An Evaluation of Alternative Weather Inputs on Fire Risk Simulations in Southern California

Alex W. Dye*
USDA Forest Service Pacific Northwest Research Station, Corvallis, OR, USA, adye@fs.fed.us

John B. Kim
USDA Forest Service Pacific Northwest Research Station, Corvallis, OR, USA, jbkim@fs.fed.us

Karin L. Riley
USDA Forest Service Rocky Mountain Research Station, Missoula, MT, USA, kriley@fs.fed.us

Introduction

Predicting fire risk at specific points on a landscape requires model inputs that accurately represent variability in the factors responsible for fire ignition and spread. In fire simulation models, observational wind vectors are used to simulate fire spread and often are drawn from one or two weather stations based on station attributes such as elevation, aspect, and length of record (Finney et al. 2011; Riley and Loehman 2016). This approach could be effective in landscapes where fire winds are similar across a landscape. However, if winds during fire vary geographically, or if winds change significantly in the future, records from a single weather station will not fully capture the spatial variability of winds that occur during fires.

In our work, we focus on the sensitivity of one specific fire risk model, the FSim large fire simulator, to alternative wind inputs in southern California. FSim is a spatially explicit, stochastic model that uses input data on historical fire occurrences, topographic and vegetation characteristics, and historical weather streams to simulate the probability of a fire occurring on the landscape in a given year (Finney et al. 2011). In addition to landscape and vegetation characteristics, fire spread rate and direction in FSim is modeled by sampling from a probability distribution of historical wind vectors. In southern California, winds play a particularly large role in the seasonal duality of the local fire regime; in fall and winter, the high-speed northeasterly Santa Ana downslope winds facilitate rapid spread of large fires, while in the summer season winds are weaker and more variable with fires driven by limited fuel moisture (Moritz et al. 2010, Faivre et al. 2014). In the future, the wind-fire relationship is projected to change (Guzman-Morales and Gershunov 2019), in addition to expected increases in fire size and frequency in response to more intense drought (Yue et al. 2014, Keeley and Syphard 2016). Southern California's seasonally variable wind-driven fire regime, coupled with its natural and anthropogenic landscape diversity, make understanding the impact of alternative weather characteristics on predicted fire risk important to plan for fire in the future.

Methods

Fire modeling framework

* USDA Forest Service Pacific Northwest Research Station 3200 SW Jefferson Way, Corvallis, OR 97333, adye@fs.fed.us

In previous work, Vogler et al. (2018) modeled fire risk in 10 southern California fire analysis areas using the FSim large fire simulator. For more detail on the modeling philosophy, input data, and calibration approach, we refer readers to this section of Vogler et al. (2018). In our work, we focus on analysis area 39 of Vogler et al. (2018) (hereafter called "the study area"), which covers much of the mountainous areas of the Los Padres National Forest northwest of Los Angeles (Figure 1). Focusing on a small study area allows us to save simulation time for this exploratory analysis; this area also experiences higher frequency of large fires (Short 2014) and has a strong occurrence of Santa Ana wind activity (Jin et al. 2015) relative to the rest of southern California. In these simulations, "large fire" refers to fires larger than 100 ha.

Variability of wind speed and direction in southern California

We extracted hourly surface wind direction and wind speed from 9 Remote Access Weather Stations (RAWS) (DRI 2018) located in the study area with consistent data coverage extending back to 1996 (Figure 1). Before 1996, RAWS data availability swiftly declines. We then merged the daily wind vectors with a fire occurrence database (Short 2014) and a chronology of Santa Ana wind days (Abatzoglou et al. 2013). We constructed wind roses summarizing speed and direction at each station during fires that ignited on Santa Ana wind days and fires that ignited on non-Santa Ana wind days. In southern California, fires linked to fall/winter Santa Ana winds exhibit different characteristics than those linked to summer season non-Santa Ana winds (Jin et al. 2015, Faivre et al. 2016); summarizing winds according to this distinction allows us to examine how each RAWS records winds during each type of fire.

Figure 1. The location of each RAWS overlaid on Google Earth. Inset map shows the study area, with approximate spatial extent linked by orange lines.

Sensitivity of fire risk to alternative winds

Keeping all input data constant from the calibrated model runs described by Vogler et al. (2018), we ran FSim for the study area an additional 8 times. Each run, we changed only the probability distribution of historical wind speed and direction, recorded at a different RAWS, that FSim draws from to simulate fire spread. All other model inputs remained constant. In this way, we quantify the effects that alternative wind characteristics have on simulated annual burn probability, mean fire size, area burned, and number of large fires. We compared each simulation with historical fire statistics as recorded in the fire occurrence database (FOD) (Short 2014). Each simulation was run for 10,000 years at a final raster resolution of 120 m x 120m. The original runs by Vogler et al. (2018) were calibrated with winds from the Warm Springs RAWS; we also ran a simulation with Warm Springs to ensure we accurately represented the calibrated model.

Results

RAWS variability in winds

We found strong variation between RAWS in terms of both wind direction and speed. Winds are typically stronger during Santa Ana fires than non-Santa Ana fires (Table 1, Figure 2); winds can range from 3.41 to 27 mph. Although many stations exhibit the classic northeasterly wind pattern during Santa Ana fires (e.g. Chilao, Acton, Warm Springs, Saugus, Mill Creek), others do not (e.g. Tanbark and Rose Valley). During non-Santa Ana fires, winds tend to come from a variety of directions around the wind rose, presumably controlled by local topographic station siting.

Table 1. Mean wind speed (mph) and direction (degrees) during Santa Ana and non-Santa Ana large fire ignition days at 9 different RAWS.

Station	Direction (Santa Ana Fire)	Direction (non-Santa Ana Fire)	Speed (Santa Ana Fire)	Speed (non-Santa Ana Fire)
Acton	42.61	0.56	13.49	5.79
Camp 9	355.97	151.13	19.81	11.98
Chilao	35.87	132.18	22.37	8.05
Devore	328.24	253.48	11.12	4.73
Mill Creek	22.49	206.65	17.76	7.39
Rose Valley	123.43	202.55	3.41	2.84
Saugus	18.28	198.41	12.86	6.58
Tanbark	26.98	295.56	5.83	2.81
Warm Springs	62.33	271.59	26.78	8.50

Alternative wind streams change simulated fire characteristics

The introduction of a new wind stream (from a different RAWS), changes the simulated fire characteristics (Table 2). Relative to the historical (i.e. FOD in Table 2) record, simulated fire patterns vary widely. RAWS with generally low average wind speeds, e.g. Tanbark and Rose Valley, tend to produce both low burn probabilities and smaller fires. Stations with high wind speeds, such as Camp 9, produce anomalously high burn probability and a high frequency of large fire events. Figure 3 compares three RAWS that produce a high (Camp 9), medium (Warm Springs), and low (Tanbark) burn probability (Figure 3).

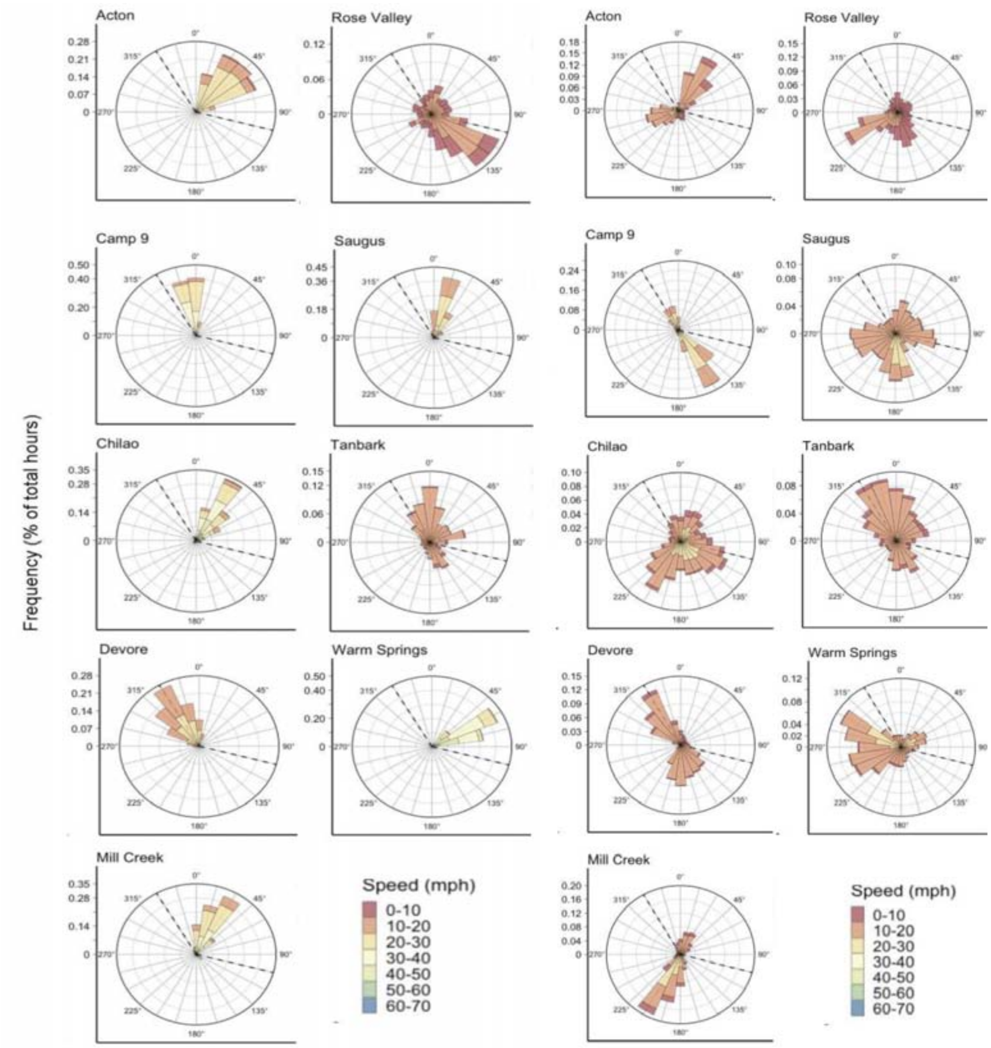

Figure 2. Wind speeds (color) and directions at 9 RAWS during Santa Ana fires (column 1) and non-Santa Ana fires (column 2).

Discussion

Our exploratory analysis shows that wind speed and direction vary geographically across southern California, likely due to local siting effects of each station. This has implications for weather station selection for fire modeling, as all stations will not equally record winds that are representative of the region as a whole. However, simulating fire using any one of these weather stations can significantly alter the burn probability of the region. This is particularly important in southern California, where winds frequently spawn large, devastating fires during Santa Ana events. Changes to regional wind patterns in the future (Guzman-Morales 2019) could consequently alter the fire regime even further; we show a basic example of how this could play out by simulating fire using separate historical wind streams at 9 weather stations. Clearly, weather stations that have consistently high wind speeds (e.g. Warm Springs and Camp 9) simulate large burn probabilities; however, the seasonal distribution of wind speed, as well as wind direction, might lend new explanations to our simulations. In future work, we plan to simulate fire risk using reasonable projected scenarios of future winds.

Table 2. Simulated fire statistics from the study area during historical fires (recorded in the fire occurrence database) and simulated by FSim using historical wind streams drawn from 9 different RAWS.

Station	Annual Number of Large Fires per million acres	Annual Area Burned per million acres	Mean Fire Size	Burn Probability	Large Fires Simulated
Historical (FOD)	2.36	18,119	7,685	0.0181	NA
Acton	3.36	42,482	12,639	0.0425	64,534
Camp 9	3.83	78,088	20,383	0.0781	75,426
Chilao	3.49	48,861	14,009	0.0489	67,570
Devore	3.13	23,125	7,378	0.0231	59,564
Mill Creek	3.53	48,116	13,624	0.0481	68,422
Rose Valley	2.68	13,908	5,186	0.0139	49,659
Saugus	3.66	57,726	15,777	0.0577	70,864
Tanbark	2.38	9,136	3,847	0.0091	42,842
Warm Springs	3.09	28,970	9,393	0.0290	58,379

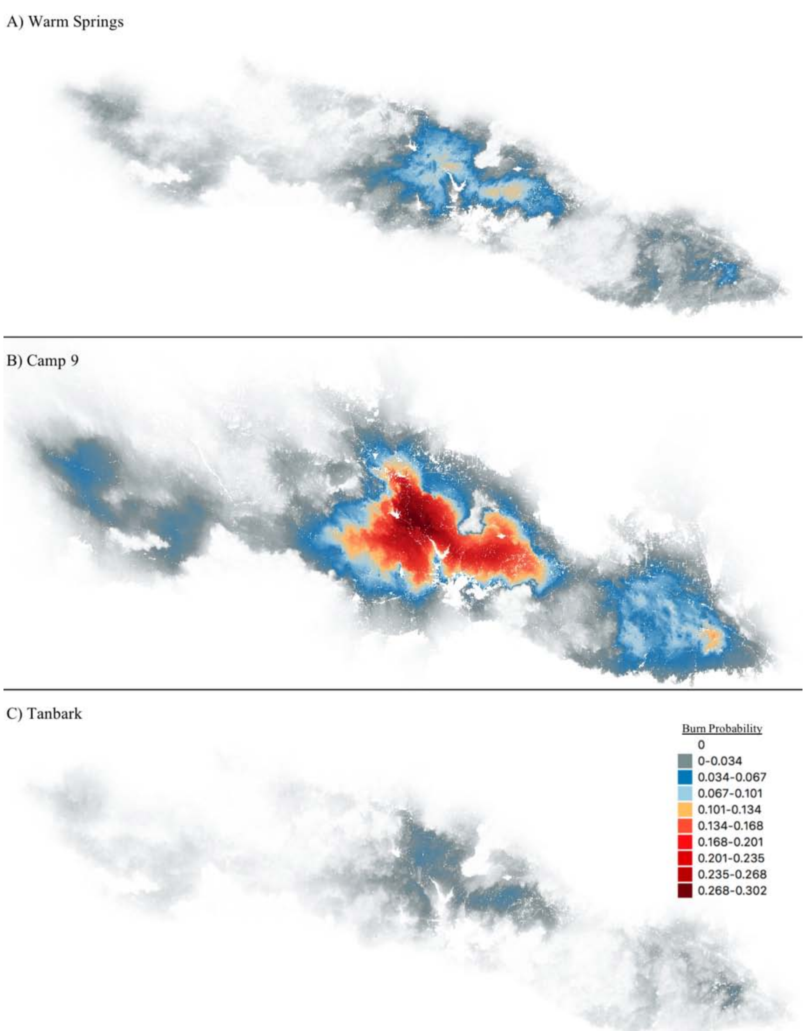

Figure 3. Examples of three RAWS that produce medium (A), high (B), and low (C) simulated burn probabilities. Burn probabilities are mapped on a 120 m raster and represent the probability that an individual cell will experience a large fire in any given year. Probabilities are constructed by simulating 10,000 possible fire years from input data. Differences exist primarily in the magnitude of burn probability, not the geographic distribution; as is shown in the figure, burn probabilities are consistently high near the center and southeast end of the study area, regardless of the RAWS used.

Acknowledgements
AWD is an ORISE fellow, supported by the USDA Forest Service Western Wildland Environmental Threat Assessment Center (WWETAC). JBK is supported in part by WWETAC.

References

Abatzoglou, J., R. Barbero, and N. J. Nauslar, 2013: Diagnosing Santa Ana Winds in Southern California with Synoptic-Scale Analysis. Weather Forecast., 28, 704–710, doi:10.1175/WAF-D-13-00002.1.

Desert Research Institute, 2018. RAWS USA Climate Archive. Accessed June 25, 2018. raws.dri.edu.

Faivre, N. R., Y. Jin, M. L. Goulden, and J. T. Randerson, 2016: Spatial patterns and controls on burned area for two contrasting fire regimes in Southern California. Ecosphere, 7, e01210, doi:10.1002/ecs2.1210.

Finney, M., C. W. McHugh, I. C. Grenfell, K. L. Riley, and K. C. Short, 2011b: A simulation of probabilistic wildfire risk components for the continental United States. Stoch. Environ. Res. Risk Assess., 25, 973–1000, doi:10.1007/s00477-011-0462-z.

Guzman-Morales, J. and A. Gershunov, 2019: Climate change suppresses Santa Ana winds of Southern California and sharpens their seasonality. Geophysical Research Letters, 46, doi: 10.1029/2018GL080261.

Jin, Y., M.L. Goulden, N. Faivre, S. Veraverbeke, F. Sun, A. Hall, M.S. Hand, S. Hook, and J.T. Randerson, 2015: Identification of two distinct fire regimes in Southern California: Implications for economic impact and future change. Environ. Res. Lett., 10, 094005, doi:10.1088/1748-9326/10/9/094005.

Keeley, J., and A. Syphard, 2016: Climate Change and Future Fire Regimes: Examples from California. Geosciences, 6, 37, doi:10.3390/geosciences6030037.

Moritz, M.A., T. J. Moody, M. A. Krawchuk, M. Hughes, and A. Hall, 2010: Spatial variation in extreme winds predicts large wildfire locations in chaparral ecosystems. Geophys. Res. Lett., 37, L04801, doi:690 10.1029/2009GL041735.

Riley, K. L., and R. A. Loehman, 2016: Mid-21st century climate changes increase predicted fire occurrence and fire season length, Northern Rocky Mountains, United States. Ecosphere, 7, e01543, doi:10.1002/ecs2.1543.

Short, K.C., 2014: A spatial database of wildfires in the United States, 1992-2011. Earth Syst. Sci. Data, 6, 297–366, doi:10.5194/essd-6-1-2014.

Vogler, K.C., A. Brough, J.W. Gilbertson-Day, and J.H. Scott, 2018: USFS Region 5 Southern California Quantitative Wildfire Risk Assessment: Methods and Results.

Yue, X., L. J. Mickley, and J. A. Logan, 2014: Projection of wildfire activity in southern California in the mid-twenty-first century. Clim. Dyn., 43, 1973–1991, doi: 10.1007/s00382-013-2022-3.