Categorization of Santa Ana Winds With Respect To Large Fire Potential

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ABSTRACT

Santa Ana winds, common to southern California during the fall through early spring, are a type of katabatic wind that originates from a direction generally ranging from 360°/0° to 100° and is usually accompanied by very low humidity. Since fuel conditions tend to be driest from late September through the middle of November, Santa Ana winds occurring during this time have the greatest potential to produce large, devastating fires when an ignition occurs. Such catastrophic fires occurred in 1993, 2003, 2007, and 2008. Because of the destructive nature of such fires, there has been a growing desire to categorize Santa Ana wind events in much the same way that tropical cyclones and tornadoes have been categorized. The Offshore Flow Severity Index (OFSI), previously developed by Predictive Services, is an attempt to categorize such events with respect to large fire potential, specifically the potential for new ignitions to reach or exceed 100 ha based on breakpoints of surface wind speed and humidity. More recently, Predictive Services has collaborated with meteorologists from the San Diego Gas and Electric utility to develop a new methodology that addresses flaws inherent in the initial index. Specific methods for improving spatial coverage and the effects of fuel moisture have been employed. High resolution reanalysis data from the Weather Research and Forecasting (WRF) model generated by the Department of Atmospheric and Oceanic Sciences at UCLA is being used to redefine the OFSI. In addition to the new methodology, social scientists from the Desert Research Institute have been contracted to evaluate how this index might best be conveyed to the user so as to maximize its effectiveness. This paper will outline the methodology for developing the improved index as well as discuss how it might benefit fire agencies, private industry, broadcast media groups and the general public.

1. Introduction

From the fall through early spring, offshore winds, or what are commonly referred to as "Santa Ana" winds, occur over southern California from the coastal mountains westward, from Ventura County southward to the Mexican border. These synoptically driven wind events vary in frequency, intensity, and spatial coverage from month to month and from year to year, thus making them difficult to categorize. Most of these wind events are associated with mild to warm ambient surface temperatures >= 18° C and low surface relative humidity <= 20%. However, during the late fall and winter months, these events tend to be associated with lower surface temperatures due to the air mass over the Great Basin originating from higher latitudes. There are a variety of ways to define a Santa Ana event through the analysis of local and synoptic scale surface pressure and thermal distributions across southern California (Raphael 2003). For our purposes, Mean Sea Level Pressure (MSLP) map types and surface wind speed observations will be the determining factors whether or not a Santa Ana wind event occurred. This is a necessary process as it helps distinguish a true Santa Ana from the normal nocturnal offshore winds that occur throughout the coastal and valley areas.

During 21 through 23 October 2007, Santa Ana winds generated multiple large catastrophic fires across southern California (Moritz *et al.*2010). Most notable was the Witch Creek fire in San Diego County, where wind gusts of 26 m/s were observed at the Julian weather station along with relative humidity values of ≈ 5%. However, high resolution model simulations at 667 meters showed that wind velocities were much higher in unsampled areas (Fovell 2012). This event generated an interest in categorizing Santa Ana winds so that, with such an index available, fire agencies and first responders, private industry, and the general public could be more informed about the degree of severity an event would have on the fire environment. This index could also help augment Fire Weather Watches and Red Flag Warnings from the National Weather Service by providing value added information about an impending event.

The Predictive Services Unit, functioning out of the Geographic Area Coordination Center in Riverside, California, is comprised of several meteorologists employed by the USDA Forest Service. In 2009, Predictive Services developed the Offshore Flow Severity Index (OFSI), which categorizes Santa Ana wind events according to the potential for a large fire to occur (Rolinski *et al.* 2011). This unique approach addresses the main impact Santa Ana winds could have on the population of southern California beyond experiencing the casual effects of windy, dry weather.

San Diego Gas and Electric (SDG&E) is a regulated utility provider across the southern portions of Orange County and all of San Diego County. During the October 2007 event, it was determined that power lines were the cause of several large fires, including the Witch Creek fire in San Diego County. The cost of these fires to date currently exceeds 2 billion dollars. As a result, SDG&E is investing in fire weather related research and technology to develop an enhanced warning system for dangerous wildfire conditions. Having advance notice of the severity and timing of a Santa Ana wind event would permit SDG&E to prepare, monitor, and deploy its resources for maximum effectiveness. In order to accomplish this, SDG&E is partnering with the local meteorological and fire community on this project.

The OFSI has been proven to be successful in terms of capturing the overall nature of a Santa Ana wind event. However its basic method in addressing complex issues such as time, topography, and fuel conditions was perceived to be overly simplistic by the scientific community and also by other users of the index. These issues have since been addressed and will be discussed in detail in the following section.

2. Background

A seven day forecast of the OFSI is currently being produced by Predictive Services on a daily basis for the southern California coastal, valley, and mountain

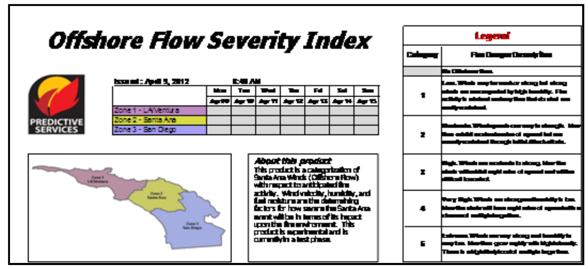


Figure 1 - A 7-day forecast of the Offshore Flow Severity Index (OFSI) displaying categories of Santa Ana winds.

areas which have been divided into three zones (Fig. 1). Zone 1 covers the southern portion of Ventura and Los Angeles Counties. Zone 2 consists of Orange County, as well as western Riverside and western San Bernardino Counties. Zone 3 represents most of San Diego County (Fig. 2). These zones were chosen in part based on the different offshore flow characteristics that occur across the region. For instance, Santa Ana winds across Zone 1 and Zone 2 are primarily a result of offshore surface pressure gradients (locally and/or synoptically) interacting with the local terrain to produce gap winds through Soledad Canyon, the Cajon Pass, and the Banning Pass (Hughes and Hall 2010; Fovell 2012). These winds also tend to precede the Santa Ana winds that occur across San Diego County by 12 to 24 hours. Across Zone 3, offshore winds take on a more "downslope windstorm" characteristic driven largely by the tropospheric stability (Fovell 2012). In addition, these zone boundaries were developed partially around political boundaries, as well as around the news media broadcast markets that cover the area.

Figure 2 - Map depicting OFSI Zones over southern California. Favored wind corridors are indicated by yellow arrows.

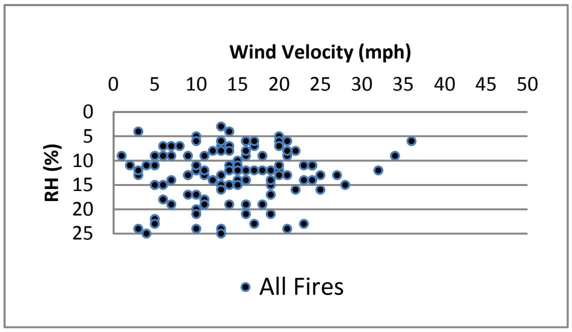


Figure 4 - Scatter plot displaying days in which a fire (any size) occurred.

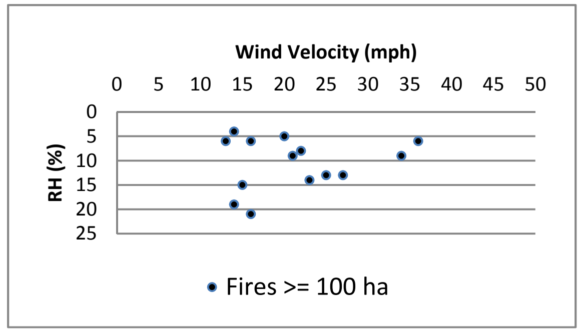


Figure 3 - Scatter plot displaying days in which a large fire (100 ha) occurred.

A large fire is defined as the 95th percentile of daily largest fires occurring over the past 20 years across the region depicted in figure 2. Thus a large fire for Zones 1, 2, and 3 is 100 ha, which is typically when additional resources will be required from outside the point of origin to suppress the fire. This large fire definition was used to develop the OFSI, which correlates historical fire information with surface wind speed and humidity from Remote Automated Weather Stations (RAWS), to initially form a four tier categorical index (Rolinski *et al.* 2011). Scatter plots of wind velocity vs. relative humidity show the frequency distribution of ignitions and 100 ha fires respectively over the dataset period during Santa Ana wind events (Figures 3 and 4). Comparing these plots with each other revealed natural breakpoints in the data that were used to define the OFSI categories. This process was repeated for multiple RAWS to determine a site that would be most effective in representing each zone. Stations near the coast sometimes indicated offshore events as being weaker and of shorter duration than the mountains. We found inland valley stations usually worked best in capturing the overall nature of the event. In the final analysis, the Saugus, Corona, and Julian RAWS were used to represent Zones 1, 2, and 3 respectively (Fig. 2). However, due to the necessarily simplistic nature of this approach, the spatial complexities inherent to offshore flow were not captured. In addition, the OFSI employed a rudimentary scheme to address fuel dryness which did not take into account other critical components of fuel moisture. Both of these aspects revealed a weakness in the initial conceptual model, but significant improvements have been made since then which will be discussed in the next section.

3. A New Methodology

a) Large Fire Potential – Meteorological Conditions

The potential for an ignition to reach or exceed 100 ha depends on a number of components: e.g. various meteorological and fuel conditions, suppression strategy, topography, accessibility, and resource availability. Current methods to evaluate fire potential include various indices from the National Fire Danger Rating System (NFDRS) and from the Canadian Forest Fire Danger Rating System (CFFDRS) (Preisler *et al.* 2008). The Fosberg Fire Weather Index (FFWI) is one such index which is a function of wind speed, humidity, and temperature with output values ranging from 0 to 100 (Fosberg 1978). While the FFWI may show elevated output values for a Santa Ana wind event, it can also show elevated values for *any* day therefore making it too generic for our purposes. The initial concept of OFSI was a first attempt to create an index more specific to Santa Ana wind events, but further studies resulted in a new approach, which we term Large Fire Potential (LFP). Assuming an aggressive suppression strategy is employed with adequate resource availability in an easily accessible area where topography is uniform, LFP becomes a function of the fuel and weather conditions preceding, during, and following the time of ignition. Supposing for the moment that fuels are fully receptive to ignitions and will support large fire growth, the weather component of LFP (e.g., LFP_w) during a Santa Ana wind event can be expressed by the following equation:

[1]

$$LFP_w = W_s^2 D_d$$

where W_s is the 6 m wind velocity (mph) based on the anemometer height used by RAWS and other stations, and D_d is the surface dew point depression (°F). It has been suggested that wind velocity has an exponential effect on the spread of fire among finer fuels such as grass and chaparral, and that wind can also have the same effect on fire spread as a fire burning upslope with little or no wind (Rothermel 1972). Dew point depression ($T-T_d$) depicts the dryness at the surface well, and has a profound impact upon fuel conditions. Also, dew point depression can sometimes differentiate better between warm and cold offshore events than relative humidity can. In our dataset, it has been noted that larger dew point depression values ($D_d >= 24$°C) have mainly been associated with warm events. While this may seem trivial, cold Santa Ana wind events (surface ambient temperatures < 16°C) are usually not associated with large fires. This may be due in part to lower fuel temperatures because in those cases more time would be needed to reach the ignition temperature. Another reason is that colder events are sometimes preceded by precipitation either by a few days or by a few weeks which would cause fuels to be less receptive to new ignitions. These are the primary reasons why temperature was excluded from equation [1] although it has been incorporated indirectly through the use of D_d and in the fuels component that will be discussed in the following section. Finally we note that while equation [1] bears some resemblance to the FFWI, a comparison of daily outputs of FFWI and LFP_w, revealed that LFP_w provides significantly greater contrast between Santa Ana days and non-Santa Ana days. Therefore, these results favored LFP_w as being the more appropriate equation for our purpose.

b) Large Fire Potential – Fuel Conditions

In addition to the meteorological conditions, large fire potential is also highly dependent on the state of the fuels. Given the complexity of the fuel environment (i.e. fuel type, continuity, loading, etc.), we decided to focus more specifically on the moisture content of fuel conditions since that component plays a critical role in the spread of wildfires (Chuvieco *et al.* 2004). For our purpose, we have condensed fuel moisture into three components: 1) dead fuel moisture, 2) live fuel moisture, and 3) the state of green-up of the annual grasses. Each of these components is complex and will be defined more specifically later. While these elements of the Fuel Moisture Component (FMC) often act in cooperation, there are times when they are out of sync with one another due to the variability in precipitation (frequency and amount) across southern California in the winter. The relationship between these three components is expressed in the following equation:

[2]

$$FMC = \left(\frac{DL}{LFM} - 1\right) + G$$

where DL is a Dryness Level index consisting of the Energy Release Component (ERC) and the ten hour dead fuel moisture timelag (10-h). Live Fuel Moisture (LFM) is a sampling of the moisture content of the live fuels indigenous to the local region, and G is the greenness of the annual grasses. Currently we are making the assumption that all the terms in equation [2] have equal weight, but further study may lead to future modification. ERC is a relative index of the amount of heat released per unit area in the flaming zone of an initiating fire and is comprised of live and dead fuel moisture as well as temperature, humidity, and precipitation. While ERC is a measure of potential energy, it also serves to capture the intermediate to long term dryness of the fuels with unitless values generally ranging from 0-100. The 10-hr dead fuel moisture timelag represents fuels in which the moisture content is exclusively controlled by environmental conditions (Bradshaw *et. al.*, 1983). Output values of 10-h are in g/g expressed as a percentage ranging from 0-35. In the case of the 10-h, this is the time required for the fuels (1/4" – 1" in diameter) to lose approximately two-thirds of their initial moisture content (Bradshaw *et al.* 1983). Thus the DL index mainly serves to capture the dead fuel moisture and has three unitless categories: *1* indicates fuels are moist, *2* represents average fuel dryness, and a *3* indicates that fuels are drier than normal.

The observed LFM is the moisture content of live fuels, e.g. grasses, shrubs, and trees, expressed as a ratio of the weight of water in the fuel sample to the oven dry weight of the fuel sample (Pollet and Brown

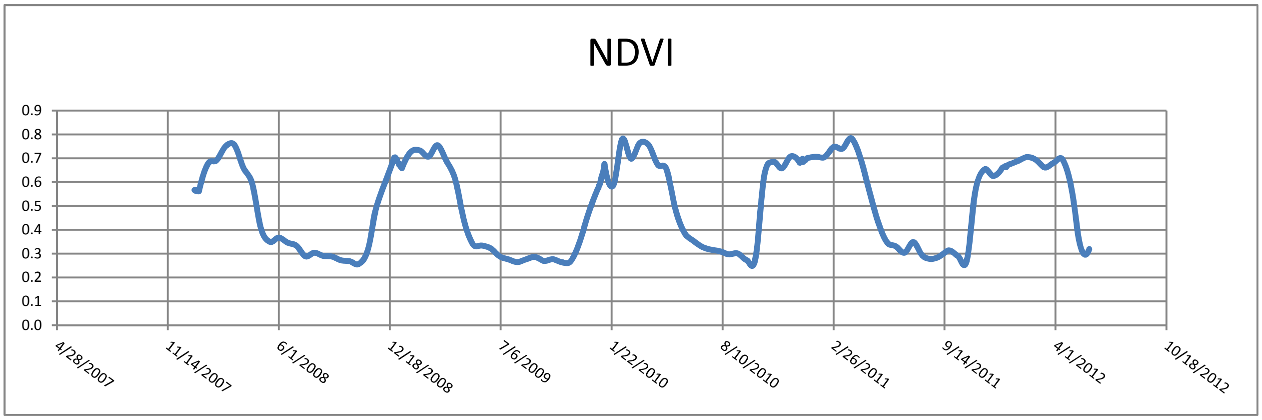


Figure 5 - Time series showing the seasonal variability of the Normalized Difference Vegetation Index (NDVI).

2007). Soil moisture as well as soil and air temperature govern the physiological activity which results in changes in fuel moisture (Pollet and Brown 2007). LFM is a difficult parameter to evaluate because of the irregularities associated with observed values. For instance, samples of different species of native shrubs are normally taken twice a month by various fire agencies across southern California. However, the sample times often differ between agencies and the equipment used to dry and weigh the samples may vary from place to place. In addition, sample site locations are irregular in distribution and observations from these sites may be taken sporadically. This presents a problem when we attempt to assess LFM over the region shown in figure 2. Apart from taking fuel samples, there are several ways of estimating LFM using meteorological variables, soil water reserve, solar radiation, etc. (Castro *et al.* 2003). One method uses satellite derived Normalized Difference Vegetation Index (NDVI) data and surface temperatures, as well as the Julian day, to form a linear regression equation which approximates the LFM content of *C. landanifer*, a shrub species common in Spain and other parts of the Mediterranean (Chuvieco *et al.* 2004). Since the climate and fuel conditions of southern California are similar to those of Spain, the authors will consider taking this same approach to estimate LFM rather than relying on the observed LFM values.

Following the onset of significant wetting rains, new grasses will begin to emerge in a process called green-up. While the timing and duration of this process fluctuates from year to year, some degree of green-up usually occurs by December across southern California. During the green-up phase, grasses will begin to act as a heat sink, thereby preventing new ignitions and or significantly reducing the rate of spread among new fires. By late spring these grasses begin to cure with the curing phase normally completed by mid-June. In equation [2], G is a value that quantifies the said green-up and curing cycles of annual grasses.

G is derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data at a resolution of 250 meters for select pixels consisting solely of grasslands. NDVI is further defined by red and near-infrared (NIR) bands in the following equation:

[3]

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$

where ρ_b= reflectance in band b (Clinton *et. al.*, 2010). It can be shown that NDVI values for Southern California grasslands generally range from about 0.25 (±0.05) to 0.75 (±0.05) for an average

NDVI	G
NDVI < 0.35	5 (Fully Cured)
0.35 = NDVI < 0.40	4
0.40 = NDVI < 0.45	3
0.45 = NDVI < 0.50	2
0.50 = NDVI < 0.55	1
NDVI = 0.55	0 (Green)

Table 1 - Greenness (G) values associated with NDVI ranges.

rainfall year (Fig. 5). There is evidence that NDVI is affected by soil color (Elmore *et. al.,* 2000), which may explain the NDVI differences (±0.05) seen among the selected Southern California grassland locations.

G is given a rating of 0-5 based on NDVI data, where 0 is green and 5 is fully cured. When applying the methodology discussed by White (White *et al.* 1997) to the general range of Southern California grasslands, green-up is estimated to have occurred when NDVI exceeds 0.50. However, we have found that this value can be closer to 0.55 for some sites. Therefore, NDVI values greater than or equal to 0.55 are assigned a value of 0, or green. Furthermore, NDVI values less than 0.35 are assigned a value of 5. This is because NDVI values are observed to be below 0.35 for all grassland sites during the dry season when grasses are known to be fully cured. A linear relationship exists between NDVI for Southern California grasslands and fire occurrence. For this reason, the transition between green and fully cured (or vice versa) was given a rating of 1 to 4 in NDVI increments of 0.05 (Table 1).

FMC modifies equation [1] in cases where fuels have not fully cured and are still inhibiting fire spread. Output values of FMC range from 0 to 1, where 0 represents wet fuels and 1 denotes dry fuels. This modifier can become so influential that it will greatly reduce or even eliminate the potential for large fire occurrence despite favorable meteorological conditions for rapid fire growth. So the final equation for large fire potential becomes:

[4]

$$LFP = W_s^2 D_d FMC$$

4. Redefining the OFSI

The time and spatial problems with the OFSI that were previously mentioned have since been addressed through the use of the Weather Research and Forecasting (WRF) Advanced Research WRF (ARW) model, run by Robert Fovell at the Department of Atmospheric and Oceanic Sciences at UCLA. Using reanalysis data from the WRF-ARW at 6 km resolution, we initially calculated a maximum

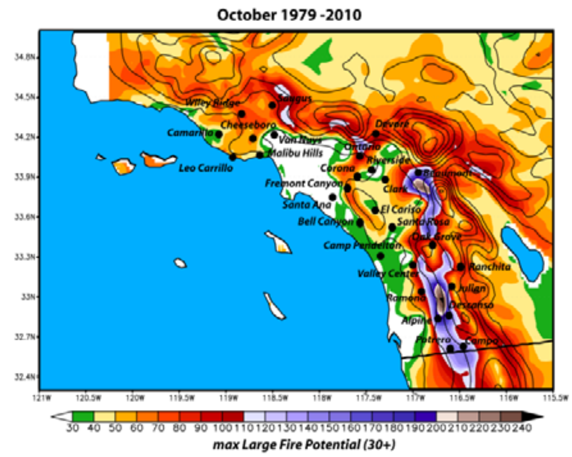


Figure 6 - Map showing maximum values of LFP (Eq. 1) for every October from 1979-2010. Solid contours indicate terrain height.

LFP_w value for each grid point in the model domain for every October between 1979 and 2010. The result was a composite map showing the areas where LFP_w is greatest (Fig. 6). The process was repeated for the same time period substituting the month of January for October (not shown). The results were similar except the areas affected by LFP_w were larger and the values were higher overall. This is because offshore wind events across southern California tend to become stronger in the winter due to more favorable atmospheric dynamics (Raphael 2003). The two composite images were used to define what are called Santa Ana regions (or sub-regions) within each zone, which were further refashioned into rectangular numbered boxes (Fig. 7).

Next, daily historical values of LFP_w were calculated for each zone, but rather than calculating LFP_w for every grid point in the entire zone (which would include areas not affected by the wind event), LFP_w was calculated for grid points only within the boxed

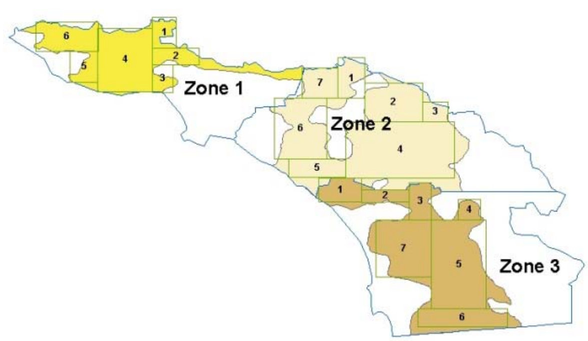
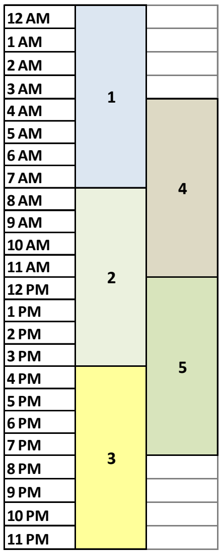


Figure 7 - Map depicting Santa Ana regions (shaded) with numbered boxed areas.

areas of figure 7. The following equation was used to calculate LFP_w at each grid point:

[5]

$$LFP_{GPx} = \frac{LFP_{hour\ 1} + LFP_{hour\ 2} + \cdots + \ LFP_{hour\ 8}}{8}$$



where LFP_{GPx} is an average LFP_w value over an eight-hour time period at grid point x. An eight hour time period was chosen because that is ample time for the finer fuels (i.e. 10-hr) to respond to the ambient atmospheric conditions. Once an average LFP_w had been calculated for each grid point, the following equation was used to evaluate LFP_w for each zone:

[6]

$$LFP_{Zone} = \frac{LFP_{GP1} + LFP_{GP2} + \cdots + \ LFP_{GPx}}{Number\ of\ Grid\ Points\ per\ Zone}$$

where LFP_{Zone} is an average of eight-hour averages at each grid point in the sub-region boxes. It is important to note that equation [6] was calculated for five different eight consecutive hour time periods (see table left) with the highest value chosen to represent each zone for the day. This is to ensure that the worst conditions are being captured on a daily basis. For instance while most Santa Ana wind events peak during the morning hours, some events can peak later in the day or at night depending on the arrival time of stronger dynamical support. Thus calculating LFP_w for only one consecutive eight-hour time period may fail to capture the worst conditions of the day. The end result from equation [6] yielded a listing of daily LFP_w values per zone for months October-April from 1982-2011.

Equation [2] for this same time period has yet to be calculated due to the absence of data. In order to complete the evaluation of FMC, ERC and 10-h must be calculated at each grid point. At the time of this writing it is undetermined whether or not the traditional algorithms (Bradshaw *et al.* 1983) will be used or if a regression equation will be employed to approximate these values. Also, algorithms for calculating LFM and G have yet to be developed. Final output from these variables is expected later this spring or early summer, at which point an in depth analysis will be performed. In this forthcoming analysis, daily LFP values for each zone will be used to derive conditional probabilities of large fire occurrence. Breakpoints within these conditional probabilities will ultimately lead to the final redefined index, which will likely be called the "Santa Ana Wildfire Threat" (SAWT) index. Despite the fact that FMC has yet to be calculated for the entire dataset, preliminary results from Zone 3 show how incorporating FMC into equation [1] modifies the LFP_w values which correlate well with observed fire activity. For example, consider the table below:

Note that LFP_w calculated for Zone 3 on 7 January 2003 had a value of 70, but when FMC was applied, the value decreased to 17. While there *were* ignitions on that particular date, no large fires occurred. The case of 31 March 2005 is a more dramatic example of a situation in which the fuels were completely unsupportive of any fire activity, as the final LFP value dropped to 0. Conversely, dates that had final

Date	EQ1 - LFP_{zone3}	DL	G	LFM	FMC	EQ4 - LFP_{zone3}	Ignitions	Large Fires	Acres
1/7/2003	70	3	0	0.86	0.249	17	Y	N	
1/1/2008	56	2	0	0.81	0.147	8	N	N	
10/22/2007	54	3	5	0.55	0.945	51	Y	Y	9472
10/21/2007	51	3	5	0.55	0.945	48	Y	Y	197990
11/30/2006	48	3	5	0.58	0.920	44	Y	Y	296
3/31/2005	48	1	0	1.19	0.000	0	N	N	
1/21/2010	46	1	0	0.70	0.043	2	N	N	
12/17/2004	45	2	0	0.76	0.164	7	Y	N	
2/2/2005	43	1	0	0.90	0.011	0	N	N	
2/6/2006	41	2	4	0.68	0.595	24	N	N	
1/10/2009	41	2	0	0.66	0.203	8	Y	N	
1/17/2008	40	2	0	0.87	0.130	5	Y	N	

LFP values exceeding 40 did result in large fires when ignitions occurred.

Currently LFP_w is being computed operationally by UCLA using the 12 UTC WRF – ARW model run at 3 km to produce maps displaying maximum LFP_w values for the three zones (Fig. 8). Evaluation of this output is being performed by UCLA, Predictive Services, and SDG&E to compare forecast output with observed values. Expanded output is planned and proposed for the coming months which will include a comparison of forecasted values with normalized values and a breakdown of which component may be contributing the most toward the final output.

5. Social Science Impact

In order for the SAWT index to be a meaningful tool for the public, it is important that the social impact of such an index be studied in a detailed manner. Understanding social behavior in this context will increase our awareness of the public's ability to prepare for, respond to, and recover from wildfires. This understanding is vital to the process of meteorological product development, which if done correctly, will ensure that sustainable, comprehensive communication is achieved. To this end, the Desert Research Institute (DRI) has been contracted to study the social aspect of this project and to make recommendations in helping condense and simplify previously discussed output into a product that is relatable to the user.

DRI is taking a multi-phased mixed method design with regard to the research methodology (Bergman 2008; Morese and Neihause 2009). Phase one involved data collection in the form of a survey of Wildland Urban Interface (WUI) areas in southern California (*n*=400) that assessed how meteorological and fire information is sourced, perceived, and processed by residents. The survey instrument also included a scale to assess residents' perceptions of wildfire risk (adapted from Trumbo et. al. 2012). In addition, in-depth interviews on meteorological fire information use and needs were conducted with fire agencies (county, state, and federal) and will continue through the coming months. The data from the survey and interviews will contribute to the upcoming second and third phases of the project. The survey results include data about WUI residents' most commonly used sources for meteorological and emergency fire information on a daily basis and during a wildfire event. This data will drive the second phase of the project, which focuses on interviews with media representatives from the identified media outlets. These interviews will be used to develop a better understanding of how meteorological and fire information is communicated in the media and how it can be influenced to become more consistent and relevant to WUI residents. Phase three will utilize data from the risk perception scale to help assess the most efficient number of levels in the index, their associated definitions, the efficacy of different modes and types of information, and potential color schemes to use in the final presentation of the index.

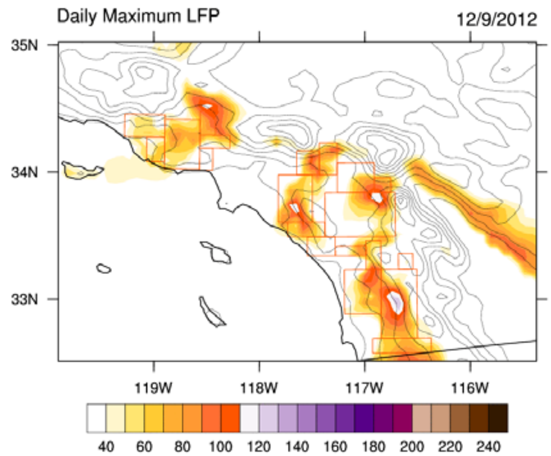


Figure 8 - Map showing forecasted maximum LFP (Eq 1) values.

Impacts from this research will govern the future of the SAWT index. In order to achieve maximum success, a detailed communication campaign strategy will be deployed to educate stakeholders of the index. It is our hope that this index will achieve the same level of success that the Saffir-Simpson scale has had regarding the classification of hurricanes, in terms of the ability to communicate a storm's severity simply and effectively to the public, the media, and to first responders.

6. Conclusion

As the WUI continues to expand across southern California, the source of ignitions will increase leading to a greater probability for large and destructive fires during Santa Ana wind events. This puts the public and firefighter safety at risk, thus the increasing need to categorize such events in terms of their effect on the fire environment.

While the initial OFSI proved to be generally successful, its ability to capture the complexity of Santa Ana wind events was limited. This however led to the development of a new methodology for a redefined index. Expressing large fire potential as a function of wind velocity, dew point depression, and fuel moisture has allowed high resolution model and satellite derived variables to be incorporated into the index. This will specifically address the problems involving spatial coverage and fuel conditions innate to the OFSI.

Fuel moisture variables for the data period will be obtained this summer, at which point a thorough analysis will be conducted to develop the final product. A prototype product is scheduled to be released to a small test group in September. Full product deployment is expected by September 2014.

The use of social science will help in the understanding of how various survey recipients react to meteorological and fire information. This knowledge will eventually dictate what the final product will become in terms of its content and aesthetic. This last phase of the project is perhaps the most important as the success of the index will be determined by what information is conveyed and how it is presented.

The benefits of categorizing Santa Ana wind events are multifold. Fire agencies and first responders, private industry, the general public, and the media will have a clearer understanding of the severity of an event based on the potential for large fires to occur. Specifically, a more effective media response will result in the general population (particularly those living within the WUI) being more proactive in its response to an impending event. In addition, a climatology of Santa Ana wind events can be developed based on this index which can be used in future research involving seasonal outlook predictions.

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