

A weekly, near real-time dataset of the probability of large wildfire across western US forests and woodlands

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Abstract. There is broad consensus that wildfire activity is likely to increase in western US forests and woodlands over the next century. Therefore, spatial predictions of the potential for large wildfires have immediate and growing relevance to near- and long-term research, planning, and management objectives. Fuels, climate, weather, and the landscape all exert controls on wildfire occurrence and spread, but the dynamics of these controls vary from daily to decadal timescales. Accurate spatial predictions of large wildfires should therefore strive to integrate across these variables and timescales. Here, we describe a high spatial resolution dataset (250-m pixel) of the probability of large wildfire (>405 ha) across all western US forests and woodlands, from 2005 to the present. The dataset is automatically updated on a weekly basis and in near real-time (i.e., a one-week lag) using Google Earth Engine and a ‘Continuous Integration’ pipeline. Each image in the dataset is the output of a machine-learning algorithm, trained on 10 independent, random samples of historic small and large wildfires, and represents the predicted probability of an individual pixel burning in a large fire. This novel workflow is able to integrate the short-term dynamics of fuels and weather into weekly predictions, while also integrating longer-term dynamics of fuels, climate, and the landscape. As a near real-time product, the dataset can provide operational fire managers with immediate, on-the-ground information to closely monitor changing potential for large wildfire occurrence and spread. It can also serve as a foundational dataset for longer-term planning and research, such as strategic targeting of fuels management, fire-smart development at the wildland urban interface, and analysis of trends in wildfire potential over time. Weekly large fire probability GeoTiff products from 2005 through 2017 are archived on Figshare online digital repository with the DOI [10.6084/m9.figshare.5765967](https://doi.org/10.6084/m9.figshare.5765967) (available at <https://doi.org/10.6084/m9.figshare.5765967.v1>). Near real-time weekly GeoTiff products and the entire dataset from 2005 on are also continuously uploaded to a Google Cloud Storage bucket at <https://console.cloud.google.com/storage/wffr-preds/V1>, and available free of charge with a Google account. Near real-time products and the long-term archive are also available to registered Google Earth Engine (GEE) users as public GEE assets, and can be accessed with the image collection ID ‘users/mgray/wffr-preds’ within GEE.

1 Introduction

Operational versus research-driven needs for wildfire prediction operate at different spatiotemporal scales, aiming either to understand the risk posed by individual fires or over the course of a fire season, or to understand the broad-scale

characteristics of fire regimes. For example, operational needs emphasize the short-term controls on fire (e.g., occurring over days to months; Brillinger et al., 2003; Martell et al., 1989; Sullivan, 2009a, 2009b) and largely ignore the longer term controls (e.g., occurring over years to decades). By contrast, research to predict across longer time frames and often larger spatial scales will omit the real-time weather patterns that drive fire occurrence (Krawchuk and Moritz, 2014; Littell et al., 2009; Urbieto et al., 2015). While many models and datasets exist to support these needs, they also reflect these different and non-overlapping scales. We sought to fill this gap by developing a dataset of large wildfire probability that integrates across spatiotemporal scales in an empirical framework, at a high spatial resolution (250-m pixel) and moderate temporal resolution (weekly), and across the western US. The resulting dataset is intended to meet multiple objectives of local to national research, management, and planning efforts.

A well-developed approach to incorporate the dynamic short-term drivers of wildfire is to simulate the spread of a fire with physics-based models (Finney, 2004; Sullivan, 2009c; Tymstra et al., 2010). Tools that allow for these simulations, such as Farsite (Finney, 2004), Flammap (Finney, 2006), and FSPro (USDA Forest Service), are used widely during wildfire incidents and in real time to understand the potential spread and behavior of burning fires. These tools can provide critical information for individual or localized fire probability and behavior in real time, but are limited in their ability to elucidate regional and cross-regional fire risk at similar time frames, and are dependent on fuels data, e.g. from Landfire (Rollins, 2009), that are not updated in real time and often not for years at a time. Although the work described herein does not attempt to model the risk or behavior posed by individual fires, it is meant to provide high-resolution data of fire probability in near real time and also across regional extents, drawing on continuously updated fuel and weather predictors. Therefore, it provides a needed, complementary dataset to existing tools that operate on short timescales.

By simulating individual fires across time and space, physics-based models can also be scaled-up to predict the long-term potential of fire at every point on a landscape (Finney et al., 2011; Parisien et al., 2005). This approach is commonly used for longer-term planning of fuel treatments and other fire risk planning and assessments (Haas et al., 2013; Thompson et al., 2017). Because they require detailed specifications of many model inputs and are sensitive to assumed model parameterizations, these landscape-scale simulations can be input- and computationally-intensive (Parisien et al., 2012a; Varner et al., 2009). At regional to national scales, user-intensive demands may also constrain the ability of analysts and planners to update datasets at both broad spatial scales and decision-relevant timescales. For example, predictive datasets may need to be updated according to changes in fuel that occur within a fire season and on an inter-annual basis.

Alternative methods to predict fire occurrence relate empirical fire data to environmental predictors in statistical models (Gray et al., 2014; Preisler et al., 2016; Stavros et al., 2014). Data availability in this case, namely the spatio-temporal alignment of accurate and high-resolution fire, weather, and fuels data, also acts as a constraint on either the spatial or temporal scale of analysis (Taylor et al., 2013). However, such statistical methods are common in predicting fire occurrence on a macro-scale because they can draw on coarse scale data to overcome this constraint (Krawchuk et al., 2009; Moritz et al., 2012; Parisien et al., 2012b). Owing to the flexibility of model specification and data inputs, as well as

increasingly accurate and high-resolution observational data, statistically-based empirical models can integrate both the dynamic short and long-term controls on fire potential.

Indeed, recent studies have explicitly compared the role of temporal scale in predicting fire occurrence, and have shown that long-term normals and variability in climate and vegetation provide complementary predictive power (Abatzoglou and Kolden, 2011, 2013; Parisien et al., 2014; Riley et al., 2013). For example, long-term climate exerts an influence on the flammability (e.g., due to biomass production, vegetation composition, and average fuel moisture) of a fuel bed, but weekly and sub-weekly weather will moderate fuel moisture in a site-specific way. Similarly, short-term disturbance events such as previous burns can regulate biomass production and subsequent fire risk on inter-annual timescales (Parisien et al., 2014; Parks et al., 2015). It follows that predictive datasets of wildfire potential should strive to integrate across complex, dynamic interactions at short- and long-term timescales. Here, we describe a time-series of the probability of large fire, updated on a weekly basis and in near real-time (i.e., to the present week) to integrate the weekly, short-term controls on fire occurrence, but which also considers the longer-term influences of land use, disturbance, climate, and topography. The complete dataset (2005-present) can also be considered a foundational dataset for understanding long-term, probabilistic exposure of forests and woodlands to large fires.

2 Methods

2.1 Modelling

We modeled the probability of large fire occurrence, which we defined as the probability that an area on the landscape will burn in a large (i.e., > 405 ha) fire, conditional on either an ignition event or fire spreading to that area. While defining large fire size is somewhat arbitrary, 405 ha is commonly used to distinguish large from small fires in western US forests (e.g., Westerling, 2006), and fires > 405 ha accounted for approximately 95% of area burned in western forests and woodlands from 1992-2015 (Short, 2017). Additionally, our method only focused on the probability of a large fire irrespective of ignition likelihood or sources. Ignitions are non-random events that adhere to spatial patterns of anthropogenic or lightning activity (Balch et al., 2017), which are not accounted for in this dataset.

We used a random forest (RF) classification algorithm (Breiman, 2001) to train predictive models of large fire probability. RF is a machine learning technique that recursively partitions variables to classify an outcome of interest, in this case small or large fire events. Multiple classification trees are fit to bootstrapped samples of the training data, but at each node, only a fraction of randomly selected predictors are available for the binary partitioning. The randomized process of recursive partitioning uncovers hidden structures in the data without over-fitting, and yields strong predictive models (Prasad et al., 2006). Thus, RF is an ideal method to predict fire occurrence across broad and diverse ecoregions, where high dimensionality is needed to account for unforeseen interactions between climate, fuels, and the landscape (Cutler et al., 2007).

The binary response variable in our RF models was a point on the landscape where there was an ignition event that resulted in a small fire (i.e., < 405 ha; '0' response) or that historically burned in a large fire (i.e., > 405 ha; '1' response). Therefore, model outputs (i.e., raster maps) can be interpreted as reflecting the probability that a given area on the landscape will burn in a large fire, conditional on either an ignition or spread of fire to that area. We sampled large fire points from the MODerate-resolution Imaging Spectroradiometer (MODIS) Burned Area (BA) dataset (Roy et al., 2008), which is a 500-m remote sensing product that contains the day-of-burn, and we sampled small fire points from a database of reported fires in the United States (Short, 2014, 2017) that contains the day-of-ignition (Sect. 2.2). To avoid autocorrelation within large fires, we drew the large fire samples from at most one large fire (see Sect. 2.2), which we matched with an equal sized random sample of small fires, to build a single RF model across the entire western US. While autocorrelation is invariably present within individual fires, burning conditions can also be quite heterogeneous over the course of a single large fire (Turner, 2010). We therefore repeated the above sampling and model building protocol with 10 different random seeds, such that each of 10 RF models were not entirely independent but contributed slightly novel information to a mean prediction across those 10 models. This type of ensemble modeling provides a means of producing models that are more accurate than the individual models that make them up, and depicting the variance across predictions, which is critical for risk assessment (Dietterich, 2000; Palmer et al., 2005).

Using 10 trained RF models, we created weekly spatial predictions of the mean and standard deviation of large fire probability at 250-m resolution across western US forests and woodlands. Spatial predictions were created for every week from 2005 through the present. See Sect. 4 below that describes the process by which new predictor data acquisitions are automatically and continuously integrated into near real-time predictions and uploaded to the cloud. Models were trained and spatial predictions created within Google Earth Engine (GEE; Gorelick et al., 2016), which is a cloud-based platform that makes terabyte-scale analysis available on an extensive catalog of satellite imagery and geospatial datasets.

2.2 Response Variables

We sampled large fires by retaining MODIS pixels that were within eight days of reported burn date of neighboring burned pixels. This boosted our confidence that connected pixels were part of the same fire (Archibald and Roy, 2009), which we also required to be connected to ≥ 15 other pixels ($\cong 405$ ha). We then used the MTBS dataset to delineate the perimeters of annual large wildfires (excluding prescribed fires), and sampled daily MODIS burned area pixels in a given year from within these perimeters. We masked burned areas according to forest or woodland land cover types classified in the 2001 US National Land Cover Dataset (NLCD, 30-m resolution; Homer et al., 2007) before drawing 10 random sample seeds across all large fires ($n \cong 900$ in each seed) from 2005-2014. Each individual large fire sample was taken as the centroid of a 500-m pixel (Figure 1). We used the 2001 NLCD product because it represents the closest complete land cover prior to the fires selected for training data in this analysis.

We drew random samples of small wildfires (also excluding prescribed fires) from the US Fire Occurrence Dataset (FOD; Short, 2014, 2017), masked by NLCD forest and woodland cover. We did not draw small samples from the BA dataset because the estimated minimum detectable burn size is approximately 120 ha, which means that smaller fires are grossly underestimated (Giglio et al., 2009; Roy and Boschetti, 2009). Within each Environmental Protection Agency (EPA) level III ecoregion in the western US, we paired an equal sized random sample of small fires with each of the 10 large fire sample seeds, resulting in spatially balanced, 1:1 training datasets across diverse ecoregions.

2.3 Predictor Variables

We derived predictor variables that describe the land surface and climate over multi-year, long-term time frames. Similarly, we derived predictor variables that describe the land surface and weather over weekly, short-term time frames (Table 1). Specifically, an individual large or small fire sample was spatially related to long-term predictors derived over a multi-year period and short-term predictors derived over the week before and after fire occurrence. The integration of predictors in this way resolves the dynamic probability of large fire into long-term drivers of fire, and short-term land surface and ambient conditions directly leading up to and following a fire event. To account for the difference in spatial scales between a large fire and the native resolution of spatial predictors (i.e., ranging from 250 m to 4 km), we used a moving window to derive the mean value of predictors within a circular kernel with a radius of 1135 meters. Predictor variables that were not in a native 250-m resolution were resampled using bilinear interpolation.

2.3.1 Long-term Land Surface Variables

To characterize long-term biomass production and water content per pixel, respectively, we used the Enhanced Vegetation Index (EVI, 250-m resolution) from the MODIS MOD13Q1 v006 product (Didan, 2015) and the Normalized Difference Water Index (NDWI, 500-m resolution), derived from the MODIS MCD43A4 v006 product (Schaaf, 2015). MODIS EVI and the Normalized Difference Vegetation Index (NDVI) both provide proxies for total vegetation, but EVI is more sensitive to canopy variations in densely vegetated areas (Huete et al., 2002). We used a multi-year time-series of EVI to capture the variability in overall biomass production across the western US, but also as a basis to capture variability in sub-pixel vegetation dynamics (e.g., Helman et al., 2015). We also included EVI to capture longer-term changes in fuel abundance due to prior burns, based on findings that forested ecoregions have shown large to moderate post-fire reductions in MODIS NDVI over a ten year period (Yang et al., 2017).

The NDWI was originally proposed as a complementary vegetation index to NDVI and EVI to detect vegetation liquid water content (Gao, 1996), and has since been shown to relate strongly to the total water content per pixel (Cheng et al., 2006; Maki et al., 2004). Similar to EVI, we included a multi-year time-series of NDWI to capture moisture gradients across space. NDWI has also been successful in estimating vegetation moisture and fire hazard when coupled with an estimate of the total vegetation, and so the interaction between EVI and NDWI may provide important information about pixel-wise fuel moistures (Maki et al., 2004).

Each of the NDWI and EVI products used in our analysis were 16-day composites computed from atmospherically corrected, bi-directional daily surface reflectance. MOD13Q1 contains pixel quality information and MCD43A4 contains pixel and band quality information. For both products, we only retained pixels that were free of ice and snow. We extracted five percentile values (10, 25, 50, 75 and 90%) of EVI and NDWI from 2000 (the year MODIS was deployed) to the approximate date of each fire occurrence. These values provided at least five complete years of observed EVI and NDWI prior to the occurrence of a given fire.

To characterize the land surface as modified by humans over the long-term, we included indices of human modification for the years 2001 and 2011 (Conservation Science Partners Inc., 2016; 30-m resolution). The index quantifies the cumulative degree of modification of natural lands attributable directly to energy, residential and commercial, transportation, and agricultural development. We hypothesized that more developed landscapes, because they are less natural and generally more fragmented, are less likely to burn in large fires. We also used the associated residential and commercial development dataset (Conservation Science Partners Inc., 2016; 30-m resolution) to compute the Euclidean distance to urban development in 2001 and 2011. Urban development in this case was approximated by a ‘moderate’ value of residential and commercial development, which is roughly equivalent to the ‘built up moderate’ class in the NLCD, except that it removes exaggerated effects of roads. We assumed that suppression resources and mandates are more readily accessed closer to urban centers and thus constrains the likelihood of large fires. Lastly, we used the Shuttle Radar Topography Mission digital elevation data (Farr et al., 2007) to characterize topographic variables, namely, elevation, slope, aspect, and terrain roughness (standard deviation of elevation), each at a 30-m resolution.

2.3.2 Long-term Climate Variables

We incorporated predictors computed from monthly climatological normals of temperature and precipitation for the period 1981-2010, as derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM; 800-m resolution; Daly et al., 1994). We selected five metrics that summarized long-term annual means, extremes, and seasonality of temperature and precipitation, and which have been used previously to capture the amount and dryness of biomass to predict fire occurrence (Krawchuk et al., 2009; Moritz et al., 2012). These metrics included annual precipitation, precipitation of the warmest month, mean temperature of the wettest month, mean temperature of the warmest month, and temperature seasonality (i.e., the standard deviation of mean monthly temperatures; O’Donnell and Ignizio, 2012).

2.3.3 Short-term Land Surface Variables

We characterized short-term live vegetation abundance and condition, as well as pixel water content, with the single EVI and NDWI observations in the month prior to fire occurrence. We included the absolute index value, as well as anomalies from the closest day-of-year in years prior and from the five percentile values. These short-term indices are meant to capture the absolute vegetation abundance and condition prior to burning, and also the deviance from its long-term state. Specifically with EVI, short-term deviances have been shown to correlate well with forest fire probability (Bisquert et al.,

2013). NDWI, when coupled with EVI, has also been shown to contribute to fire risk on sub-monthly timescales (Maki et al., 2004).

We used the MODIS MOD11A2 daytime Land Surface Temperature (LST) eight-day composites (1-km resolution; NASA LP DAAC, 2015), which represent average values of clear-sky LSTs, to similarly characterize the ground temperature immediately leading up to a fire occurrence. Due to a feedback between LST and near-surface humidity, remotely sensed LST has been used to predict vapour pressure deficit, which itself is a good short-term predictor of fine dead fuel moisture and fire danger (Boer et al., 2017; Nolan et al., 2016). We included both the absolute value of LST from the eight days prior to fire, as well as the LST anomalies from the five percentile values and from the closest day-of-year in years prior.

2.3.4 Short-term Weather Variables

Standard meteorological variables known to influence the daily fire and fuel environment were taken from the GRIDMET gridded daily surface meteorological dataset (4-km resolution; Abatzoglou, 2013). We incorporated the total precipitation, mean minimum and maximum temperature, mean minimum and maximum relative humidity, mean wind speed and direction and the mean Palmer drought severity index (PDSI) for the two weeks surrounding fire occurrence.

Standard weather variables have also been compiled into indices that more directly address the processes by which they effect fires and fuels, including the Energy Release Component (ERC), the Burning Index (BI), and 100- and 1000-hr dead fuel moistures (fm100 and fm1000). These indices are components of the US National Fire Danger Rating System (NFDRS) and are derived from models built on the combustion physics and moisture dynamics of the fuel environment, here assuming a consistent fuel model ‘G’ typified by short needle pine and heavy dead loads (Abatzoglou, 2013; Schlobohm and Brain, 2002). The fm100 and fm1000 represent the modeled moisture content of large dead fuels and are functions of the latitude, day-of-year, temperature, relative humidity, and precipitation duration over the previous 24 hours (fm100) or seven days (fm1000). ERC is a cumulative fuel moisture index reflecting the contribution of all live and dead fuel moistures on the potential heat release, and is also an input into the BI, which additionally incorporates the potential rate of fire spread. GRIDMET assumes that the persistent fuel environment includes all size classes of dead fuels, as well as herbaceous and woody live fuels, and all contribute to the derived values of these indices. We incorporated the mean values of ERC, BI, fm100, and fm1000 in the two weeks surrounding fire occurrence.

3 Dataset Evaluation

Using all training data from 2005-2014 (i.e., no independent testing data), we compared models and extracted variable importance in R using the ‘caret’ package (Kuhn, 2008). Variable importance was determined using a normalized mean decrease in accuracy when that variable was not included. Across the 10 models, overall accuracy was consistently

between 0.7 and 0.72 and area under the receiver operating curve (AUC) was consistently from 0.78-0.79. More importantly, we examined the main differences across models in the top 20 important variables. Out of 76 total predictor variables, human modification or distance to urban development, the mean BI, and the lowest percentiles of NDWI were consistently in the top five variables. Topographic roughness and mean ERC were consistently in the top 10 variables. Slope, LST, mean 1000-hr FM, the highest percentiles of NDWI, precipitation of the warmest month, and EVI (both short- and long-term) were consistently in the top 20 variables. Other variables showed up inconsistently in the top 20 variables.

To independently evaluate the model on data from 2015-2016, we used the MODIS BA and FOD datasets to draw a testing sample from within all large fires, and an equal-sized random sample of small fires (response value of ‘0’ and ‘1’, respectively; $n \cong 400$ large fires). Again, large samples were taken as the centroid of 500-m pixels. Using weekly predictions (i.e., raster maps) of large fire probability in 2015 and 2016, we extracted predicted values at the time (i.e., the closest prediction in time prior to fire occurrence) and location of individual testing points. We used the R package ‘OptimalCutpoints’ (López-Ratón et al., 2014) to determine an optimal cutoff between zero and one that simultaneously maximized the sensitivity (true positive rate) and specificity (true negative rate) of predictions. In this case, using a probability cutoff of 0.45 to predict binary large (> 0.45) versus small (< 0.45) fire resulted in the greatest rate of true positives and negatives in our testing datasets. Based on an optimal cutoff of 0.45 and two years of independent data, the overall accuracy of the dataset was 0.79, and the area under the receiver operating curve (ROC) curve was 0.88 (Figure 2). We took another step to visualize model performance by mapping the rate of false positives and false negatives (i.e., the number of false positives or false negatives normalized by the number of testing samples) within each EPA level III ecoregion (Figure 3).

4 Continuous Integration

We developed a continuous integration (CI) ‘pipeline’ to generate new predictions as soon as the dynamic predictors upon which the model is conditioned become available in GEE. The refresh rate of each predictor varies based on the data sources. For example, gridMET assets are updated approximately every two days, whereas the MODIS products are updated approximately every eight days (Table 1). The pipeline, which tests for the availability of predictors against the requirements of the model, runs on a schedule — compiling each morning at 4am Pacific Standard Time. If all of the criteria are met, a new prediction is generated and appended to the existing collection. We used [GitLab.com](https://gitlab.com) because GitLab offers continuous integration (CI) services at no cost. The builds are executed using a custom Docker image, which is a bare-bones Ubuntu image configured with the Google Earth Engine Python API client library and its dependencies.

5 Band Descriptions

- Band 1 - ‘mean’ : Mean probability of large fire across 10 trained models. Values range from 0-1.
Band 2 - ‘stdDev’ : Standard deviation of the probability of large fire across 10 trained models.

Band 3 - 'modis_QA' : For the MODIS products described above, only good quality pixels were retained for model training, but all pixels were retained when creating spatial predictions. Therefore, final predictions contain a band named 'modis_QA' which indicates if one of the short-term MODIS predictors (i.e., MOD13Q1, MCD43A4, or MOD11A2 immediately preceding the prediction date) had unreliable quality.

- 5 0 = All MODIS pixels were processed and good quality
- 1 = At least one MODIS pixel was not processed or had bad quality

6 Data Availability and Source Code

Weekly large fire probability GeoTiff products from 2005 – 2017 are archived on Figshare online digital repository with the DOI [10.6084/m9.figshare.5765967](https://doi.org/10.6084/m9.figshare.5765967) (available at <https://doi.org/10.6084/m9.figshare.5765967.v1>). Near real-time
10 weekly GeoTiff products and the entire dataset from 2005 on are also continuously uploaded to a Google Cloud Storage bucket at <https://console.cloud.google.com/storage/wffr-preds/V1>, and also available free of charge with a Google account. Near real-time products and the long-term archive are also available to registered GEE users as public GEE assets, and can be accessed with the Image Collection ID 'users/mgray/wffr-preds' within GEE. All source code is available at a GitLab repository (<https://gitlab.com/wffr>).

15 7 Conclusions

The dataset we describe here of weekly predictions of the probability of large forest or woodland fire across the western US invokes interacting effects over multiple timescales that contribute to a site's dynamic fire potential. By drawing on weather, climate, and land surface dynamics at multiple timescales to predict large wildfire probability at a high spatial and temporal resolution, this dataset fills a gap in existing datasets. The result is highly relevant to research, planning, and
20 management objectives that span the western US, ranging from short-term outlooks to long-term planning.

More strategic planning for fuels management is critically needed to adapt to an inevitable increase in wildfire in the west in the coming decades (Schoennagel et al., 2017). For instance, fuels treatments as currently implemented are limited in their ability to mitigate broad scale effects of wildfire, because it's relatively rare that treatments actually encounter wildfire (Barnett et al., 2016). Strategically targeting areas for treatment based on large wildfire potential, coupled
25 with estimates of burn severity, will lead to more cost- and ecologically-effective decisions (Scott et al., 2016; Thompson et al., 2017). However, tools currently used for this purpose are often built off of input- and computationally-intensive stochastic simulation models that may constrain the ability to update results at both broad spatial scales and timescales concurrent with the changing fire environment. For example, the Wildland Fire Potential dataset is available for the entire US at 270-m resolution, and describes fire potential as of 2007, 2012, and 2014 (Dillon et al., 2015). The dataset we describe
30 here is automatically updated to match the dynamics of the fuel and fire environment, which can easily change and critically effect fuels management decisions on annual timescales.

Another area where probabilistic fire exposure analysis can help with strategic fuels and fire planning is at the wildland urban interface (WUI; e.g., Haas et al., 2013). WUI lands in the western US have expanded dramatically over the past few decades, and roughly 40% of these lands are predicted to experience moderate to large increases in the probability of wildfire in the next 20 years (Schoennagel et al., 2017). Considering also that a large percentage of potential WUI lands are still undeveloped, strategic planning for both fuels management and infrastructure development can make communities more resilient to wildfire. This dataset can help guide development plans at multiple scales (e.g., city, county, or state), drawing on a rich time series that gives analysts and planners access to the observed trends, means, and extremes of the potential for large wildfire over time.

In contrast to longer-term predictions, near real-time predictions of large fire potential provide operational fire managers with immediate, on the ground information to closely monitor how changing conditions affect active fires, and the likelihood that fire suppression will require outside resources. In the US, near real-time predictions are widely used during the peak fire season (Owen et al., 2012). Available products through the US Predictive Services program (<http://psgeodata.fs.fed.us/>) and the Wildland Fire Assessment System (www.wfas.net; Preisler et al., 2016), consider fuel and weather conditions changing on daily to weekly timescales, while ignoring longer-term climate and fuel variability that moderate a site's current fire potential. Simulation models that are used in near real-time, such as FARSITE, provide critical information for individual or localized fire probability and behavior, but are limited in their ability to elucidate real-time regional and cross-regional fire risk, and are additionally dependent on fuels data, e.g. from Landfire (Rollins, 2009), that are not updated in real time. The dataset described here provides near real-time predictions across the western US, while simultaneously accounting for dynamic fuel and landscape compositions that are shaped over the short and long term, and thus is needed addition to operational products of near real-time fire potential.

As the observational record grows longer to include more temporal variability and new normals, we will continue to re-train models on the same basis of predictors and update and evaluate this dataset. This will allow for any non-stationary relationships between wildfire, climate, fuels, and the landscape to be easily integrated into predictions. For example, if underlying relationships such as the precipitation of the wettest month or average early May EVI change in the future, models would simply need to be re-trained on updated datasets to integrate such non-stationarities. In future development, forecasted climate, weather, and fuels data may also be integrated into the analysis in order to create predictions of large fire probability into the future.

8 Author Contributions

MEG developed the fire models and data products, with critical contributions from both LJZ and BGD. LJZ developed the continuous integration algorithm. All authors contributed to the paper

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Table 1. Spatially explicit climate and land surface predictors of large fire probability, including the data source, spatial resolution, and description of how variables were derived from the source data. Gray shading in the table indicates grouping of predictor variables depending on whether they are derived over a short term (sub-monthly) or a long term (multi-year).

5 The accompanying graphic indicates the approximate time period that these variables are drawn from, relative to fire occurrence.

Predictor	Source	Resolution	Description
1. Long-term climate variables			
Annual precipitation, Temperature seasonality, Precipitation of the warmest month, Mean temperature of the wettest month, Mean temperature of the warmest month	PRISM	800 m	Derived from 1981-2010 monthly normals.
2. Long-term land surface variables			
EVI percentiles	MODIS	250 m	10 th , 25 th , 50 th , 75 th , and 90 th percentiles from 2000 to the date of fire occurrence.
NDWI percentiles	MODIS	500 m	
Human modification, Distance to urban development	CSP 2016	30 m	Index or distance value at 2001 for fires pre 2011, and 2011 for fires post 2011.
Elevation, Slope, Aspect, Topographic Roughness	USGS	30 m	
3. Short-term land surface variables			
EVI absolute and anomalies	MODIS	250 m	Absolute value and percent change from 2000 to the fire year, immediately preceding fire occurrence.
NDWI absolute and anomalies	MODIS	500 m	
LST absolute and anomaly	MODIS	1 km	
4. Short-term weather variables			
100-hr fuel moisture, 1000-hr fuel moisture, Burning index, Energy Release Component, Precipitation, Temperature, Relative humidity, Specific humidity, Potential evapotranspiration, Solar radiation, Wind speed, Wind direction, PDSI	GridMET	4 km	Mean values in the two weeks surrounding fire occurrence

11 Figure Captions

Figure 1. Example of how the MODerate-resolution Imaging Spectroradiometer (MODIS) Burned Area (BA) dataset was used to draw 10 random sample seeds from within large fires. Each seed, across all large fires in 2005-2014, was used to train a random forest model to predict large fire probability. MTBS fire perimeters greater than 405 hectares are included because they were used to restrict BA sampling within individual wildfires.

Figure 2. Receiver Operating Curve (ROC) for an independent testing dataset of small and large fires that occurred from 2015-2016. Sensitivity and (1-Specificity) values are shown for the point where large fire probability values >0.45 are classified as a large fire, and values <0.45 are classified as a small fire, since this value was found to simultaneously maximize sensitivity and specificity.

Figure 3. Large fire probability for the week of July 30, 2015. MTBS fires greater than 405 hectares, and that started in August 2015, are overlaid on the map.

Figure 4. False positive (FP) and false negative (FN) rates of an independent testing dataset of small and large fires from 2015-2016, mapped across EPA level three ecoregions. No testing data was available for those ecoregions that are not displayed.

Figure 1

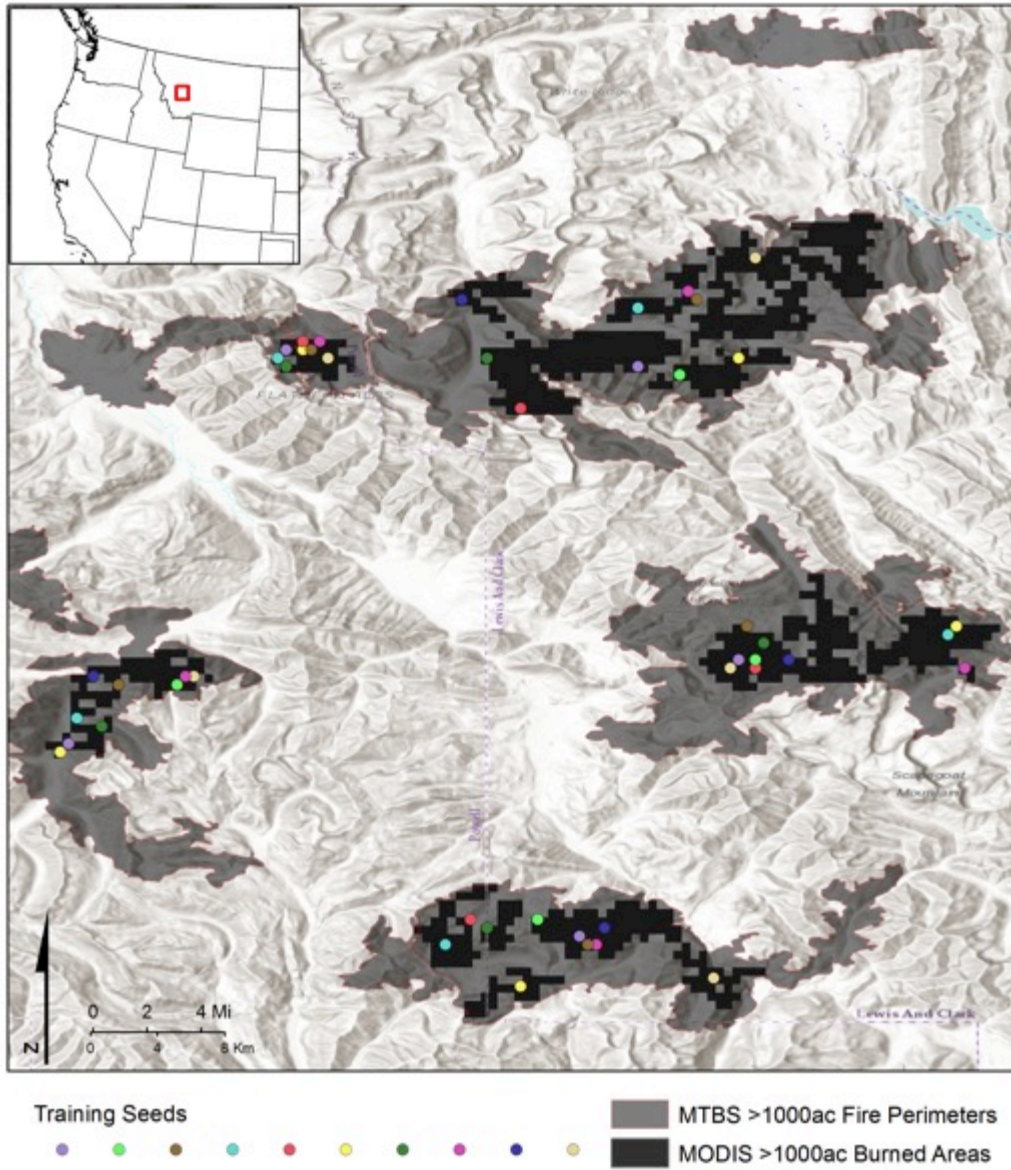
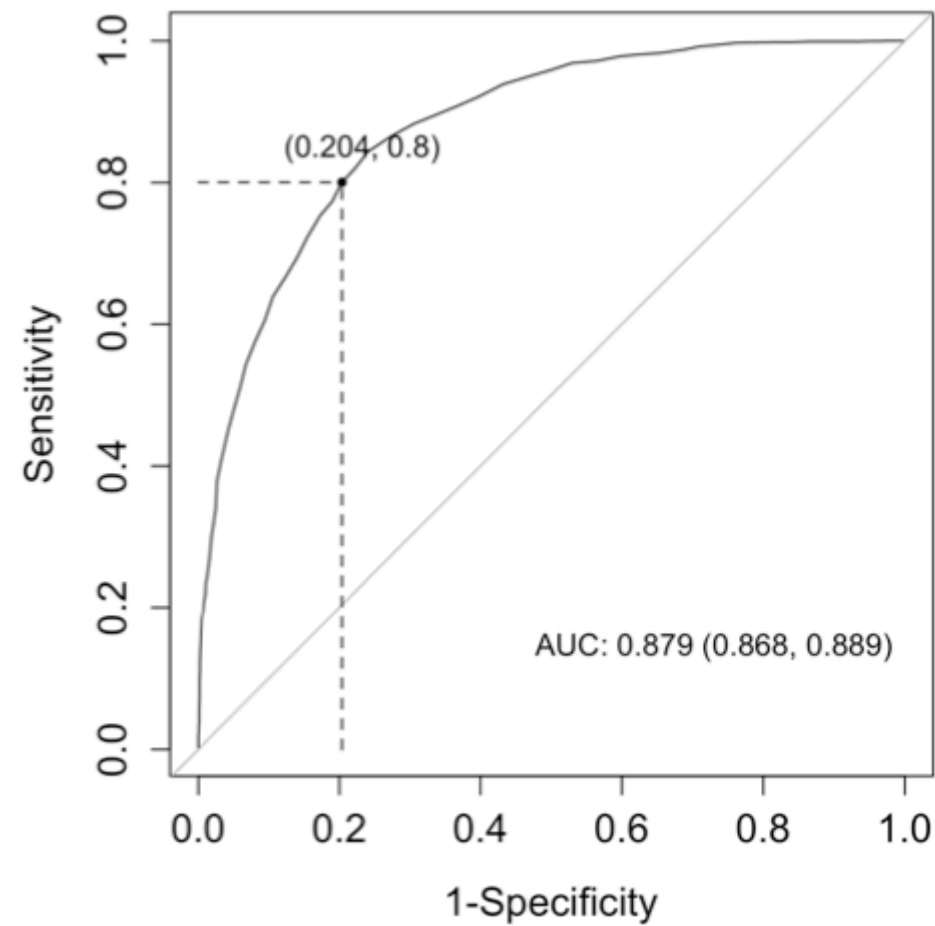


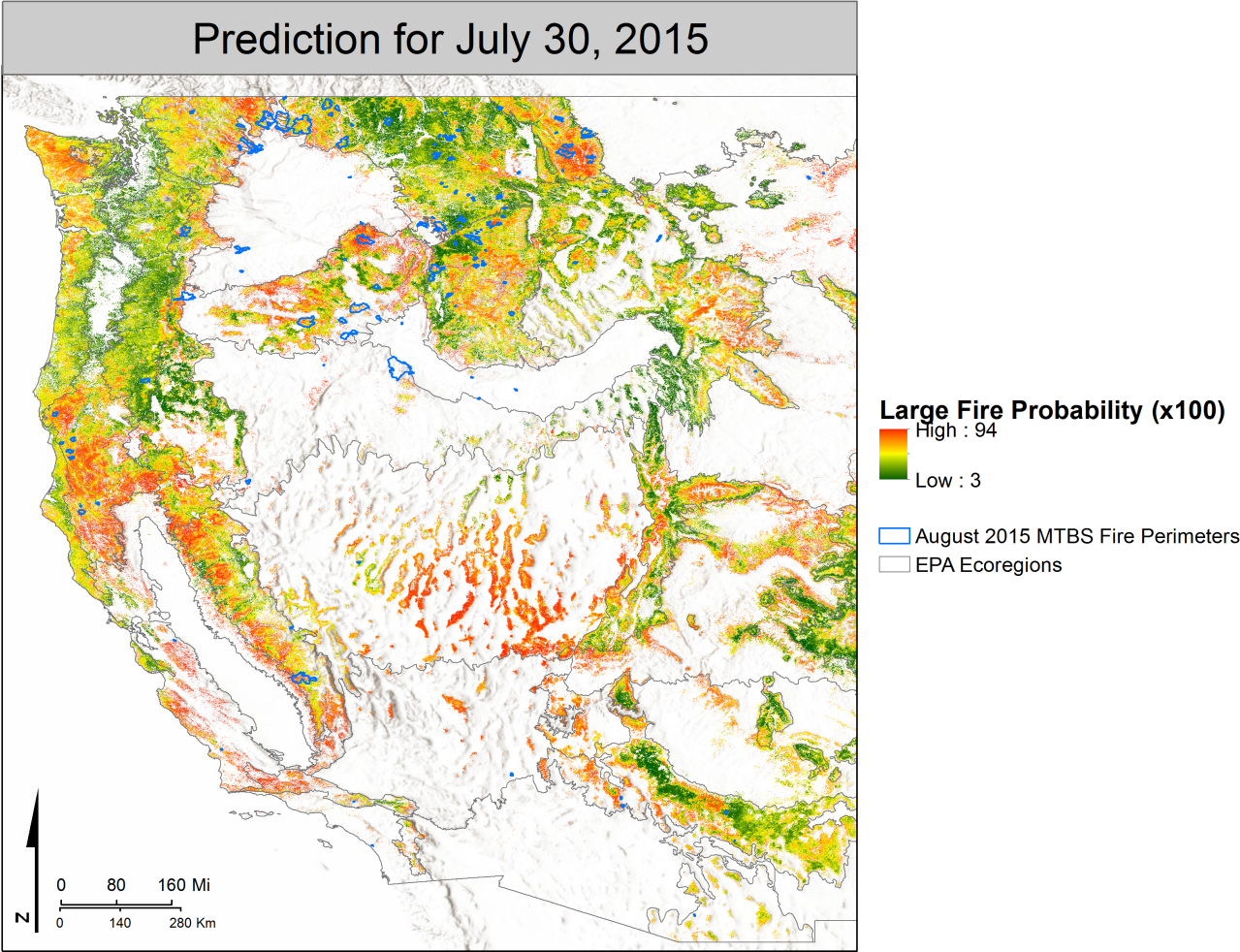
Figure 2



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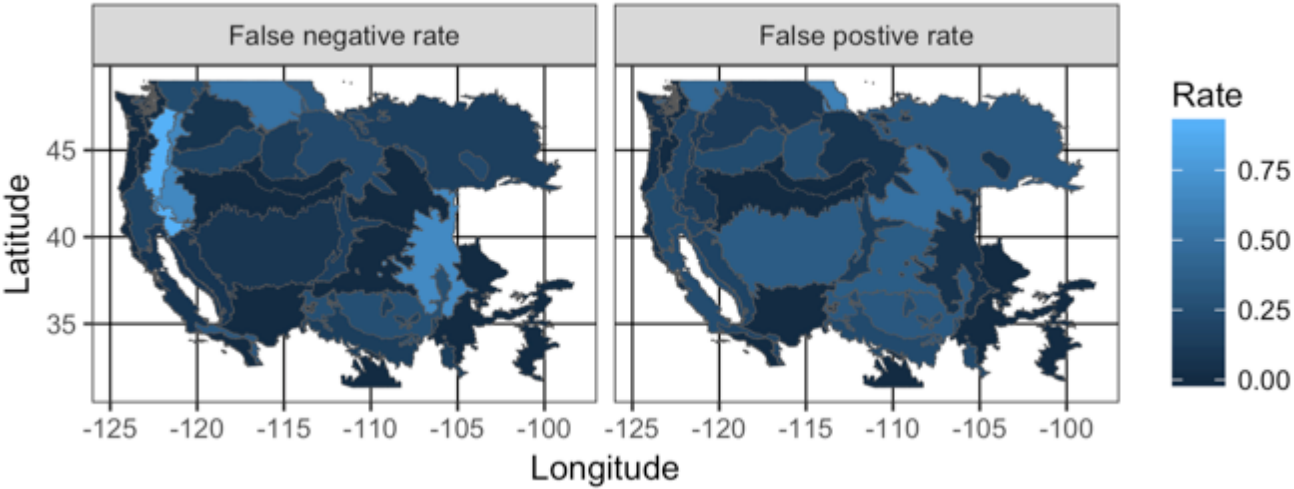
Figure 3



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Figure 4



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