside of the fire. In longer duration fires, relatively more cases arise from transmission within the fire.
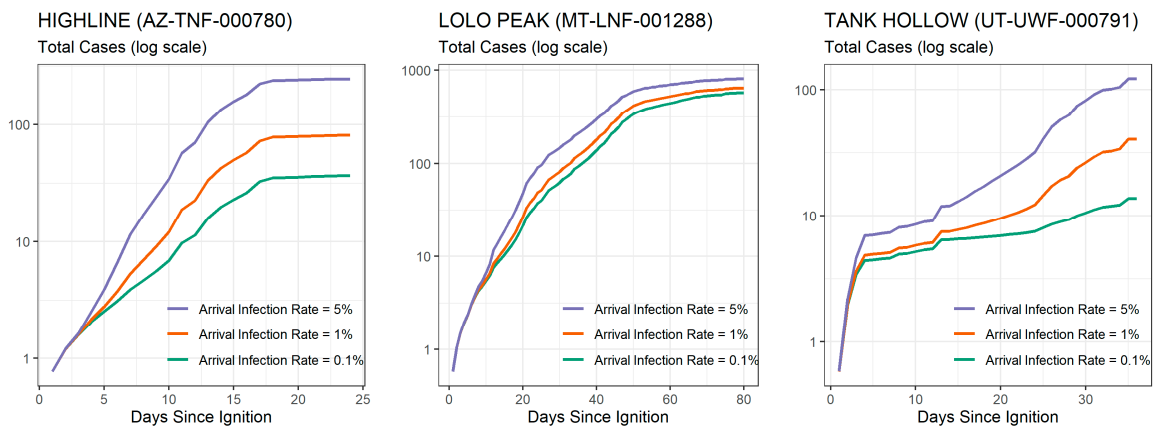
Figure 4. Total number of infected individuals over the duration of each incident under the low (0.1%), medium (1%), and high (5%) entry rates of infected individuals. Note that the vertical axis is log scaled. All simulations assume R0 of 2.68.

We explored the impact of aggressive social distancing by varying the transmission rate derived from R0 (the basic reproduction number, or the number of secondary cases resulting from a single case). Reducing contacts in the camp by dispersed camping or remote briefings will reduce transmission. Figure 5 compares the total number of infections on each fire under low, medium, and high transmission scenarios, corresponding to different levels of social distancing. Social distancing is comparatively more effective than screening, and can substantially reduce cases, especially on long-duration fires like Lolo Peak.
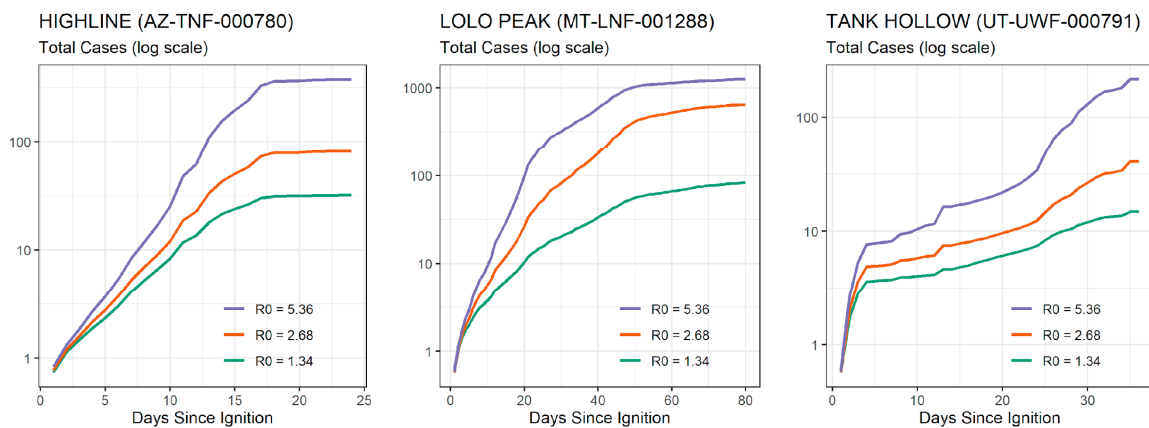

Figure 5. The total number of infected individuals over the duration of each incident under the low (R0 = 1.34), medium (R0 = 2.68), and high (R0 = 5.36) infection rates. Note that the vertical axis is log scaled. All simulations assume the infection rate of 1% of the arriving personnel.

Beyond the direct health impacts, infected persons are also unable to work, reducing the workforce available to contain the fire. These impacts affect not only the contemporaneous incident, as modeled here, but could carry forward to reduce the workforce capacity for weeks into the future, depending on the severity of the illness. The loss of personnel can be substantial: up to 10% of the workforce may be infectious on a single day with the maximum number of personnel on the fire (Figure 6), in the worst-case scenario, though other scenarios show smaller effects (less than 5%). The most promising option appears to be implementing both aggressive screening and social distancing measures on-site at the fire camp (Figure 7; best case). Certainly, results are driven by the assumption that incoming

infections and infection rates can be reduced; nevertheless, results do suggest that aggressive mitigation can help sustain firefighting capacity over time.
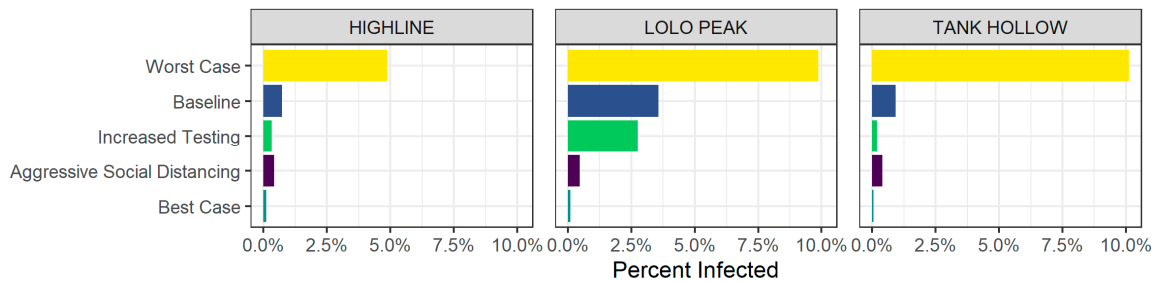
Figure 6. A comparison of the percentage of the workforce infected on the day with the largest number of personnel working across fires and scenarios.
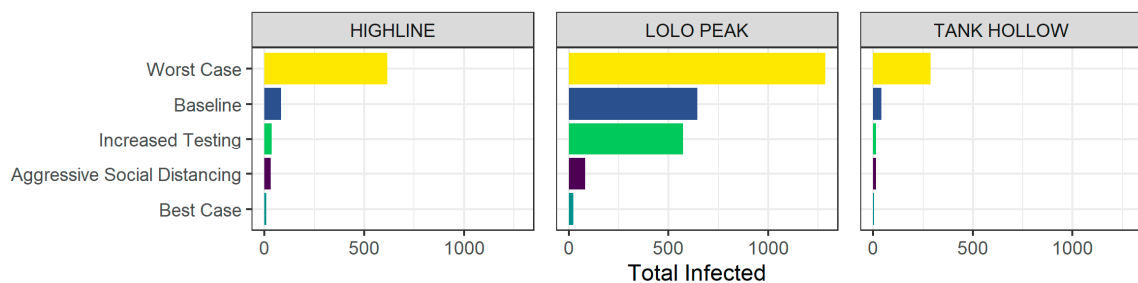
Figure 7. A comparison of the total of infected persons across fires and scenarios. Total infected for the best-case scenario is approximately 8, 21, and 4 individuals for the Highline, Lolo Peak, and Tank Hollow fires, respectively.

4. Discussion

Models are, by definition, an abstraction of reality and are subject to the accuracy of the parameters. Wildfires and the COVID-19 pandemic are each complex dynamic phenomenon, and the combination of the two produces great uncertainty. Therefore, we stress the limits of our model and highlight the qualitative results of the analysis rather than the estimated numbers.

In this study, we focused on two sources of case growth on an incident. The first is the introduction of infection by personnel arriving on an incident. As the fire grows and the incident becomes more complex, resource orders will be filled by available personnel, some of whom may come from other counties or states. Given the variation in the COVID-19 prevalence around the country at any given point in time, the firefighters from different areas will introduce variable risk to the camp. While current policies require or request symptomatic individuals to report their conditions and inform supervisors, evidence suggests that many infected people may experience very mild symptoms [25]. These asymptomatic individuals may remain infectious for weeks [26,27], perhaps posing the greatest risk of infection through a camp. The combination of exposure risk posed by the high turnover of personnel coming from a large number of places in concert with the exposure risk due to non-quarantined infectious individuals highlights the potential merits of developing testing strategies for early identification, which could include testing asymptomatic individuals without known or suspected exposure [28]. The utility of such testing strategies is conditioned by the availability, timeliness, and reliability of viral tests, and the optimal testing strategy design could be the subject of future research.

The second source of case growth on an incident that we examined was the spread among personnel while assigned to the fire. In the event that personnel arrive at an incident exposed or infected, their level of interaction with others will determine the rate of transmission within the camp. The rate of transmission will depend on the level of interaction between the personnel at the incident

and the nature of those interactions. Under normal circumstances, personnel may gather in large groups, for example, for briefings or meals. These interactions are similar to potentially infectious interactions in the general public that public health agencies have deemed ill-advised. Some of these interactions could be made less risky using current social distancing and mitigation recommendations; for example, masks appear to provide a barrier to the spread of SARS-CoV-2 [29]. Recognizing that a range of mitigations is already being planned or put into place by incident management personnel [9], these analyses provide a proxy for a business-as-usual baseline as a point of comparison.

We studied two types of interventions corresponding to the two types of source growth identified above: the screening of personnel arriving at the incident to address the case growth by the entry of the virus and the spread from non-quarantined infectious individuals, and social distancing measures within the fire camp to address the case growth from the spread among individuals in the camp. While both interventions mitigate transmission and lead to fewer cases, screening measures are relatively more effective on shorter incidents with a frequent resource turn over. In contrast, social distancing measures are relatively more effective on prolonged campaigns where most of the cases are due to transmission within the community.

While the total number of infections and the associated mortalities are clearly crucial measures for fire mangers to consider due to their health impacts on personnel, outbreaks also have implications regarding the possible degradation of workforce capacity. Wildfires rarely occur in isolation; most fire seasons in the recent past (2014–2018) have seen a scarcity of wildfire response personnel as several large wildfires occur simultaneously [30]. Thus, personnel that must leave a fire to recover from an infection may not easily be replaced and could leave the wildfire shorthanded. In addition, personnel may move between fire camps, and a large outbreak at one camp could be the source of infection for several following wildfires. If simultaneous fires incurred outbreaks, the entire wildland fire response system could be stressed substantially, with a large portion of the workforce quarantined.

The results from this model do imply that outbreaks of COVID-19 in wildland fire camps could be a serious threat to the firefighting mission and that mitigation measures could help reduce the risk of an outbreak. At the beginning of a fire incident, a manager has limited ability to predict which incidents will turn into extended campaigns. Thus, early and consistent intervention is crucial, with mitigations being implemented during initial fire operations. Our model suggests that even with mitigations in place, under certain circumstances, if infected individuals do enter the general population, there is enough time to support substantial transmission within the firefighting community (see Figure 3). The periodic reassessment of incident risk should play an important role in guiding mitigations and interventions. As managers observe key risk factors increasing (such as the number of personnel on the fire or fire duration), they might consider increased vigilance, which could include more aggressive social distancing or additional screening measures.

Our model has some important limitations. First, our analysis is deliberately limited in scope because our objective is to assess plausible disease dynamics and qualitative differences in interventions. While our models provide numerical results based upon the particular sets of parameters and fire data we used, these results should not be interpreted as making a prediction about any future events that fall outside the scope of the scenarios we examined. In particular, this model does not attempt to predict any events in the current or coming fire seasons.

As with all models, our assumptions guide our results. Thus, as we update this model throughout the season in response to additional gained knowledge about COVID-19 in fire camps, we could see substantial variation in our results. For example, COVID-19 symptoms overlap with common health issues observed on fires due to the exposure to high levels of particulate matter (cough) and substantial exertion (fever). Thus, COVID-19 symptoms in fire camps could be misattributed, leading to a substantially longer infectious period than our assumption of three days. In addition, the presence of asymptomatic infection would also increase the length of the infectious period. Similarly, there is substantial uncertainty in the effect of social distancing measures in reducing contact; changes in this parameter may substantially affect the model results. The underestimation of key disease parameters

such as the infection period and transmission would result in an outbreak where a substantially larger portion of the population is infected. In addition to the uncertainty surrounding COVID-19, specifically in fire camps, other scientific knowledge about COVID-19 will likely continue to grow, with updated parameter estimates that may be more relevant to fire camps in the United States than those that were available during the time period when we developed this scenario analysis.

We consider firefighter health and workforce outcomes only on single incidents. Future analyses could extend this to multiple fires in order to capture the risk posed by individuals moving across incidents. For instance, a severe outbreak at one fire may expose many firefighters to the virus, some of whom may be reassigned to other incidents, seeding further infection at those incidents. In addition, a long incubation period could lead to exposed individuals being reassigned in large numbers to future wildfires, leading to outbreaks that increase in severity over the season. The seasonal implications of COVID-19 are complex, important, and need to be addressed by a substantially more complex model than we present here.

In addition, the model is limited by only having four classes of infectious states for personnel with only one pathway between each state. That is, personnel move directly from susceptible to exposed to infectious to removed, and each of these pathways has a single rate associated with it. However, there are more possibilities for infectious pathways than the simple one modeled here. For example, an asymptomatic individual that tests positive might quickly move from infectious to removed, while an undetected asymptomatic individual might move to the removed class much slower. In addition, a new quarantined class is needed to better test the impact of infections on the workforce, as the current model only tracks the total number removed from the incident due to infection, but not the timing of how long they are out of the workforce. This would be particularly important for modeling the impacts of COVID-19 outbreaks on multiple incidents.

The model is deterministic and only approximates the stochastic nature of disease transmission. In large populations, random fluctuations in contacts and transmission tend to cancel each other out, making the deterministic model a good approximation of transmission dynamics in the population. In relatively small populations (e.g., hundreds of people), random transmission events can propagate through the system, altering the course of the epidemic. Quantifying the magnitude of this uncertainty is a crucial extension to the modeling framework we have proposed.

Our current approach relies on a simplifying assumption that the population at a fire camp mixes randomly and evenly across space and time. If contact patterns vary among individuals at a fire, interventions can be targeted to individuals or groups that are most likely to transmit the virus. For example, members of incident management teams have, in the past, spent much of their time inside a mobile trailer that is used as office space. This closed environment with a high level of contact between many people may be much riskier than the interaction that occurs out of doors between personnel on the fireline. Risk management plans may consider contingency plans in case substantial fractions of the leadership team become infected.

Not only is there uncertainty in the levels of contacts between individuals in a heterogeneous population, but there is also uncertainty in how the spread parameters might be influenced by some of the characteristics of the fire camps themselves. While some personnel on incident management teams may spend a substantial amount of time inside, most interaction in a fire camp occurs outdoors, which may be correlated with fewer spread events [31].

There are additional systematic and cultural factors that may prove challenging to implementing mitigation methods at the fire camp. Wildland firefighting is fraught with risks, and the agencies involved have implemented systems and protocols to minimize risk and ensure firefighter safety. However, these systems are generally focused on exposure risk to the individual (i.e., falling snags or burnovers). The nature of disease transmission risk is fundamentally different because it depends on the collective behavior of the group rather than a simple sum of individual actions. The risk of injury due to falling snags (weak or dead trees that may fall unexpectedly) is linear in the sense that in a scenario with ten people in a snag-prone environment, the potential for injury is ten times the number

of people, relative to a single person in that environment. The nonlinear nature of disease spread means that the introduction of ten infected firefighters in a population poses a much larger risk than ten times the risk posed by a single infected firefighter. In addition, the probabilities of infection are not independent over time in the way of snag risk (provided the number of snags remains constant).

The health impacts of COVID-19 on the wildland fire workforce based upon their health status is also an important consideration with substantial uncertainty. Wildland firefighting requires strenuous work in hot and smoky conditions, and firefighters must pass an arduous physical fitness test prior at least once every three years to prove they are capable of the strenuous work required [32–34]. Thus, wildland firefighters are generally considered to be fit. However, previous studies have found that wildland firefighters' lung function is affected by their work [35], and over the course of a season, and wildland firefighters experience a decrease in their metabolic and cardiovascular health [36]. Therefore, the impacts of COVID-19 on firefighters are highly uncertain, with the lowered risk of severe symptoms due to their general overall fitness possibly at odds with the higher risk due to the stress on their respiratory and cardiovascular systems [37,38].

Despite the model limitations, uncertainties, and challenges to the implementation of mitigation measures, the work presented in this paper does provide an approach for modeling and gaining insight about the potential spread of SARS-CoV-2 in fire camps. As we learn more about this threat, better information can be included in the model, and the model structure itself can be updated. Even prior to such updates, the implications of the efficacy of the two mitigation methods tested in this paper are valuable as fire managers prepare to fight fires during a global pandemic, unlike anything they have experienced in the past.

5. Conclusions

As society faces the confluence of a global pandemic and a possibly severe fire season [39], models can provide key insights into the consequences of disease transmission and highlight promising interventions to protect firefighting personnel. We modeled the spread of SARS-CoV-2 in wildland fire camps to gauge the risk posed by COVID-19 to the wildland fire community. Our results suggest that SARS-CoV-2 may spread rapidly within a fire camp during extended campaigns. One of the key insights of the model is that screening may be more effective on shorter incidents with large numbers of personnel entering and exiting, whereas social distancing measures may be more effective on longer campaigns. The relatively long incubation period inhibits rapid growth on short duration incidents relative to long campaigns. As the season progresses, the wildland fire community will continually learn the consequences of COVID-19 and how to cope with the risk of illness.

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