Ensemble Based Learning for Automated Safety Labeling of Prescribed Fires*

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Abstract. Prescribed fires are controlled burns of vegetation that follow a burn plan to reduce fuel build-up and mitigate unanticipated wildfire impacts. To understand the risks associated to a prescribed burn, modern fire simulation tools can be used to simulate the progression of a prescribed fire as a function of burn conditions that include ignition patterns, wind conditions, fuel moisture and terrain information. Although fire simulation tools help characterize fire behavior, the unknown non-linear interactions between burn conditions requires the need to run multiple fire simulations (ensembles) to formulate an allowable range on burn conditions for a burn plan. Processing the ensembles is often a labor intensive process run by user-domain experts that interpret the simulation results and carefully label the safety of the prescribed fire. The contribution of this paper is an algorithm of ensemble based learning that automates the safety labeling of ensembles created by a modern fire simulation tool. The automated safety labeling in this algorithm is done by first extracting important prescribed fire performance metrics from the ensembles and learn the allowable range of these metrics from a subset of manually labeled ensembles via a gradient free optimization. Subsequently, remaining ensembles can be labeled automatically based on the learned threshold values. The process of learning and automatic safety labeling is illustrated on 900 ensembles created by QUIC-Fire of a prescribed fire in the Yosemite, CA region. The results show a performance of over 80% matching of learned automated safety labels in comparison to manually generated safety labels created by fire domain experts.

Keywords: Prescribed Fire · QUIC-Fire · Safety · Automated Labeling · Gradient-free Optimization

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1 Introduction

As the extent of landscapes burned by wildfires continuously grow, it is important to take advantage of prescribed fires to manage the risk of uncontrollable wildfires. A prescribed fire is a controlled burn of vegetation and ignited intentionally to meet fuel and vegetation management objectives, such as reducing hazardous fuels, sustain the natural landscapes, and avoid extreme wildfires. Compared to a wildfire that is unplanned, prescribed fire can be controlled by reducing the risk of a fire escape.

There are many positive effects of a prescribed fire on soil, vegetation, or even some cultural artifacts, and periodic fire plays an important role in the balance of many ecosystems [1–3, 12, 14]. Therefore, prescribed fire can be used as a tool to manage the forest area in various ecological aspects, such as preventing invasive vegetation and facilitating the recovery of specific species [6]. However, people are averse to the risk of a prescribed fire due to the lack of scientific knowledge about the benefit of a prescribed fire in an ecosystem management [13].

Environmental or burn conditions that include the landscape, terrain, fuel moisture, wind speed, wind direction and ignition pattern are important factors for the progression of the fire. Extensive modeling efforts have been documented that help with the prediction of the fire spread as a function of the burn conditions [4, 5, 8, 9, 11, 16]. With the advance of the science and technology, various software tools have been developed to numerically simulate the progression of a prescribed fire. QUIC-Fire [10] is a three-dimensional fire simulation tool that provides dynamic fuel consumption over time.

Although the progression of the consumed fuel can be simulated by QUIC-Fire, the trade-off between controlled fuel consumption and the safety of the prescribed burn must be taken into account when deciding on the allowable burn conditions. In practice, the unknown non-linear interactions between burn conditions requires the need to run multiple QUIC-Fire simulations (ensembles). The ensembles can be labeled as safe, marginal and unsafe by fire domain experts manually to formulate an allowable range on burn conditions. The manual labeling process is labor intensive and time consuming, and a fast and accurate automatic labeling algorithm that incorporates and learns the expertise of a fire domain expert is desirable.

The contribution of this paper is an algorithm of ensemble based learning that automates the safety labeling of ensembles created by a modern fire simulation tool. The automated safety labeling in this algorithm is done by first extracting important prescribed fire performance metrics from the ensembles based on a desired burn boundary within a burn plan. Any fire escapes outside the desired burn boundary is characterized as a *slop-over* and performance metrics identify the size, spacing and the number of slop-overs. Subsequently, manually labeled ensembles are used to learn the allowable range of the slop-over metrics to distinguish between safe, marginal and unsafe fire conditions. With some integer-valued metrics, the learning is formulated via an gradient-free optimization based on a genetic algorithm [7] that has the capability to deal with integer-valued functions.

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The optimized (learned) allowable range of the slop-over metrics and the environmental conditions such as wind speed and fuel moisture are configured as parameters in the automatic labeling. The numerical values of these parameters are used in the automatic labeling algorithm. The optimization ensures an optimized prediction accuracy of the automatic safety labeling of the ensembles. In order to authenticate the performance of the automatic labeling, the use cases of 900 ensembles of a prescribed fire in the Yosemite, CA area are utilized. Learning and matching 100% of the manually assigned safety labels of a subset with 48 out of the 900 ensembles, the automatic labeling is used to provide safety labels for the remaining ensembles. With a success rate above 80%, the proposed automatic labeling algorithm works efficiently and accurately, and can be used as a tool to design the burn plan of the prescribed fire.

2 QUIC-Fire Output Data

With the information of the surface moisture, fuel type, wind conditions, and ignition pattern, QUIC-Fire [10] can simulate the spread of the prescribed fire. The typical output produced by QUIC-Fire at each simulation step is the fuel consumption as depicted in Figure 1.

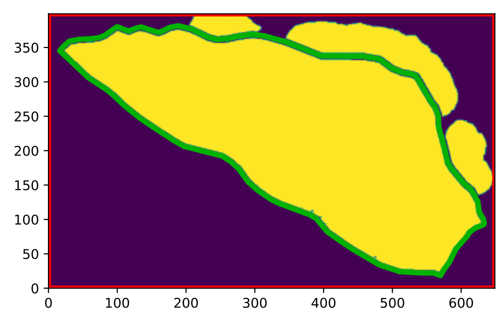

Fig. 1: Output (fuel consumption) of QUIC-Fire. The green line represents the desired boundary and the red line represents the allowable boundary. The yellow area is the burn area (fuel consumed) with $y = 1$ and the dark blue area is the unburned area (fuel not consumed) with $y = 0$.

Similar to [15], the burn area is represented by the yellow area with $y = 1$, and the unburned area is represented by dark blue area with $y = 0$. The value of each pixel can be expressed as

$$y_{i,j} = f([i,j], b) = \begin{cases} 0, & \text{if } b < 0.001 \\ 1, & \text{if } b \geq 0.001 \end{cases} \tag{1}$$

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where $[i, j]$ describes the position of the target pixel in the image, b is the absolute difference value between the fuel densities before the prescribed fire starts and after the prescribed fire ends, and y is the value of pixel at $[i, j]$ and used to distinguish between the burn area and unburned area.

In Figure 1, the provided desired boundary is drawn by a green line, which defines the area inside the desired boundary that is expected to burn, and the allowable boundary is drawn by red line, which separates buffer area and non-allowable burn area where fire is definitely considered to be unsafe. The allowable boundary is determined by the size of the fuel domain used for the simulation in QUIC-Fire. Without loss of generality, whether a fire escapes outside the allowable boundary can be distinguished by checking whether there is a pixel with $y = 1$ outside the closed polygon representing the allowable boundary. On account of the fact that the shape of the fire is arbitrary, deciding the fire safety by only depending on predetermined boundaries is not enough.

The yellow area outside the desired boundary in Figure 1 is regarded as the slop-over, and the number of the disconnected yellow area outside the desired boundary is regarded as the number of slop-overs. Hence, the simulation shown as Figure 1 includes three slop-overs. With the definitions of desired boundary and allowable boundary, slop-over plays an important role in evaluating the safety of the prescribed fire. If the slop-over has the potential to spread outside the allowable boundary, and is hard to control, the corresponding prescribed fire can be unsafe. For identification of the fire safety for each simulation (ensemble), three levels are used: safe, marginal and unsafe.

3 Feature Definitions

Following the summary of the nomenclature given in Table 1, a short explanation is given for the inputs and parameters used in the automatic labeling of ensembles. After collecting the manual labels provided by fire domain experts, the number of the slop-over k_s, the total area of the slop-over A_s, and the distance between each slop-over l_s, can be used to evaluate the safety of the prescribed fire. The total area of the slop-over directly reflects the result of a simulated prescribed fire. Hence, it is an important factor in measuring the fire safety. Limited by the number of firefighters, large number of slop-over or large distance between slop-overs can both result in an uncontrollable prescribed fire.

To quantitatively measure these three terms, some parameters are created in the automatic labeling algorithm. A_{max} and A_{mar} represent the maximum and marginally allowable total area of slop-over, k_{max} denotes the maximum allowable number of slop-over, and l_{max} and l_{mar} indicate the maximum and marginally allowable distance between each slop-over. In addition to simply exploiting the information of slop-over, the complex environmental conditions are also taken into consideration.

For additional flexibility, the parameters α and β are utilized as the constant amplification coefficients to enlarge the potential risk of the slop-over. As a prescribed fire can be more dangerous when the wind speed is higher, the surface

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Table 1: Nomenclature of inputs and parameters for automatic labeling

Inputs:	
A_s	total area of slop-overs
k_s	number of slop-overs
l_s	distance between each slop-over
w_s	wind speed
s_s	surface moisture
Parameters:	
A_{max}	maximum allowed total area of slop-overs
A_{mar}	marginally allowed total area of slop-overs
k_{max}	maximum allowed number of slop-overs
α	expansion coefficient
β	expansion coefficient
l_{max}	maximum allowed distance between each slop-over
l_{mar}	marginally allowed distance between each slop-over
w_t	threshold value of wind speed
s_t	threshold value of surface moisture
k_{t_1}	the first threshold value of number of slop-over
k_{t_2}	the second threshold value of number of slop-over

moisture is lower, and the number of the slop-over is larger, four threshold values are created to better distinguish the effect of the total area of slop-over and the distance between each slop-over in different situations. The parameters k_{t_1} and k_{t_2} are established as the number of the slop-over when the risk level of prescribed fire varies significantly, while s_t and w_t are the threshold values for the surface moisture and wind speed respectively. If wind speed is larger than w_t, or surface moisture is smaller than s_t, more caution is required to decide the risk level of the prescribed fire. With these parameters, an automatic safety labeling algorithm can be formulated.

4 Automatic Labeling Algorithm

4.1 Postprocessing of QUIC-Fire Output

To calculate the previously mentioned A_s, k_s and l_s for each ensemble of prescribed burn, the slop-overs should be characterized by removing the burn area inside the desired boundary as shown in Figure 2. Following the definition of y in (1), all slop-overs have $y = 1$ as shown in Figure 2(a).

To further distinguish the slop-overs, different non-zero values for y are assigned to different slop-overs. For the numerical implementation, `label` function in the package of scikit-image [17] in Python is a good tool to achieve this goal. It first detects the slop-overs according to the connectivity, and then assigns different values of y to different slop-overs. From Figure 2(b) it can be observed that three slop-overs are plotted by different colors, where yellow, magenta, and cyan correspond to $y = 1$, $y = 2$, and $y = 3$ respectively.

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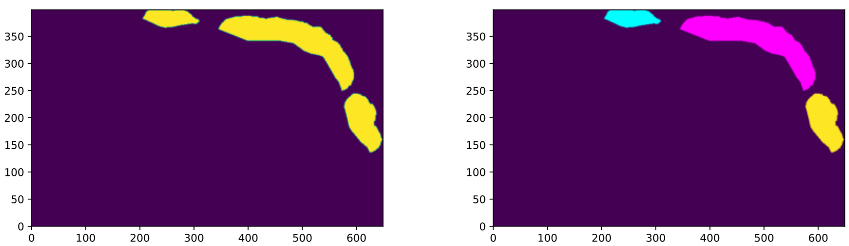
Afterwards, the number of the slop-over can be determined by the number of different non-zero values of y, and the area of each slop-over can be calculated by summing up the number of pixels with corresponding y. Finally, the distances between the centers of the smallest vertically oriented rectangles that separately contain each slop-over serves as the distances between each slop-over.



(a) Plot of slop-overs with same y. (b) Plot of slop-overs with different y.

Fig. 2: Extracted slop-overs.

4.2 Process of Automatic Labeling

Since a distance between slop-overs exists only when there are more than one slop-over, the number and the total area of the slop-over are more important and are utilized first for labeling the fire safety. Due to the limited resource of the fire fighting, it is impossible to control the slop-overs of one prescribed fire simultaneously if multiple slop-overs are far away from each other. Therefore, the distance between slop-overs should also be measured.

Additionally, wind speed and surface moisture around the prescribed fire also affect the fire spread. Even a small slop-over can grow out of control in a short time when the wind speed is large and the surface moisture is low. To account for these situations, two expansion coefficients α and β are applied on the total area of the slop-overs to reflect the emphasis on the effect of the extreme environment. For each ensemble, with computed metrics A_s, k_s and l_s, and provided data of w_s and s_s, the automatic process can be described as follows.

At first, the prescribed fire ensemble is assumed to be safe. Any prescribed fire ensemble with the total area $A_s > A_{max}$, or number of slop-overs $k_s > k_{max}$ is labeled to be unsafe. When the wind speed $w_s > w_t$, the surface moisture $s_s < s_t$, and the number of the slop-over $k_{t_1} < k_s \leq k_{max}$, the prescribed fire is more likely to be unsafe. For that purpose, αA_s is compared to A_{max}. If $\alpha A_s > A_{max}$, the prescribed fire ensemble is regarded as an unsafe fire.

To evaluate the safety of a prescribed fire ensemble by the distance between slop-overs, a prescribed fire ensemble with the number of the slop-over $k_{t_2} < k_s \leq$

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k_{max}, and the maximum distance between each slop-over $max(l_s) > l_{max}$ is classified as unsafe. If a prescribed fire is not unsafe, then it will be checked whether it is marginal. The process of judging whether a prescribed fire is marginal is similar, and another expansion coefficient β is set up to put more cautions in the judgement when the environment is more suitable for the spread of the prescribed fire. The automatic labeling algorithm is summarized in Algorithm 1.

Algorithm 1 Automatic Labeling Algorithm

Inputs: A_s, k_s, l_s, w_s, s_s
Parameters: A_{max}, A_{mar}, k_{max}, α, β, l_{max}, l_{mar}, w_t, s_t, k_{t_1}, k_{t_2}
Output: Label of the simulated prescribed fire

Assume the prescribed fire is safe at the beginning.
if the prescribed fire move outside the allowable boundary **then**
    the prescribed fire is unsafe
else if $A_s > A_{max}$ **then**
    the prescribed fire is unsafe
else if $k_s > k_{max}$ **then**
    the prescribed fire is unsafe
else if $k_{t_1} < k_s \leq k_{max}$ and $w_s > w_t$ and $s_s < s_t$ and $\alpha A_s > A_{max}$ **then**
    the prescribed fire is unsafe
else if $k_{t_2} < k_s \leq k_{max}$ and $max(l_s) > l_{max}$ **then**
    the prescribed fire is unsafe
else if $A_s > A_{mar}$ **then**
    the prescribed fire is marginal
else if $k_{t_1} < k_s \leq k_{max}$ and $w_s > w_t$ and $s_s < s_t$ and $\beta A_s > A_{mar}$ **then**
    the prescribed fire is marginal
else if $k_{t_2} < k_s \leq k_{max}$ and $max(l_s) > l_{mar}$ **then**
    the prescribed fire is marginal
end if

5 Optimization

It is clear that the accuracy of the automatic labeling is dependent on the numerical values of the parameters listed in Table 1. The numerical values of the parameters can be optimized by using safety labels created by fire domain experts. The formal problem of learning the numerical parameters on the basis of manually labeled fire safety data can be stated as the optimization

$$\begin{gathered} \min_{\mathbf{u}} \sum_{i=1}^{N} d_i \frac{u_i}{q_i} - c(\mathbf{u}), \\ \text{subject to: } p_i \leq u_i \leq q_i \text{ for } i = 1, 2, \ldots, N \\ A_{mar} \leq A_{max}, \quad l_{mar} \leq l_{max}, \quad k_{t_1}, k_{t_2} \leq k_{max} \\ c(\mathbf{u}), A_{mar}, A_{max}, k_{t_1}, k_{t_2}, k_{max}, w_t \in \mathbb{Z} \end{gathered} \tag{2}$$

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where $\mathbf{u} = [\alpha, \beta, A_{mar}, A_{max}, k_{max}, k_{t_1}, k_{t_2}, l_{mar}, l_{max}, s_t, w_t]$, N is the number of parameter, and d_i is the weighting coefficient with $\sum_{i=1}^{N} d_i = 1$. u_i represents the i_{th} parameter in $\mathbf{u}$, and p_i and q_i are the lower bound and upper bound of the i_{th} parameter respectively. The value of p_i and q_i can be obtained from the burn plan that includes the information of the fuel domain, the wind conditions and the surface moisture for the simulated prescribed fire.

In (2), $c(\mathbf{u})$ denotes the number of safety match between the automatic labels created by Algorithm 1 and the manual labels created by a fire domain expert, where $\mathbf{u}$ represents the parameters. With $u_i \leq q_i$ from Equation 2 and $\sum_{i=1}^{N} d_i = 1$, it can be verified that

$$\sum_{i=1}^{N} d_i \frac{u_i}{q_i} \leq \sum_{i=1}^{N} d_i = 1 \tag{3}$$

since $c(\mathbf{u})$ is the number of matches between the automatic labeling and manual labeling, any change in $c(\mathbf{u})$ when $\mathbf{u}$ varies is greater than or equal to one.

With (3), an inequality can be derived for the change in $c(\mathbf{u})$, denoted by $\Delta c(\mathbf{u})$, when varying $\mathbf{u}$. The value of $\Delta c(\mathbf{u})$ is bounded by

$$\sum_{i=1}^{N} d_i \frac{u_i}{q_i} \leq 1 \leq \Delta c(\mathbf{u}) \tag{4}$$

and therefore the optimization will first focus on increasing the number of matches between the automatic labels and manual labels, and then decrease the numerical value of the parameters. As a result, the parameters obtained by the optimization will achieve the goal of gaining the maximum match number with the necessary minimum values of the parameters, representing the allowable range on the slop-over metrics.

Because $c(\mathbf{u})$ is an integer-valued function, and there is no analytic expression of $c(\mathbf{u})$, a gradient-free optimization method that can also deal with the integer-valued function should be applied. The genetic algorithm is an explicit and effective solution to this problem. The genetic algorithm will repeatedly modify the population of individual solution. Three steps are included in the genetic algorithm. At first, a random initial population is created. Then, a sequence of new populations are created iteratively based on the previous populations by scoring the fitness of each member of the population, selecting pairs of the members relied on the fitness, and generating the new population by applying crossover and mutation. The last step is to stop the algorithm when the change in value of the fitness function for the best member is less than a tolerance value, or after a predetermined maximum number of iteration. The procedure of the genetic algorithm is summarized in Algorithm 2.

6 Numerical results

6.1 Ensemble Based Learning

For illustration of the ensemble based learning for automated safety labeling, two fire domain experts work together to manually label the fire safety of 900

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Algorithm 2 Genetic Algorithm

Input: Population size m, maximum number of iterations t_{max}, and stopping criterion ϵ

Output: Global optimal solution, $\mathbf{u}_{opt}$

1: Create the initial m members $\mathbf{u}_j(j = 1, 2, \ldots, m)$ of population, and let $t = 0$.
2: Scoring the fitness value of each member, and find the member with best fitness value $f(t)$.
3: select pairs of members from previous population based on fitness value.
4: Apply crossover and mutation to generate the new population.
5: $t = t + 1$.
6: Stop when $t = t_{max}$ or $f(t) - f(t-1) < \epsilon$; Otherwise, go back to step 2 to repeatedly modify the population.

ensembles of a prescribed fire in the Yosemite, CA region. QUIC-Fire simulations for the 900 ensembles are created by varying ignition patterns, wind speed, wind direction and fuel moisture for each of the ensembles.

To ensure the validity of the manual labels used for learning, 48 out of the 900 ensembles are labeled by two fire domain experts separately and carefully. Some typical cases in these 48 ensembles with same manual labels are shown as Figure 3. In Figures 3(a), 3(b), 3(c) and 3(d), the total area of the slop-overs are small enough and there is a certain distance between the slop-overs and the allowable boundary. Hence, they are labeled as safe prescribed fires. It can be noticed that the sizes of the slop-overs in Figures 3(e) and 3(f) are relatively large, and the top parts of the slop-overs are fairly close to the allowable boundary. Therefore, the safeties of these two prescribed fire are labeled to be marginal. For Figure 3(g), the prescribed fire crosses the allowable boundary, and for Figure 3(h), the total area of the slop-overs is larger than A_{max} despite that the fire does not escape outside the allowable boundary. As a result, both of them are considered to be unsafe. At last, the slop-overs in Figure 3(i) are large and cross the allowable boundary. Therefore, these slop-overs obviously constitute unsafe prescribed fire conditions.

The ensemble based learning only uses the 48 out of the 900 ensembles, whereas the remaining 852 labels will be labeled automatically based on the optimized parameter values of Table 1 obtained by the learning. For cross validation of the accuracy of learning and labeling, both the 48 ensembles used for learning and the 852 ensembles not used for learning but used for labeling only are compared.

From this cross validation, a 100% accuracy has been achieved for both sets (48 ensembles) of the manual labels created by two fire domain experts respectively. As expected, the optimized parameters for each fire domain expert are slightly different, as each fire domain expert will interpret and label the ensembles slightly differently. As such, the rules used by the two fire domain experts are not completely the same, but either of them can be captured by the learning algorithm. The parameters, $\mathbf{u}^1$ and $\mathbf{u}^2$, optimized by the two sets of manual labels are summarized in Table 2.

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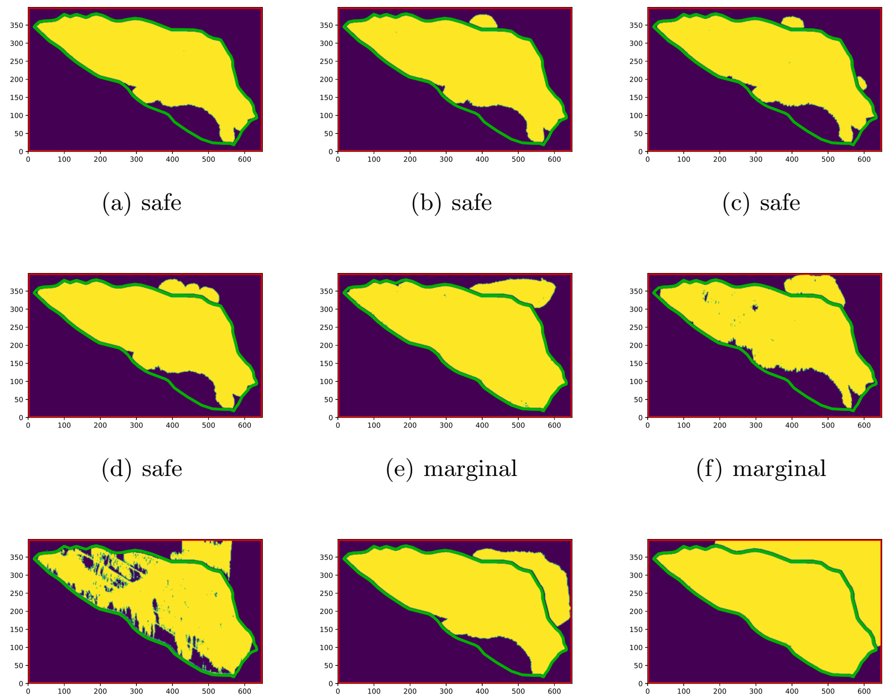

(a) safe (b) safe (c) safe

(d) safe (e) marginal (f) marginal

(g) unsafe (h) unsafe (i) unsafe

Fig. 3: Typical cases in the training data set.

By inspecting the numerical values of the parameters in Table 2, it can be observed that fire domain expert, from whom $\mathbf{u}^1$ is learned, is more cautious than the fire domain expert, from whom $\mathbf{u}^2$ is learned, because $\mathbf{u}^1$ has smaller values for A_{mar} and A_{max}. Furthermore, α in $\mathbf{u}^1$ is larger than one, and β in $\mathbf{u}^1$ is close to one. This means $\mathbf{u}^1$ is more focused on identifying unsafe prescribed fire conditions. In addition, $\mathbf{u}^1$ takes advantage of the distance between each slop-over to judge the risk level of the prescribed fire. In comparison, $\mathbf{u}^2$ has a higher tolerance for the threat of a prescribed fire, and $\mathbf{u}^2$ has higher probability to assess the risk level of prescribed fire as marginal instead of unsafe with α close to one and β larger than one. Since both l_{mar} and l_{max} in $\mathbf{u}^2$ are close to zero, it can be assumed that the distance between each slop-over is not utilized, which is also supported by $k_{t_2} = k_{max}$.

6.2 Automated Safety Labeling

Due to the large workload for a single fire domain expert to label the remaining 852 ensembles, the 852 manual labels are created together by the two fire domain

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Table 2: Parameters, $\mathbf{u}^1$ and $\mathbf{u}^2$, optimized by the two sets of 48 manual labels respectively.

	A_{mar}	A_{max}	α	β	w_t	s_t	l_{mar}	l_{max}	k_{t_1}	k_{t_2}	k_{max}
$\mathbf{u}^1$	8280	10655	1.31	1.01	0	0.2001	133.31	263.72	1	2	3
$\mathbf{u}^2$	9723	17719	1.04	1.37	3	0.3501	1.06	1.96	0	3	3

experts, effectively mixing their fire safety labeling expertise in the remaining data set of ensembles. To cross validate the performance of the automatic labeling, manual labels of the 852 ensembles, not used for learning, are compared to the labels created by Algorithm 1 with the parameters values $\mathbf{u}^1$ and $\mathbf{u}^2$ listed in Table 2 separately.

The match accuracy between the manual labels and the automatic labels created using $\mathbf{u}^1$ is 76.76%; the match accuracy between the manual labels and the automatic labels created using $\mathbf{u}^2$ is 76.88%; the match accuracy between the manual labels and the automatic labels created using either $\mathbf{u}^1$ or $\mathbf{u}^2$ is 80.52%. As a consequence, more than 80% manual labels can be captured by the automatic labeling using either $\mathbf{u}^1$ or $\mathbf{u}^2$.

6.3 Re-evaluation of Manual Labeling

To investigate the inconsistency between manual and automatic labeling, 12 ensembles (Figure 4) are chosen as canonical cases from the 852 ensembles, in which the manual labels are different from the automatic labels created using either $\mathbf{u}^1$ or $\mathbf{u}^2$. Without loss of generality and with the purpose of reducing the workload, only one fire expert, by whose manual labels $\mathbf{u}^1$ was optimized, relabeled these 12 ensembles and 10 revised manual labels were the same as the automatic labels created by Algorithm 1 with $\mathbf{u}^1$.

In Figures 4(a) and 4(b), the total area of the slop-overs is small enough. Therefore, both of them should be regarded as safe prescribed fires. In addition, Figure 4(b) is similar to Figure 3(c), which further confirms that the fire shown in Figure 4(b) is safe. For Figures 4(c) and 4(d), since the slop-overs are larger and hard to control, they should be unsafe. For Figures 4(e) to 4(i), the prescribed fires cross the allowable boundary in different locations and are unsafe. It is worthwhile to note that the re-evaluation helped to further improve the number of match between manually and automatically created labels by correcting the previous manually applied safety labels.

Since there is no ensemble with four or more slop-overs included in the 48 ensembles used for learning and more slop-overs will lead to more dangerous fire conditions, k_{max} is optimized as 3, and all the prescribed fires with four or more slop-overs will be considered as unsafe fires in the automatic labeling. For Figures 4(j) and 4(k), both of them have four slop-overs and the difference between them is that all four slop-overs in Figure 4(j) stay together while one slop-over is far away from the other three slop-overs in Figure 4(k), which further

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increase the difficulty in controlling the prescribed fire. Hence, the prescribed fires shown by Figure 4(j) and Figure 4(k) are considered to be marginal and unsafe respectively by the fire expert.

6.4 Further Improvements

To further improve the automatic labeling, a user-defined marginally allowed number of slop-overs k_{mar} and a user-defined maximum allowed number of slop-overs k_{max} can be imported into Algorithm 1. Expanding the training data to include more scenarios can also improve the performance of automatic labeling at the price of having to provide more manually labeled ensembles.

To make sure the user-defined k_{mar} and k_{max} will not change during the optimization process, two more linear equality constraints on k_{mar} and k_{max} can be added to (2). At last, for Figure 4(l), even the fire domain expert cannot give an exact answer based on the current data. It means more information, like topography, vegetation, and contingency resources are needed.

In summary, the automatic labeling, Algorithm 1, has a good ability to create the label for the safety of the prescribed fire. Since the label is created by measuring the number of slop-overs, the total area of the slop-over, and the distance between each slop-over, the automatic labeling can not only create the label but also give a feedback about which rule is used to create the label so that people can get access to the interpretation of the automatic labeling.

7 Conclusions

This paper introduces an automatic labeling algorithm to establish the safety label for each ensemble of a simulated prescribed fire. The automatic labeling is based on prescribed fire safety metrics that include the number of slop-overs, the total surface area of slop-overs, and the distance between slop-overs. In addition to the safety label, the automatic labeling algorithm can provide an explanation why a prescribed fire is considered to be safe, marginal, or unsafe. Necessary parameters are optimized in the automatic labeling algorithm via a genetic algorithm to assist in determining the label of each ensemble of the simulated prescribed fire. A numerical validation based on 900 ensembles with manually generated safety labels of a prescribed fire in the Yosemite, CA area showed a 100% match of safety labels for the training data (48 out of 900 ensembles) and a larger than 80% match on the cross validation of safety labels not used in the training data (852 out of 900 ensembles).

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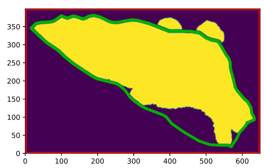
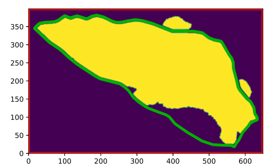


(a) PML: unsafe
AL: safe
RML: safe



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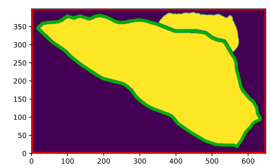

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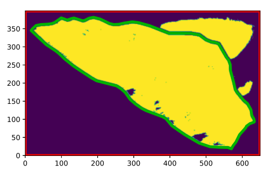

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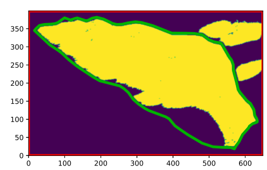

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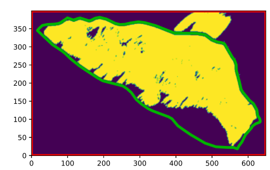

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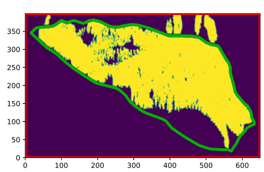

(g) PML: safe
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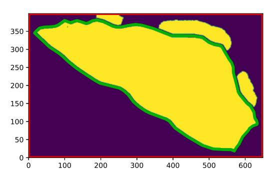
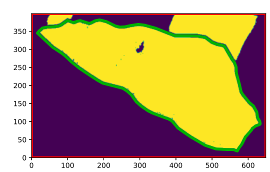
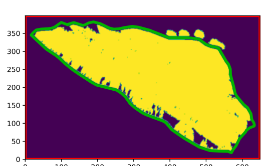
RML: unsafe



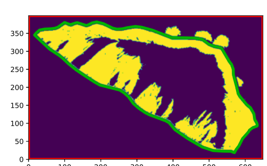
(h) PML: safe
AL: unsafe
RML: unsafe



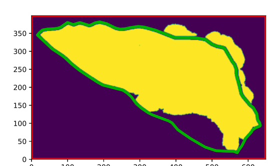
(i) PML: marginal
AL: unsafe
RML: unsafe



(j) PML: safe
AL: unsafe
RML: marginal



(k) PML: marginal
AL: unsafe
RML: unsafe



(l) PML: unsafe
AL: safe
RML: marginal

Fig. 4: Canonical mismatch cases. PML stands for previous manual label, AL stands for automatic label by applying $\mathbf{u}^1$, and RML stands for revised manual label.

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