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k-PERIL: probabilistic creation of trigger boundaries for rural communities evacuating from a wildfire

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Abstract

Evacuation is a critical part of wildfire emergencies. Emergency managers must be prepared to issue evacuation notices to areas that could be in the path of a wildfire to protect lives. There are methods of establishing when an evacuation should be called for any given urban area. One option is the creation of trigger boundaries around populated areas. This boundary is formed so that, should the wildfire cross it, a triggered evacuation will be complete before the wildfire becomes a threat to the area by threatening the community.

Models already exist for calculating the trigger boundary around an area, and each have their strengths and limitations. WUIVAC by Li et. al. (2015) is a robust tool that can calculate the trigger boundary of an urban area, for any one simulated fire. However, it can only model trigger boundaries for one wildfire at a time and thus cannot capture the susceptibility of the area to any possible wildfire. Ramirez et. al. (2019) created a tool to calculate the probabilistic trigger boundary of an area by simulating all possible fires that may threaten the urban area. This tool is effective for management and planning, but is incredibly resource-intensive and limited in terms of letting the user specify which area is most likely to suffer from a wildfire.

To address this, the k-PERIL algorithm was developed to calculate the trigger boundary of an urban area, as an upgraded version of the PERIL algorithm (Mitchell et. al, 2019). The user can load a single simulated wildfire, through software like FARSITE, and an evacuation time and get an exact trigger boundary for a specified urban area. The user can also load multiple wildfire simulation results for a given area, and K-PERIL will then generate a probabilistic trigger area. The user can then choose to retrieve a singular boundary of the area based on a probability value; It was made as part of the WUINITY project, by Ronchi et. al (2020), a self-contained wildfire simulation and evacuation planning tool.

To introduce k-PERIL as a tool of calculating trigger boundaries, this paper presents the a study on creating trigger boundaries for Roxborough Park, an urban area near Denver, CO, USA. A fire ignition area was specified and a number of wildfires with varying weather inputs were created, and a probabilistic boundary was created. The testing program allowed the user to specify the average weather values and standard deviations of their area of interest, specify an area where ignition is most likely, and specify the number of simulated wildfires. Testing for single-wildfire boundaries will be conducted in the full paper.

The results show that the results follow the current understanding of wildfire propagation. The resulting shapes are more accurate when more test cases are loaded, and are wider when the input variables are more varied. K-PERIL can thusly be used to create both specific and probabilistic boundaries around an inhabited area, either for immediate response or long-term planning.

1. Introduction

Wildfire emergency managers currently rely on their experience and intuition to call an evacuation when a Wildlife-Urban Interface (WUI) area is at risk [Pyne, Andrews, Laven 1996]. If the evacuation is called too soon, critical resources may be diverted from an area that needs them more; if it is called too late, lives may be at risk [Thomas, McAlpine 2010]. Trigger boundaries are a method of calculating the ideal time to trigger an evacuation, by coupling the decision-making process with the physical position of the fire.

1.1. Trigger Boundaries

Trigger boundaries set an area around an urban area at risk. For a given Wildfire Required Safe Egress Time (WRSET), the boundary is formed so that, when the fire reaches any point in the boundary, the urban area has an ASET amount of time before the fire reaches the urban area. This can be explained schematically using Figure 1.

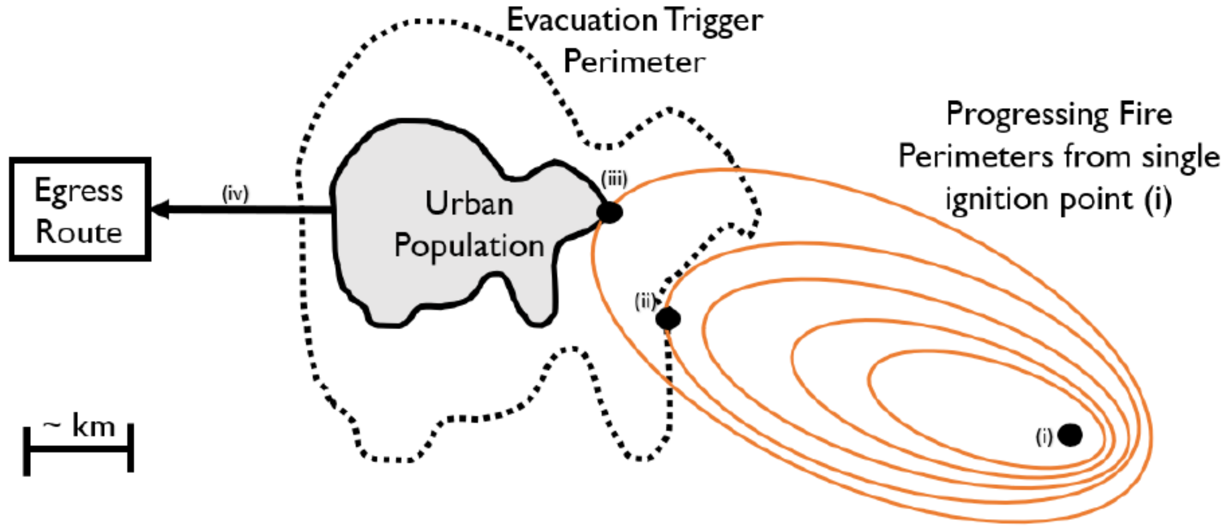

Figure 1- Schematic of the function of trigger boundaries (here referred to as trigger perimeters) [6]. A fire starts at timestep (i). At timestep (iii) the fire has reached a designated urban population. An ASET amount of time before timestep (iii), the fire was at timestep (ii). The locus of all the points where the fire is an ASET amount of time away from the urban node is the trigger boundary.

Currently there is no universally used method of analytically deducing trigger buffers by practitioners, but there is a number of models that attempt to calculate the safety boundary. The most popular such model is HURREVAC [A Hurricane Decision Support Tool For Government Emergency Managers] although it is made to calculate trigger boundaries for hurricane-prone coastal areas. Below is a presentation of trigger boundary calculation programs created specifically for wildfire risk.

1.2. Previous models

1.2.1. WUIVAC

WUIVAC [Dennison, Cova, Mortiz 2007] [Li, Cova, Dennison 2015] is an open-source model that uses Rate of Spread data from wildfire simulations to calculate the trigger boundary for any given urban area. WUIVAC has been used in applied test cases such as one involving the 2003 Cedar Creek fire [Larsen et. al. 2011], though none of them have been experimentally validated. One setback of the program is it can only be used to create one boundary at a time, so if a sensitivity or long-term planning study was needed, the program would be cumbersome to use.

1.2.2. Ramirez et. Al.

Ramirez et. Al [Ramirez et. al. 2019] calculate safety buffers using a different approach. They simulate wildfires as well, but set the simulated time duration equal to WRSET, and then run one hundred simulations, with normally distributed starting conditions. While this method is very thorough, it is also computationally expensive and inefficient. It also does not account for the acceleration phase of wildfires or other effects that fully developed wildfires may induce [Thomas, McAlpine 2010]. It also cannot run a study for a singular fire, should that need arise.

1.2.3. PERIL and K-PERIL

PERIL [Mitchel, Rein 2019a] [Mitchell et al. 2019b] is a program created based on the working principles of WUIVAC. It too uses wildfire simulations to calculate arrival times, and then creates a weighted point network to find the trigger boundary. The long-term goal of PERIL is to be integrated in the greater WUINITY project [Mallick, 2021] [Ronchi et al. 2020] [Wahlqvist et al. 2021]. WUINITY is a project aiming to provide a coupled wildfire-evacuation model that accounts for wildfire propagation, pedestrian and vehicular evacuation.

k-PERIL is the next iteration of the PERIL program, which enables the running of both single-fire studies and probabilistic studies. It uses the same core algorithm as PERIL but outputs a matrix of all the points that are inside the trigger boundary. It can then compound each output matrix for multiple cases and thus create a probabilistic boundary based on how many boundaries include each point. PERIL has been used in a real case before, but k-PERIL has only been verified in simple cases, when compared to PERIL. This is the first study where k-PERIL is used in a real-life situation.

2. Objectives

In this study, we set out to test k-PERIL in a real-life case. The urban area selected for the test is an area around Roxborough Park, an urban area south of Denver, CO, USA (figure 2) that has undergone extensive evacuation testing and documenting thereof as part of the WUI-NITY studies [Mallick 2021]. The primary risk of fire considered is ignition in the shrubland south of the area, with southern winds guiding the fire towards the urban area.

3. Methods

For this analysis, a custom testing suite was created, that generated several custom FARSITE [Finney 1998] simulations and run them through a command-line version of FARSITE [Fire Behavior Applications and libraries 2021]. The results were then given to k-PERIL and the boundary of each simulation was calculated. The boundaries were then summed to a probabilistic overall boundary around the urban area. FARSITE was used here because of its position as a universally accepted accurate wildfire simulation model, and because of the availability of the command line version. However, any wildfire simulation software (or, in fact, any Rate of Spread data) can be used to create the inputs, such as WFDS or Prometheus.

The inputs to FARSITE were specified assuming a normal distribution of all the available weather input values. A sample of the normal distribution of the input data for a test case is given in Figure 3. The fuel moisture was specified as constant and identical for all fuels, as fuel moisture data is difficult to obtain. The wind direction was made to always point towards the urban area to ensure the simulated wildfire would always reach the urban area (this was in accordance with the average wind direction given by the closest Remote Automatic Weather Station (RAWS)). The temperature and moisture data were extrapolated to a diurnal profile. The ignition location was chosen randomly from a specified area in the raster (figure 2). The WRSET time was set at 110 minutes, from [Mallick, 2021].

The parameters used for the fuel moisture are:

- Fuel models: 0 -245
- 1-Hour Fuels: 4 tons m^{-2}
- 10-Hour Fuels: 6 tons m^{-2}
- 100-Hour Fuels: 13 tons m^{-2}
- Live Herbaceous moisture content: 30%
- Live Woody moisture content: 60%

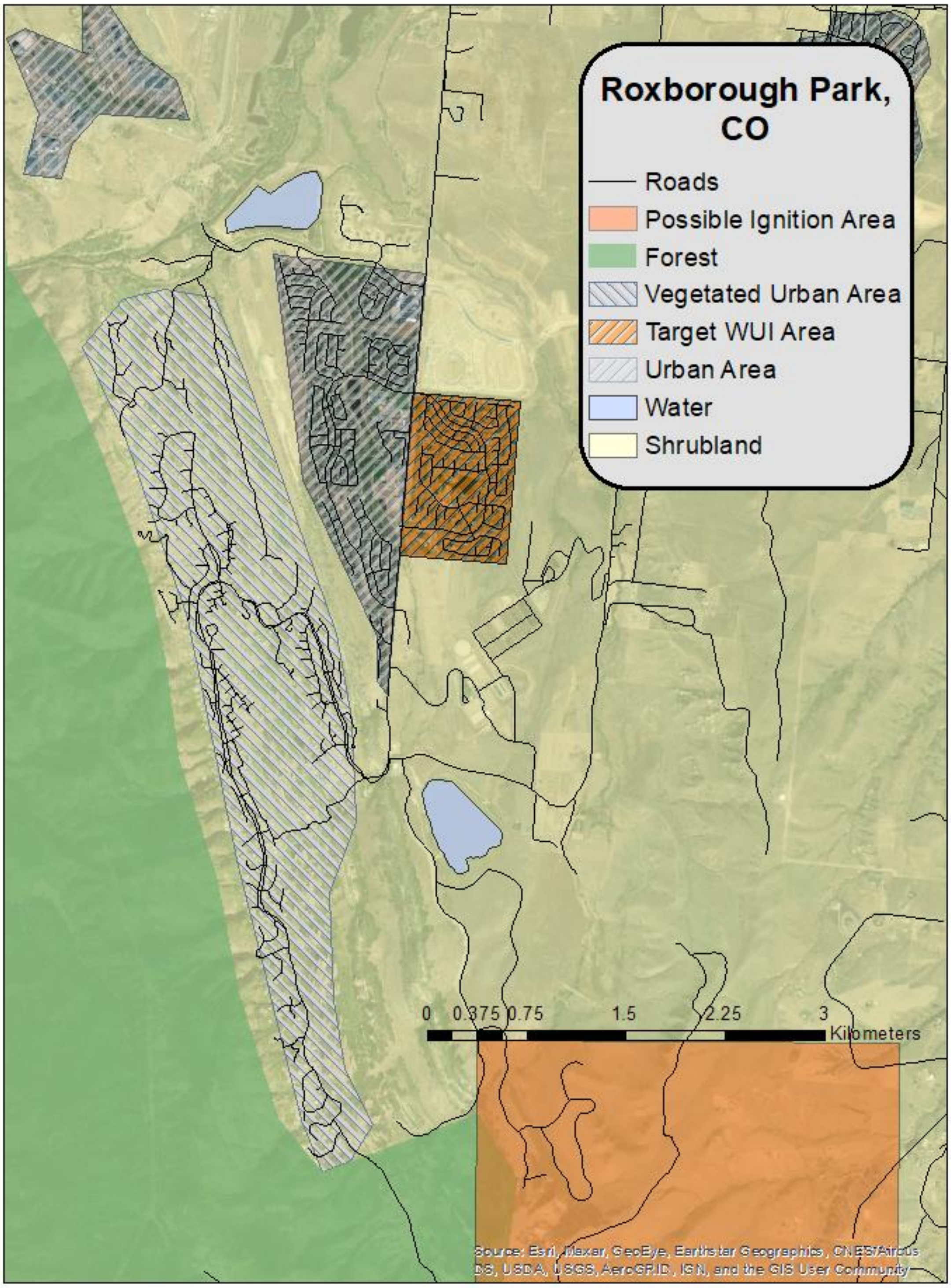

Figure 2- ArcGIS map of area selected for this study - a neighbourhood in Roxborough Park, CO, USA. Target urban area is highlighted in Pink. A populated region of Roxborough Park was chosen as the at-risk community. The fire risk has been identified as any fire starting on the south, with northwards winds.

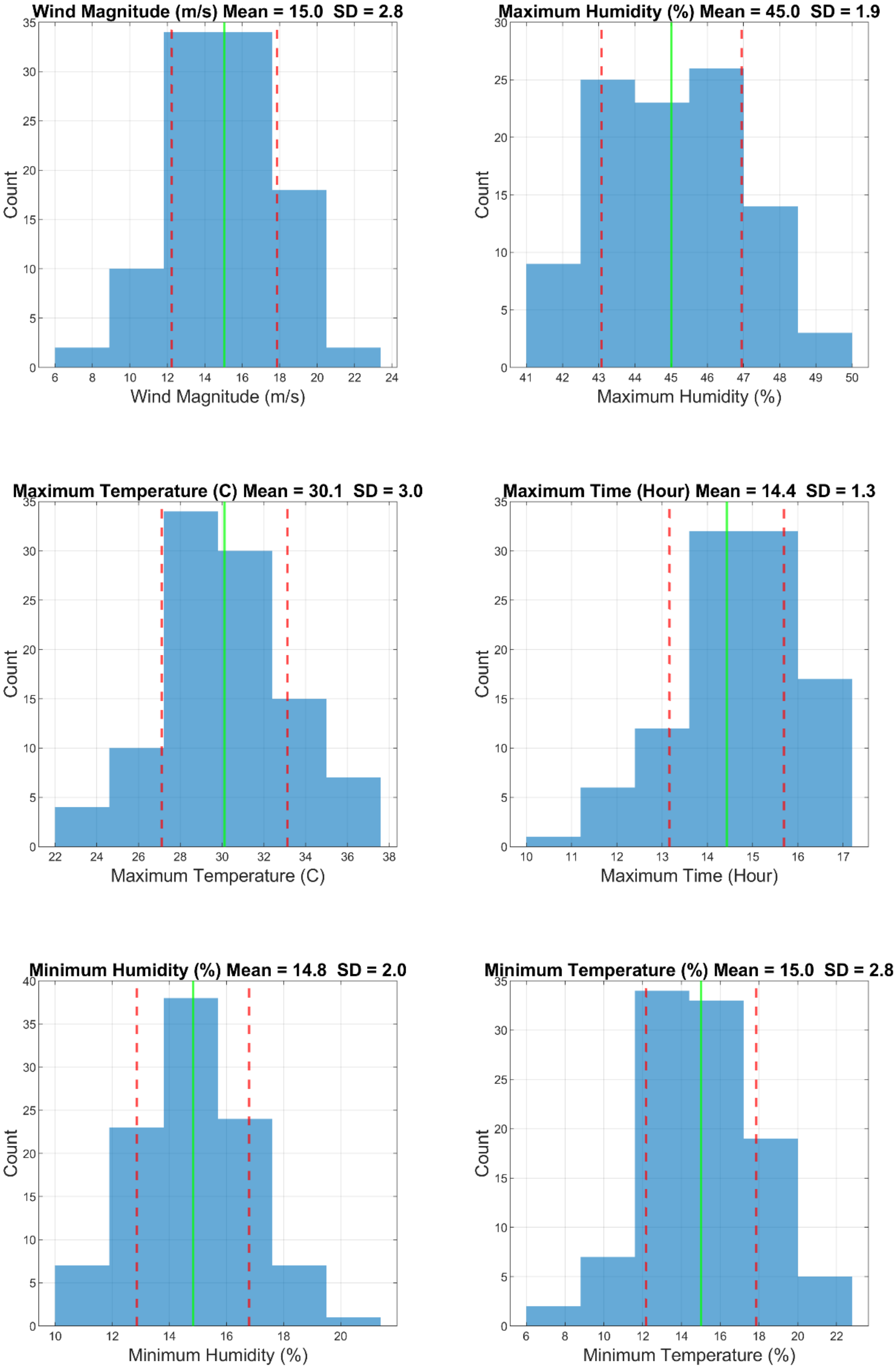

Figure 3- All the weather related values are given as normally distributed values. This data is plotted above for a simulation with 100 cases.

4. Results

A number of studies were conducted with varying input data, as shown in table 1. The first three sets of tests examine the effect of number of simulated cases to the probabilistic boundaries. The latter three cases test the effect of wind magnitude (both average value and standard deviation) for a larger ASET, to exaggerate the effect of the change.

Table 1- Input variables for the simulated cases.

Case No.	ASET (min)	Wind Magnitude (ms^{-1})	Wind Standard Deviation (ms^{-1})	Simulated cases
1	110	15	3	10
2	110	15	3	25
2	110	15	3	100
3	300	15	3	100
4	300	35	3	100
5	300	35	15	100

The results of the studies are shown in Figures 4, 5, and 6. Specific discussion on the results and what they suggest is given in the Discussions section.

The probabilistic boundaries are given as probability values on a raster. One can choose whether to keep all the nonzero cells as their trigger boundary, and get a conservative boundary that would cover all simulated cases. One could equivalently choose the boundary where 90% of all the boundaries meet, to exclude any outliers or one-off glitches. The user could ultimately even choose the 0% boundary value, which only shows the area common to all the boundaries. To illustrate the shape and gradient of the trigger boundaries, values ranging from 100% inclusion to 0% inclusion are shown in figures 4 and 5.

5. Discussion

The studies ran in this paper have a level of uncertainty due to uncertainties in the input data. While the wind data is consistent with the average readings of the nearest RAWS station, said RAWS station is more than 20 miles away from the target area. The generated wind magnitude and direction data are also considered temporally uniform which is inaccurate for any area.

For all the reasons above, it is challenging to tell whether the probabilistic or direct results of k-PERIL are accurate to the target area. What can be done is a qualitative analysis of the boundaries based on their characteristics and their change based on changing input variables. In this analysis, the formed boundaries seem to agree with the expected results. In figures 4, 5, and 6 the boundaries are uniform which stems from the fact that the fire spread is steady and uniform in a uniform shrubland. The boundary's southern border is thicker as it is meeting the faster-spreading head of the fire. On the northern border there is a large area on the north-western corner, which also makes sense since the fire turns when it is past the urban area as it is spreading upwards and to the unburned area. Figure 4 shows that more simulations form a better boundary as they filter out outlier simulations; 25 to 100 simulations are enough for a consistent 75% Boundary. Figure 5 shows that a larger ASET does result to larger boundaries as expected, but larger wind or deviation thereof does not seem to affect the probabilistic boundaries. This might be because the wind magnitude is not as strong an influence for

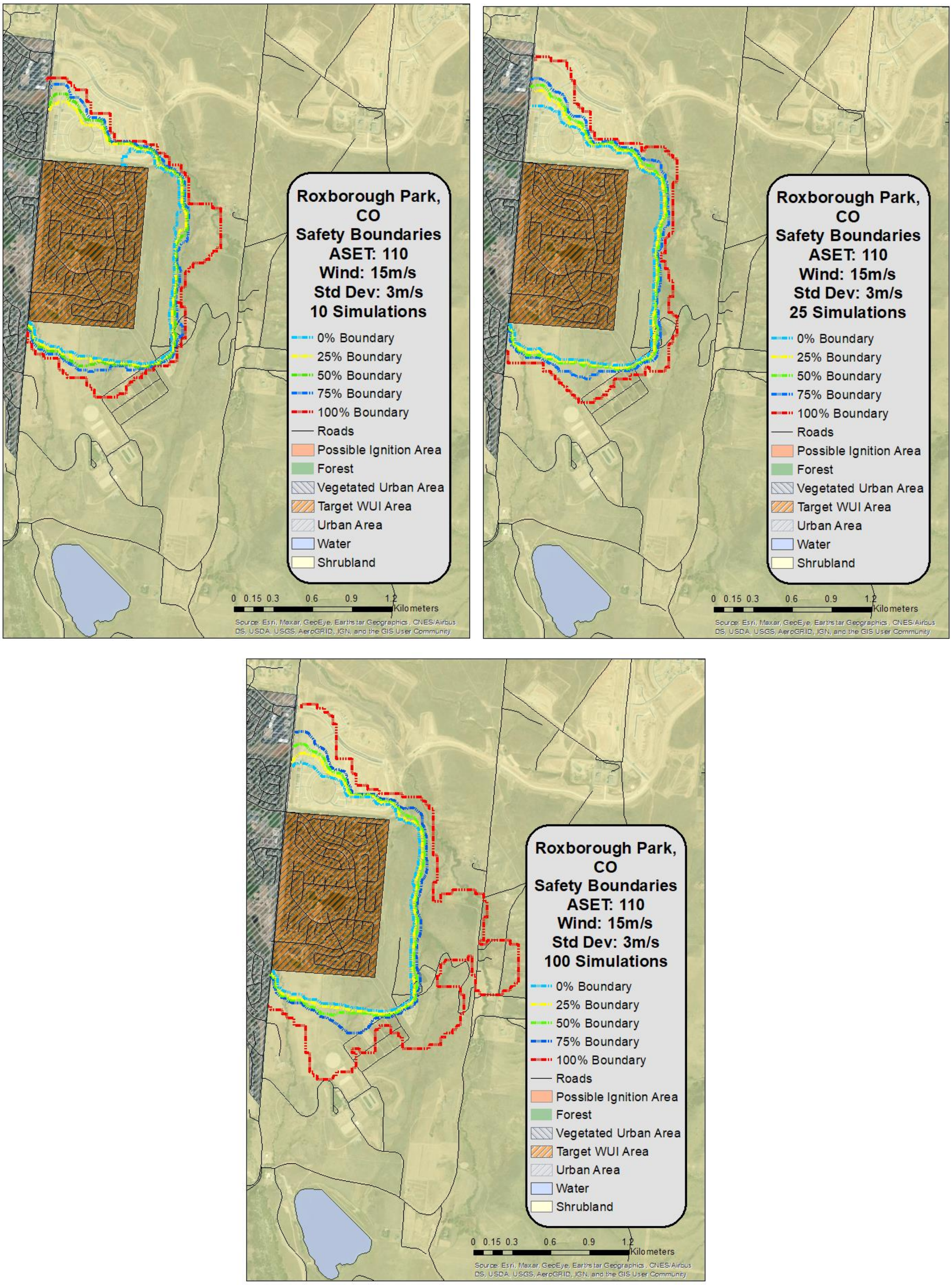

Figure 4- Top Left: Probabilistic safety Boundary for an ASET of 110 minutes, wind magnitude of 15 ms^{-1} with a standard deviation of 3 ms^{-1} and 10 simulated cases. Top Right: Safety boundary for the same case as the Left, with 25 simulated cases. Bottom: Safety boundary for the same case as previous, with 100 simulated cases.

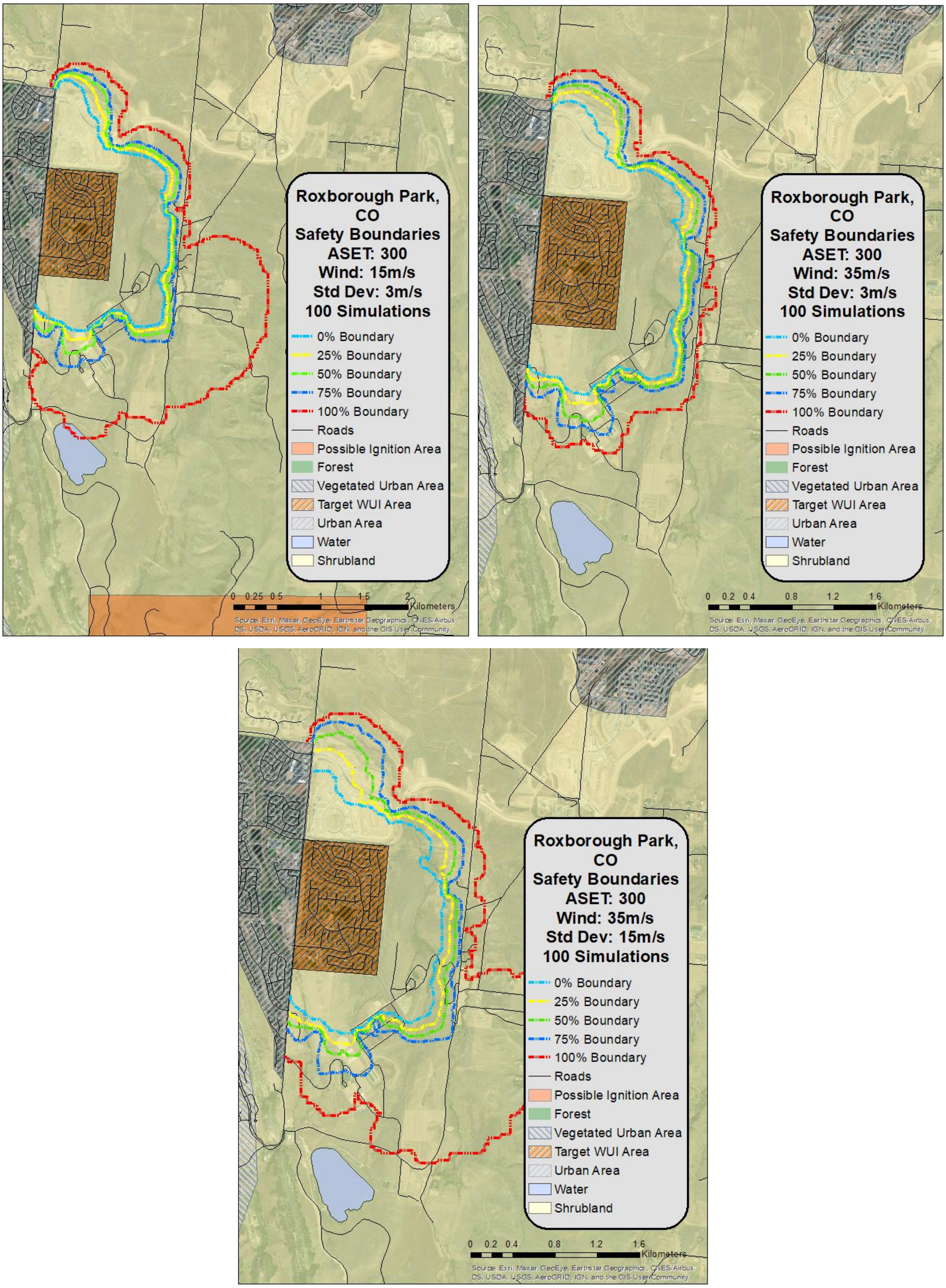

Figure 5- Top Right: Safety Boundary for an ASET of 300 minutes, wind magnitude of 15 ms^{-1} with a standard deviation of 3 ms^{-1} and 100 simulated cases. Top Left: Similar case to A with a wind magnitude of 35 ms^{-1}. Bottom: Similar to B with a wind magnitude standard deviation of 15 ms-1.

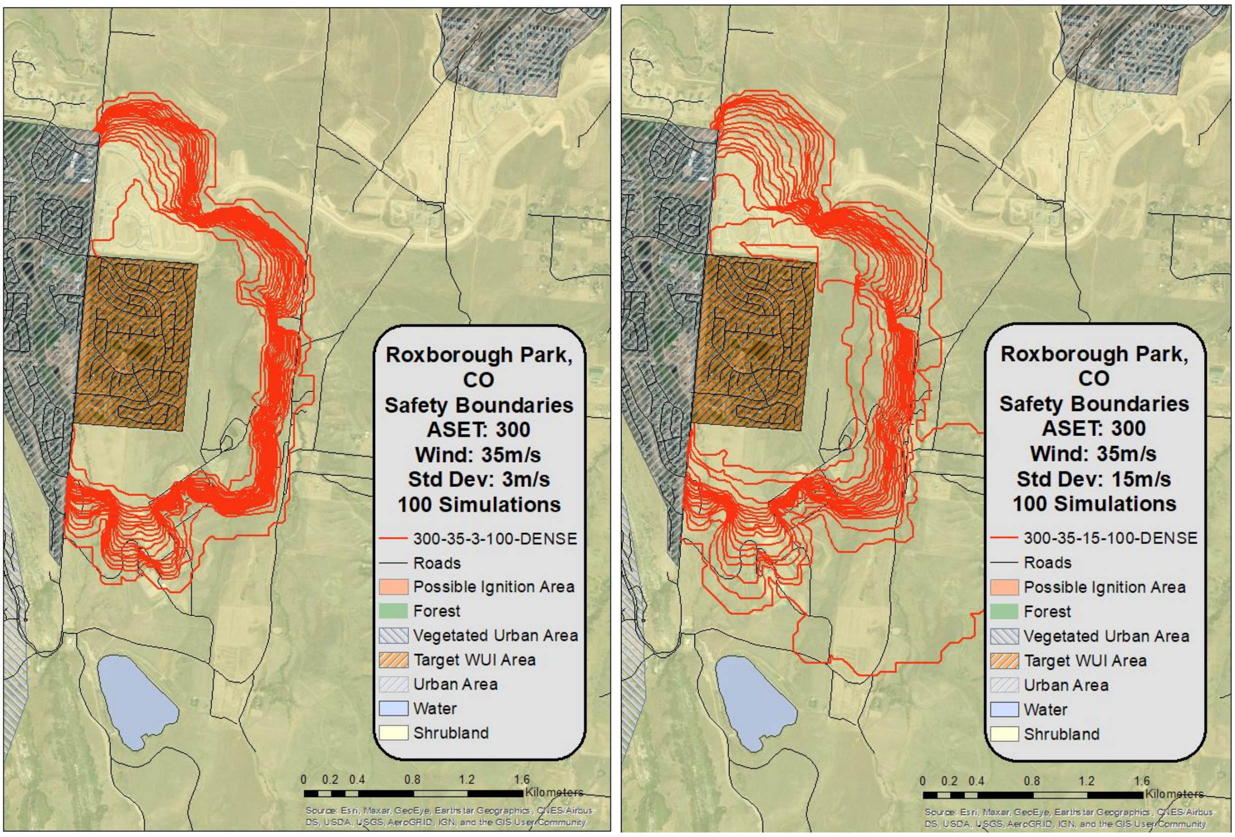

Figure 6- Right: Safety Boundary for an ASET of 300 minutes, wind magnitude of 35 ms^{-1} with a standard deviation of 3 ms^{-1} and 100 simulated cases. Left: Similar case to A with a standard deviation of 15 ms^{-1}. Both plots have equal isoprobabilistic boundaries.

this type of vegetative fuel. From Figure 6 it is evident that a greater standard deviation in wind input results in wider probability boundaries, although the magnitude of the change is small compared to the change in standard deviation. The difference in output between the last two cases can be better appreciated when more probability lines are drawn, as in Figure 6.

6. Limitations

Although k-PERIL is an upgrade compared to previous versions, it is still limited in many aspects. One critical limitation is that verification and validation can only be done with real wildfire data. Using simulated wildfire data to validate k-PERIL would only verify that the program is self-consistent, since these data are an input layer to the algorithm. To truly verify k-PERIL, the trigger boundaries would need to be generated for a real area, then a wildfire should be initiated, and the propagation of the fire and time of arrival should be recorded and compared with the predicted trigger boundary. The accuracy of k-PERIL will then be limited by the accuracy of the modelling engine used to obtain the simulated spread data. A point of future work is to find recorded rate of spread data of a real wildfire, and use it to test the validity of k-PERIL.

Another critical limitation of k-PERIL is that its results are limited by the accuracy and abilities of the wildfire model used to create the ROS input data. Most such programs can model surface fires, crown fires and spotting effectively. However, most models cannot model complex physical effects, such as long-range spotting, plume collapse, sudden wind shift, or other eruptive fire events. These are avenue of future work but may require radical changes.

7. Future work

Two future work possibilities have been discussed on the Limitations section above. Another critical area of improvement is expanding the coupling between the wildfire propagation and the evacuation simulations.

Currently the model reduces the entire evacuation procedure into one number (WRSET) and cannot account for event such as egress route blockage, probability of traffic accidents, or lane reversals initiated while the fire has crossed the trigger boundary. There is little real-time interaction between evacuation modelling and wildfire modelling; k-PERIL is supposed to be a link between the two, but at its current form it does not provide a robust coupling of the two models.

8. Conclusion

The above analysis shows that the boundaries are reasonable according to current wildfire behaviour understanding, and as such k-PERIL creates boundaries appropriate for future application. K-PERIL's results are as close to verified or tested as they can feasibly be, and as such k-PERIL has been proven to produce actionable results.

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