

Daily PM_{2.5} concentration estimates by ZIP code in 11 western states differentiated by total, wildfire, and prescribed fire, 2008-2014

C.E. Reid^{a,*}, M.M. Maestas^b, G. Li^b, E. Considine^b, N.H.F. French^c, M. Billmire^c, M. Jerrett^d

^a*Department of Geography, Guggenheim 110, 260 UCB, Boulder, Colorado 80309*

^b*4001 Discovery Dr., SEEC Building Suite S348, UCB 611, Boulder, CO 80303*

^c*Michigan Tech Research Institute, Michigan Technological University, 3600 Green Court, Suite 100, Ann Arbor, MI 48105*

^d*UCLA Fielding School of Public Health, 650 Charles E. Young Drive South, 56-070B CHS, Los Angeles, CA 90095*

Abstract

Differential risks to public health posed by air pollution from wildfires and prescribed fires are poorly understood, and a necessary pre-requisite to addressing this issue is a method to assess exposure to PM_{2.5} differentiated among wildfire, prescribed fire, and other sources.

We developed a machine learning model to use earth observations to create multi-year spatiotemporal fine particulate matter (PM_{2.5}) estimates attributed to prescribed fires and wildfires for 11 western states from 2008-2014. The training data are PM_{2.5} observations from the Environmental Protection Agency's database [check name of database], field campaigns, and monitors deployed near fires by the US Forest Service and others, and the predictor variables include MODIS and GOES aerosol optical depth (AOD), MODIS fire products, MODIS snow cover, Landsat land cover, and other Earth observations. To estimate the fraction of PM_{2.5} due to each fire type, we used source-apportioned PM_{2.5} output from the Comprehensive Air Quality Model with Extensions (CAMx). [Discuss machine learning method, e.g., discuss random forest, etc.] [3 sentences describing results] [1 sentence describing how this work is applicable/relevant in a broader context or describing need for further research]

Keywords: wildfire, prescribed fire, PM_{2.5}, spatiotemporal exposure, smoke

1. Introduction

The increase in frequency and severity of landscape fires occurring in the western US (Dennison et al., 2014; Steel et al., 2015) and the decrease in other

*Corresponding author

URL: <https://www.colorado.edu/geography/colleen-reid-0> (C.E. Reid)

sources of air pollution (US EPA, 2017, accessed November 9, 2017) mean that
5 smoke from landscape fires will be an increasingly large fraction of total air
pollution. The increase in wildfires has prompted increasing pressure to en-
gage in more prescribed burning (Stephens and Ruth, 2005), and we still don't
fully understand the public's exposure to either wildfire smoke or prescribed
fire smoke. Fire is a necessary part of many ecosystems in the western US, and
10 complete fire suppression is not feasible. To help minimize the risk of often
catastrophic unplanned wildfires, prescribed fires are used as a management tool
to reduce fuel loads and the risk of large uncontrolled wildfires while allowing
ecological benefits of fire. Previous research indicates that prescribed fires im-
pact air quality less than wildfires on a per-fire basis. Increasingly, researchers
15 are statistically blending information from remotely-sensed Earth observations,
atmospheric models, and air quality monitoring data to obtain improved spa-
tiotemporal air pollution exposure surfaces for health studies. To our knowledge,
previous studies have not considered if air pollution from prescribed fires and
wildfires pose differential risks to public health. [1 sentence citing several pa-
pers with short descriptions of what has been done in this area of research] [1
20 sentence saying what additional studies need to accomplish]

Add citation

Increasingly, in the wildfire-health literature, researchers are 'blending' satel-
lite AOD data and air quality models together to estimate air quality exposures
in locations far from monitoring sites, (e.g., Reid et al. 2016, 2015; van Donkelaar
25 et al. 2011; Gan et al. 2017) as these two data sources have different strengths
and weaknesses but merged together can better estimate exposures. Satellite
AOD data is a measurement but of the full atmospheric column rather than at
ground level, whereas ground-level PM_{2.5} estimates can be extracted from air
quality models, but there are uncertainties inherent in the models. Blending
30 these data sources over large geographic areas and long periods of time, includ-
ing many fires in different locations, can provide the statistical power needed to
detect if there are differential health impacts from smoke from prescribed fires
and unplanned wildfires. Previous machine learning studies to estimate pollu-
tion have not considered wildfires, no [few?] studies estimating surface PM_{2.5}
35 have done source attribution between wildfire smoke and prescribed fire smoke.

Check if true

Knowledge about the health impacts associated with fine particulate matter
(PM_{2.5}) from fires is important for air quality managers and public health de-
partments, particularly in western US states where fire can often cause public
health and air quality emergencies. Air quality is managed at the state and
40 local levels to conform to air quality standards set by state and federal policy.
Decisions about when to set prescribed fires involve air quality management
agencies for states, tribal, and sometimes local areas in order to mitigate im-
pacts that are both regulated and of concern for public health. State and local
land management agencies are tasked with writing smoke management plans
45 whenever they put fire on the ground (Achtemeier et al., 2001). Smoke plans
involve planning burns that produce minimal smoke with maximum ecological
benefit and fit within specific land management plans that consider the benefits
of fire while minimizing risks related to both fire and smoke. When projected
emission levels are lower than the air quality standard for fine particulate matter

(PM_{2.5}), it is assumed that there are no health impacts, however, it is possible that health impacts could occur at that level or lower, and sometimes air pollution levels from prescribed fires reach levels higher than smoke planning tools predict. Prescribed fires often occur in more rural areas, thus large datasets over broad geographic areas for many years are needed for statistical power, and studies cannot rely solely on monitoring data for air pollution exposure estimation as these monitors are often far from fire-impacted areas. Better understanding of health impacts associated with exposure to smoke from wildfires and prescribed fires could allow better planning for future prescribed burning and targeted mitigation strategies in the face of unplanned wildfire events.

In this paper, we estimate the proportion of total PM_{2.5} per day attributed to all sources, and then specifically for wildfires and prescribed fires to better understand the exposure of the public to air pollution from wildfires and prescribed fires as a prerequisite for future studies to examine the impacts of smoke exposure from both prescribed fires and wildfires on health. To accomplish this, we create a multi-year daily spatiotemporal total PM_{2.5} exposure surface for an 11-state area in the western US for the years 2008-2014, model the transport of air pollutant emissions from each fire type (wildfire and prescribed fire), daily for the study area, and calculate daily estimates of wildfire-attributed and prescribed fire-attributed PM_{2.5} for all ZIP codes in the study area for all 7 years. [1 sentence giving context, e.g., describe geographic region] [2 sentences stating what previous studies on the topic found] Air quality managers and public health professionals in the western US want empirical evidence of the health impacts associated with prescribed fires to inform their smoke management plans and public health interventions and messaging. The objective of this paper is to use machine learning to blend MODIS and GOES aerosol optical depth (AOD), MODIS fire products, MODIS snow cover, Landsat land cover, and other Earth observations with source-apportioned fine particulate matter (PM_{2.5}) estimates from an air quality model to create multi-year spatiotemporal PM_{2.5} estimates attributed to prescribed fires and wildfires for 11 western states from 2008-2014. [Starting text from proposal - need to integrate with text above/delete:]

Fire is an integral part of many ecosystems, yet many fires are suppressed to protect human populations, property, and infrastructure (Bowman et al., 2009). This suppression can lead to a build-up of fuels that contribute to the increased intensity of wildfires in the western US (Schoennagel et al., 2017). Prescribed fires are used as a management tool to decrease fuel loads and risk of large uncontrolled wildfires while allowing for the ecological benefits of fire (Schoennagel et al., 2017). Previous research indicates that prescribed fires may impact air quality less than wildfires on a per-fire basis (Liu et al., 2017). In planning prescribed fire, air quality managers are obligated to understand and plan for the impacts of smoke on air quality and to minimize the impact of smoke on populations (see more from the National Interagency Fire Center at <https://www.nifc.gov/smoke/index.html>). Prescribed fires, therefore, are intended to last for short durations and under ideal weather conditions for allowing smoke to be transported away from settlements, making it less of a concern than wildfires which often burn under adverse conditions for smoke

management. Currently, there is tension between entities that want more prescribed fires and those who oppose them, who often cite air quality and health concerns as their primary opposition to prescribed fires. Air quality managers are often caught in the middle. Empirical information on the health impacts of historical prescribed fires, which is not currently available, could help quantify the benefits of prescribed burning and scientifically inform the ongoing debate about whether it is prudent to increase prescribed burning in the western US.

A differential risk for health for prescribed fires is plausible because prescribed fires (1) typically burn at lower temperatures with more smoldering than high intensity wildfires which can lead to differences in chemical composition of emissions, (2) tend to occur during different times of the year than wildfires, and this could lead to burning wetter fuels, affecting particle chemistry and quantity, (3) are lower intensity which can lead to lower atmospheric injection height and therefore more air quality impacts where people breathe, and (4) have to be repeatedly set to have an impact on controlling larger fires, potentially leading to more chronic exposure to smoke (Williamson et al., 2016; Torvela et al., 2014). Thus, although studies have documented lower air pollution levels from prescribed fires (Liu et al., 2017), it is not clear that the health impacts would be less than those caused by wildfires.

To understand if there are differential health impacts of smoke from prescribed fires and wildfires on population health, a very large dataset needs to be created and analyzed. We therefore propose to create estimates of $PM_{2.5}$ source-apportioned to each fire type for a 7-year period (2008-2014) over an 11-state region of the western US (see Figure 1). To date, there have been no empirical studies of the health effects of prescribed fires compared to wildfires, despite some theoretical publications (Haikerwal et al., 2015; Schweizer and Cisneros, 2017) on the important considerations related to these two sources of air pollution that are increasing in importance in the western US. Therefore, our study will be ground-breaking in its ability to attribute fine particulate matter, both emitted (primary $PM_{2.5}$) and chemically-created (secondary $PM_{2.5}$), to wildfires and prescribed fires in the historical record and then to estimate the health impacts from these fire types on cardiovascular and respiratory health outcomes among the elderly, a particularly sensitive subpopulation about which we have a consistent national dataset.

The results from these studies will be important not just for furthering the science of the health implications of wildfire and prescribed fire smoke, but will also be used by decision makers in both air quality management and public health, as evidenced by our letters of support from WESTAR and EPHTN. The state partners of these groups have expressed enthusiastic support for our project with intent to use our results for current and future smoke and public health preparedness planning.

We will also pilot the first, to our knowledge, investigation into the health impacts of repeated exposures to smoke from prescribed fires and wildfires.

Papers/resources to look into: https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1293

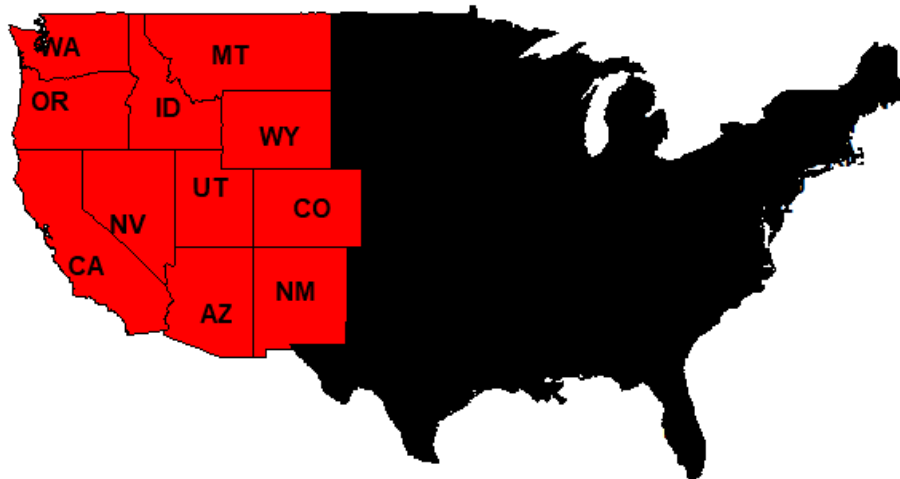


Figure 1: Map of 11-state study area.

2. Materials and Methods

Setting. [11 western US states, 2008-2014]
[1 short paragraph]

Data Sources. [Describe data sources here.]

[starting text from NASA proposal:]

We will use the following NASA Earth observations data sets as inputs for our machine learning methods to model a spatiotemporal surface of $PM_{2.5}$ at daily resolution: (1) aerosol optical depth (AOD) data from the MODerate Resolution Imaging Spectroradiometer (MODIS) product with the Deep Blue retrieval algorithm (MOD04.L2 and MYD04.L2) (Sayer et al., 2013), (2) fire detection locations, size, and fire radiative power from the MODIS Thermal Anomalies/Fire Daily L3 Global 1km (MOD14 and MYD14) (Giglio et al., 2006), (3) Fire occurrence data from the Visible Infrared Imaging Radiometer Suite (VIIRS) (VNP14IMGTDL_NRT) fire data products (Schroeder et al., 2014), (4) MODIS/Terra and Aqua Burned Area Monthly L3 Global 500 m SIN Grid V006 (MCD64A1) (LP DAAC, 2017, accessed November 12, 2017), (5) Landsat-derived burned area essential climate variable (BAECV) fire activity data (Hawbaker et al., 2017), (6) classified land cover information from the Landsat-derived National Land Cover Database 2011 (NLCD 2011) (Homer et al., 2017), and (7) snow cover data from the MODIS Snow Cover Daily L3 Global 500m Grid, Version 6 (MOD10A1 and MYD10A1) (Hall and Riggs, 2016).

We will use the following NASA and NASA-supported products and resources as input for the CAMx: (8) Fuel Characteristic Classification System (FCCS) fuelbed map (McKenzie et al., 2012), which is based on Landsat imagery and the (9) Wildland Fire Emissions Information System (WFEIS), the

development of which was entirely supported by NASA (MTRI, 2017 accessed November 7, 2017), developed by Co-I’s French and Billmire (French et al., 2014). Items (2)-(4) above will also be used as input for the CAMx.

170 In addition to the NASA Earth observation data listed above, we will include the Geostationary Operational Environmental Satellite West (GOES-West) Aerosol Smoke Product (GASP-West AOD) (NOAA NCEI, 2017, accessed November 2, 2017) in the machine learning methods.

175 Finally, we will use several other Earth observation data sets that are not derived from satellite data for the machine learning methods: meteorological data from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) (Mesinger et al., 2006; NCEP, 2005), dust storm records (US National Weather Service, 2017, accessed November 2, 2017a), roadway information from the National Highways Planning Network
180 (Federal Highway Administration, 2017, accessed November 7, 2017), elevation data from the 3D Elevation Program (USGS, 2017, accessed November 6, 2017), and PM_{2.5} measurements from the US Environmental Protection Agency (US EPA) Air Quality System (AQS) (US EPA, 2017, accessed November 2, 2017b) including the Interagency Monitoring of Protected Visual Environments (IM-
185 PROVE) network (US EPA, 2017, accessed November 2, 2017d).

2.1. Data Sources for Machine Learning: Spatiotemporal Surface of PM_{2.5}

For the creation of the spatiotemporal daily exposure surface via machine learning, a large number of data sets will be collected as discussed below. The dependent variable will be daily 24-hour PM_{2.5} from monitoring data.

190 We will download PM_{2.5} data from both the US EPA AQS Air Data Query Tool (US EPA, 2017, accessed November 2, 2017b) and the IMPROVE monitors that capture air quality information in more rural areas (US EPA, 2017, accessed November 2, 2017d) for the 11-state region (Figure 1) including any of the following parameter codes: 88101, 88500, 88502, 81104 (US EPA, 2017, accessed
195 November 2, 2017a,,). In 2014, there were approximately 1600 PM_{2.5} monitors (Figure). For the 7-year study period, we anticipate approximately 1.4 million monitor-days.

study period (NASA LAADS DAAC, 2017, accessed November 2, 2017a,,). The GASP product is available at a 4 km resolution at nadir with retrievals every 30
200 minutes during daylight hours and is available from 2006 onward (NOAA NCEI, 2017, accessed November 2, 2017). Our previous work has demonstrated that the higher temporal and spatial resolution of the GASP product better predicts PM_{2.5} compared to MODIS, but both contributed important information to our forecasting model (Reid et al., 2015). Our previous work (Table 3 from Reid et
205 al., 2015), however, used the Dark Target retrieval algorithm rather than the Deep Blue AOD from MODIS. It is possible that the MODIS AOD from the Deep Blue algorithm will be a more informative predictor in our study area, as it has many reflective surfaces for which Deep Blue performs better than Dark Target (NASA, 2017, accessed November 2, 2017).

210 Product (NOAA OSPO, 2017, accessed November 3, 2017). We will then estimate missing values within validated smoke plumes, but not within clouds, using

radial basis functions as was done in our previous work (Reid et al., 2015). Radial basis functions are exact interpolation functions that will return observed AOD values where they exist but can interpolate higher values than nearby
215 observations in missing locations, which is needed since the missing values were removed due to their high reflectivity (Reid et al., 2015).

We will collect data about fire detection locations, size, and fire radiative power from the MODIS Thermal Anomalies/Fire Daily L3 Global 1km (MOD14 and MYD14), Landsat-derived burned area essential climate variable (BAECV)
220 fire activity data, MODIS/Terra and Aqua Burned Area Monthly L3 Global 500 m SIN Grid V006 (MCD64A1), and the Visible Infrared Imaging Radiometer Suite (VIIRS) (VNP14IMGTDL_NRT) (Giglio et al., 2006; Hawbaker et al., 2017; LP DAAC, 2017, accessed November 12, 2017; Schroeder et al., 2014). Using GIS techniques, we will create daily clusters of fire points and use these
225 to calculate: (1) the distance to the nearest fire cluster by day and (2) the sum of Fire Radiative Power (FRP) of the nearest clusters of fires by day as it is likely that smoke levels are higher closer to fires. The MODIS product spans longer than our study period (2008-2014) at daily temporal resolution and has a spatial resolution of 1 km. VIIRS was launched in 2011 and has 12 h
230 temporal resolution with 750 m resolution. The BAECV can detect fires larger than 4 km² and provides an estimate of the date of the fire and is available from 1984-2015.

Classified land cover information from the Landsat-derived NLCD 2011 (Homer et al., 2017) will be used to calculate estimates of the percentage of
235 urban development (codes 22, 23, and 24), agriculture (codes 81 and 82), and vegetated area other than agricultural land (codes 21, 41, 42, 43, 52, and 71) within buffer radii of 100 m, 250 m, 500 m, and 1000 m around each monitor. The buffer distance that is most highly correlated with PM_{2.5} will be entered into each model. NLCD 2011 has a spatial resolution of 30 m and uses circa
240 2011 Landsat satellite data.

We will use snow cover data from the MODIS Snow Cover Daily L3 Global 500m Grid, Version 6 (MOD10A1 and MYD10A1) (Hall and Riggs, 2016) because snow coverage is a known contributor to wintertime PM_{2.5} concentrations in mountain valleys (Whiteman et al., 2014). Daily MOD10A1 and MYD10A1
245 data are available since 2002 and have 500 m spatial resolution.

Elevation can influence PM_{2.5} concentrations; for example, PM_{2.5} can accumulate in mountain valleys during persistent cold air pools (commonly referred to as inversions) during winter (Whiteman et al., 2014). We will get elevation data from the 3D Elevation Program, which has resolution of 1/3 arc-second.
250 This resolution is approximately 10 m north/south and varies east/west with latitude (USGS, 2017, accessed November 6, 2017).

We will obtain meteorological data from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) (Mesinger et al., 2006; NCEP, 2005) because it includes all of the standard
255 meteorological variables but also has planetary boundary layer height, which has proved to be an important variable for converting AOD to PM_{2.5} (Liu et al., 2005). We will calculate 24-hour averages from 3-hourly data for temperature,

relative humidity, sea level pressure, surface pressure, planetary boundary layer height, dew point temperature, precipitation, and the U and V components of wind speed. NARR has 32 km resolution and is available from 1979 onward.

Dust storm records will be included in the machine learning algorithm because they can be a significant indicator of airborne particulate matter from sources other than fires. Dust storm records are available from 1993-2017. The spatial resolution varies, but includes either forecast zone or county (US National Weather Service, 2017, accessed November 2, 2017a,, 2016, accessed November 2, 2017).

Since traffic emissions are a well-known source of $PM_{2.5}$, we will create a proxy for proximity to traffic emissions as the total distance of major roads within the buffer radii used for the land cover data. We will use the National Highways Planning Network, which includes approximately 450,000 miles of interstates, principal arterials, and rural minor arterials (Federal Highway Administration, 2017, accessed November 7, 2017).

We will also use total $PM_{2.5}$ and the fire-type source-apportioned $PM_{2.5}$ from the Comprehensive Air Quality Model with Extensions (CAMx) (Ramboll Environ, 2017, accessed November 7, 2017). See Data Sources for CAMx Modeling of Source-Attributed Air Quality Modeling (Section 2.1.1) below for further details about CAMx.

2.1.1. Data Sources for CAMx Modeling of Source-Attributed Air Quality Modeling

For meteorological inputs, the CAMx modeling will use archived daily 27-km Advanced Research Weather Research and Forecasting (WRF-ARW) grids available via NOAA Real-time Environmental Applications and Display sYstem (READY) servers for the entire study area and time period (Wang et al., 2007; Rolph et al., 2017). For the study years 2008-2012 and 2014, we will use fire emissions datasets prepared by the Western Regional Air Partnership (WRAP) and the National Emissions Inventory (NEI) (US EPA, 2017, accessed October 23, 2017) based on aggregated source-tagged fire occurrence data sources, the FCCS (Ottmar et al., 2007), and Consume (Prichard et al., 2009) modeling. For the study year 2013, we will prepare a fire emissions dataset using the same aggregated source-tagged fire occurrence data sources and FCCS/Consume modeling framework in the NASA-funded Wildland Fire Emissions Information System (WFEIS) (MTRI, 2017 accessed November 7, 2017) developed by Co-I's French and Billmire (French et al., 2014). Fire occurrence datasets include MODIS (MOD14/MYD14 and MCD64A1) and VIIRS (VNP14IMGTDL_NRT) fire data products (Giglio et al., 2006; LP DAAC, 2017, accessed November 12, 2017; Schroeder et al., 2014). For non-fire emissions during the entire study period, we will use the dataset prepared by WRAP for year 2008.

Statistical Analysis. [Describe statistical analysis here]

2.1.2. Spatiotemporal Surface of Total $PM_{2.5}$

In previous work (Reid et al., 2015), we used machine learning techniques to select among 10 statistical algorithms and 29 variables from globally available data sets for $PM_{2.5}$ for the 2008 northern California wildfires that had a CV- R^2 of 0.80 using the generalized boosting method (GBM), using 13 of the 29 predictor variables (Reid et al., 2015). When we re-analyzed the data with only certain subsets of the data, we found that tree-based algorithms such as GBM and random forest could get very high predictive performance (CV- R^2 values ≥ 0.70) with different satellite measures of AOD and meteorological data (see Figure 4 “Table 3 from Reid et al., 2015”). We will catalyze on this method to create a similar model for a much larger spatial area (11 western states: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming) and longer time period (2008-2014). This larger area and longer time period are necessary to have the statistical power to detect associations between $PM_{2.5}$ from prescribed fires and health, as prescribed fires tend to occur in more rural areas and at lower concentrations.

To make our daily fine spatial resolution total $PM_{2.5}$ model for the western US, we will use as potential predictor variables the data sets described in Data Sources for Machine Learning: Spatiotemporal Surface of $PM_{2.5}$ (Section 2.1). The model is trained on $PM_{2.5}$ values from monitoring data. All statistical modeling will be done in R (R Core Team, 2017) using the caret (Kuhn, 2017) and caretEnsemble (Mayer, 2017) packages. We will use 10-fold cross validation to select the optimal number of variables to minimize the root mean squared error (RMSE) for a given statistical algorithm. Comparing cross validated (CV) RMSE across algorithms can yield the optimal subset of covariates for the optimal statistical model. Although we hypothesize from our previous work and that of others (Reid et al., 2015; Brokamp et al., 2017; Pandey et al., 2013), that a tree-based model such as GBM or Random Forest will provide the best results, ensemble learners, models that combine results from multiple algorithms, are increasingly being used and often have higher predictive performance (Davies and van der Laan, 2016). Therefore, we will not only assess the performance of the following algorithms (generalized linear models, generalized additive models, random forest, generalized boosting models, elastic nets, multivariate adaptive regression splines, support vector machines, partial least squares, k nearest neighbors, and neural networks) that represent a diversity of statistical approaches, we will also assess if a linearized combination of these algorithms, one type of ensemble, improves predictive performance.

We will select the optimal algorithm or ensemble based on the smallest CV-RMSE, its agreement with observed data, characteristics of its residuals, and its model fit. We will set aside a portion of the $PM_{2.5}$ monitoring data as a validation data set that will not be used in any of the folds of training data in the machine learning algorithm. We will also calculate the RMSE that compares the validation data with the corresponding estimates from the optimal algorithm. The CV-RMSE of the model gives us a sense of the uncertainty in the model estimates that will then be used in the epidemiological analysis to

adjust for the error in using this model to estimate exposures (see below).

345 *2.1.3. Attribution of PM_{2.5} to Prescribed Fires and Wildfires*

Attributing PM_{2.5} to prescribed fire and wildfire requires (1) tagging fire occurrences by fire type, (2) calculating quantity and timing of emissions from those occurrences, and (3) tracking those emissions as they disperse throughout the atmosphere.

350 To achieve (1), we will take advantage of existing fire occurrence datasets that have been tagged by fire type. For years 2008, 2011, and 2014, we will use datasets developed for the EPA NEI using the SmartFire v2 information system (AirFire Team, 2017; Raffuse et al., 2009). SmartFire v2 aggregates fire occurrence data from multiple sources. Several of these sources include fire type designations, e.g., Incident Command Summary (ICS-209) reports by on-the-ground
355 fire managers and Monitoring Trends in Burn Severity (MTBS) (FEMA, 2017, accessed November, 2017; Eidenshink et al., 2007) Landsat-derived fire perimeters. For sources that do not include fire type designations (e.g., MODIS/VIIRS Active Fire and Burned Area Products), fire type is inferred based on land
360 cover (e.g., agricultural land cover is assumed to indicate prescribed agricultural burning) and timing (i.e. fires occurring during region-specific fire seasons are assumed to be wildfire). Under previous work, the Western Regional Air Partnership (WRAP), used similar methods to tag fire type to fire occurrence data sources for the non-NEI years 2009, 2010, and 2012. To fill out the 2008-
365 2014 time series, we will use the same methods to tag known and inferred fire type to ICS-209, MTBS, and MODIS- and VIIRS-derived fire occurrence data sources for 2013.

To achieve (2), we will rely on existing fire emissions datasets developed via the BlueSky (US Forest Service Air Fire Team, 2017, accessed November
370 1, 2017) modeling framework for NEI (2008, 2011, 2014) and by WRAP (2009, 2010, 2012). For 2013, we will calculate emissions using the 2013 fire occurrence datasets described in (1) and the NASA-funded Wildland Fire Emissions Information System (WFEIS) (MTRI, 2017 accessed November 7, 2017) developed by Co-I's French and Billmire (French et al., 2014). The WFEIS uses the same
375 modeling framework used by both BlueSky for NEI and the Fire Emissions Tracking System (FETS) (Western Regional Air Partnership, 2017, accessed November 7, 2017) used by WRAP. This framework uses the 1-km Fuel Characteristic Classification System (FCCS) (Ottmar et al., 2007) fuelbed map as well as the Consume consumption calculator (Prichard et al., 2009). We will
380 use the same set of updated emissions factors used in FETS (see WRAP (2017, accessed November 7, 2017)). The output of this step will be daily geospatial representation of fire emissions for 2008-2014 tagged by fire type for the entire study area.

For (3), the fire emissions data described under (2) will be formatted for
385 input to the CAMx 6.40 gridded photochemical dispersion model (Ramboll Environ, 2017, accessed November 7, 2017). WRAP previously modeled source-apportioned fire emissions using CAMx for 2008 and 2011, and so we will model years 2009-2010 and 2012-2014 in CAMx with WRAPs consultation to ensure

similar parameterization to the 2008 and 2011 runs. CAMx was the photochemical model used by WRAP primarily due to its particulate source apportionment technology (PSAT) tool, allowing the tagging and tracking of the emissions sources that contribute to downwind particulate concentrations. We will prepare PSAT to track two fire types (wildfire and prescribed fire) as well as a third category indicating non-fire. For non-fire emissions inputs, we will use the baseline 2008 non-fire emissions dataset prepared by WRAP for all modeled years, with the assumption that non-fire emissions do not vary significantly from year to year. For meteorological inputs, we will use archived daily 27-km WRF-ARW grids available via NOAA READY servers (Wang et al., 2007; Rolph et al., 2017). We will use Message Passing Interface (MPI) and Open-MultiProcessing (Open-MP) multiprocessing approaches on MTRI’s computing cluster to expedite modeling runs. Outputs for this task will include daily 27-km grids of source-apportioned $PM_{2.5}$. For each $PM_{2.5}$ source and ZIP code, we will calculate daily mean $PM_{2.5}$ concentration as well as the ratio of that sources $PM_{2.5}$ to total $PM_{2.5}$. Uncertainty in smoke modeling outputs will be assessed by comparing surface-level CAMx modeled $PM_{2.5}$ concentrations to $PM_{2.5}$ monitor data from the monitoring data described above.

2.1.4. Measurement error

[Consider accounting for measurement error via a nonparametric bootstrap, see Keller et al. (2017) (not sure if this applies for the paper that is just on exposure)]

3. Performance Measures

During our project kick-off meeting, partners from state air quality and public health departments will present about their respective state-specific baseline performance measures on decision-making related to prescribed fires and wildfires. This will allow us to benchmark current decision-making processes, identify difficulties in communicating across state-level bureaucracy, and identify what information is limiting their decision-making. These states have already identified that a lack of information on health impacts associated with prescribed fires means that they are making decisions based on the assumption that the levels of $PM_{2.5}$ denote where health impacts occur, but that empirical evidence for historical fires could help inform or improve those decisions.

Some of the state partners have already provided us with information on how they currently measure performance related to fire smoke. For example, the department of health in Washington measures baseline performance as the levels of $PM_{2.5}$ and the number of deaths, hospitalizations, and emergency department visits for respiratory and cardiovascular health endpoints on days with smoke. New Mexico is trying to allow more prescribed fires in their interagency smoke coordination and communication plan that they review annually, but they get pushback from the public with many complaints about prescribed fire planning and smoke levels. They plan to measure baseline as the number of complaint

calls to the department of health and the environment department and then see if those numbers change after providing information to the public from our proposed project about associations between air pollution from prescribed fires and wildfires and respiratory and cardiovascular health.

435 For our project, we will use the following measures to denote performance:
(1) how much does each agency use empirical information of the health impacts of fires for their decision-making, and (2) how well do the public health and air quality managers in a given state collaborate/communicate with each other related to their decision-making related to prescribed and wildfires. We will
440 assess this repeatedly through the project. Therefore, we will be at an ARL 3 (detailed characterization of the user decision-making process completed) by the end of the first quarter of the grant, having started at ARL 2 (decision-making activity to be enhanced by the application identified).

In each annual meeting with the state partners, we will assess the extent to
445 which they are using health-based information in their smoke decision-making and that the results from our investigations are influencing those decisions. We hope to be at ARL 4 by the end of year 1 of the grant, and getting to ARL 7 by the end of the project. This will be demonstrated by states proving that they are using information on the health impacts of prescribed fires in their smoke
450 management plans and in their public health messaging during such fires. To get beyond ARL 7 we recognize will require further funding, which our group hopes to pursue during the third year of this grant such that the decision-making activity can be further enhanced with more health information. By engaging with our state-level health partners, we expect to learn more about their needs
455 in order to contribute to a sustained decision-making process.

4. Discussion

[text from NASA grant as starting point]

This work directly addresses NASA’s desire to “discover and demonstrate innovative and practical uses of Earth observations” by using several Earth
460 observations, including several MODIS, Landsat, and VIIRS products, to spatiotemporally estimate ground-level PM_{2.5} concentrations and combine this information with Medicare data so that we may better understand the health impacts of smoke from both prescribed fires and wildfires in the western US. Using satellite data and other Earth observations allows us to estimate air quality
465 in locations without air quality monitors. **Our results will be used by both state air quality managers in updating their smoke management plans and state health departments for targeted communication related to health-protective measures during prescribed fires and wildfires.** All of this work is directly applicable to NASA’s Health and Air Quality
470 Application area’s interest in the use of Earth observations in air quality management and public health. By working with the NASA Earth Science Division (ESD)/Applied Sciences socioeconomic consortium to coordinate our research and results, the work proposed could be of interest to other NASA Applied Sciences activities.

475 Our work falls under NASA’s Second Strategic Goal in the 2014 Strategic
Plan to “advance understanding of Earth and develop technologies to improve
the quality of life on our home planet” within the realm of Objective 2.2 to “ad-
vance knowledge of Earth as a system to meet the challenges of environmental
change, and to improve life on our planet.” Wildfires are a significant source of
480 air pollution that impacts the health of human populations, particularly in the
western US. Prescribed fires are one way to decrease high-intensity catastrophic
fires, but without empirical knowledge of the health impacts of prescribed fires
compared to wildfires, it is difficult for all stakeholders to come to consensus
about the use of prescribed fires. Our work will inform how the western US de-
485 cides to manage its forests to minimize health harms from ecologically necessary
fires on the landscape.

The relevance of our work to decision-makers in both air quality and public
health is apparent by the **incredible outpouring of support we have re-
ceived from WESTAR and EPHTN as well as their state partners.**
490 This is exemplified in the letters of support that are part of our proposal submis-
sion. We had more letters of support than we were allowed to submit with this
application, thus EPHTN and WESTAR leaders offered to compile one letter of
support from all of their state partners who were interested. The WESTAR let-
ter of support implies that all state air quality managers provide their support,
495 even though they are not enumerated. We also received individual letters of
support from some air quality managers before they knew about the combined
WESTAR letter. We have included the letter from Colorado as an example of
these letters that we also received from New Mexico and Washington.

5. Anticipated Results and Improvements

500 Many state smoke management programs were put into place to assist states
with implementing measures to reduce regional haze. Smoke management and
difficulties communicating across agencies are often seen as impediments to more
prescribed fires in the US (Sneeuwjagt et al., 2013). In addition to this, decisions
about when and where to set prescribed burns are made based on air quality,
505 but without information related to the health impacts associated with smoke
from wildfires and prescribed fires. Since these decisions are being made without
complete information, the baseline performance of these decisions is based on a
presumption that if the air quality impacts of the prescribed fire are low, then
the health impacts will also be low. According to our state partner collaborators,
510 no information on health impacts associated with smoke from prescribed fires
is known but just assumed because no one has yet done an analysis such as the
one presented here.

The state partners are enthusiastic about this project because it will provide
them with information to influence their smoke management planning and pub-
lic health messaging. For example, if we find that there are significant health
515 impacts of prescribed fires at levels below the national ambient air quality stan-
dard, this could cause smoke management plans to modify the use of prescribed
fires to have lower impacts on air quality. On the other hand, if we find that

there are no significant health impacts from prescribed fires, or that they begin to occur at higher levels of PM_{2.5}, then smoke management plans may be modified to allow more burning. Similarly in regards to public health decision-making, more targeted messaging for how to protect oneself during fires could be employed for different types of fires if there are indeed differential health impacts. Currently, messaging is the same regardless of fire type (US EPA, US Forest Service, US CDC, and California Air Resources Board, 2016).

Our project can provide information that will help at the state air program/state health department interface. In years 2 and 3, we have budgeted funds for members of the research team (a to-be-determined subset of Drs. Reid, Maestas, and French) to travel to conferences/meetings attended by the state air quality managers and by the state public health departments to update them on progress in the grant and disseminate results that can influence their decision-making.

Given that **the decision-making we aim to influence is done through combined intersections of air quality managers and public health professionals, our partnering with both groups is essential.** We have received enthusiastic support from all state air quality managers in our region who are part of WESTAR and all state public health departments who are part of EPHTN. By having support from both agencies in most states in our region (not all western states are part of EPHTN), we hope that we will have the most success in those states (Arizona, California, Colorado, New Mexico, Oregon, Utah, and Washington) for using empirical evidence of the health impacts of smoke from prescribed fires and wildfires. Through our collaboration with air quality managers in the other states (Idaho, Montana, Nevada, and Wyoming), we hope to make connections to their public health departments and provide them with data and results from our analyses. We recognize that this endeavor will be a long-term process that may not occur for all states within the three years of this project. As we learn more about the decision-making related to prescribed fires and the challenges each state has with effective communication, we will be able to identify ways forward through further projects and grants.

6. Transition & Sustainability Plan

Research translation to decision-making will be an on-going activity during our three-year project, and will proceed based on consultation with our state-level partners. The information that is co-developed between the research team and state decision-making partners will be the most impactful. We will have regular meetings with the research team and collaborators to ensure that we all understand the goals of the project and to update our decision-makers about our progress.

We will begin with a project kick-off in Boulder, Colorado at the beginning of the grant in summer 2018. We have budgeted funds for travel for many of our participants and will additionally have web-cast capabilities through Earth Lab at CU Boulder to involve those who cannot attend in person. Each spring,

the researchers will travel to a conference attended by the WESTAR state partners, such as the WESTAR business meeting, and one attended by the EPHTN states, such as the Environmental Public Health Tracking Workshop. To ensure
565 effective adoption of the information, it is essential for us to start the project on the same page of what the intended methods, outcomes, and uses of the data are by all parties.

Throughout the tenure of the grant, we will be meeting in person (at conferences the decision-makers attend) annually and by phone/internet biannually,
570 with the state air quality managers and public health professionals. These meetings will be ways to update our partners on our progress and hear from them about ways that we could better meet their informational needs related to decision making for prescribed fires and wildfires.

In the last year of the grant, we will survey our state partners about how
575 they intend to use the information we have provided, whether they will continue to use this information, and what information they still need for continued use of the information in prescribed fire decision making. Sustained development and transition of the products will depend on the needs identified through this process. Since data on health impacts from prescribed fire has not been available
580 before this project, we anticipate our project to be just the beginning of a long-term exchange of how valuable science-based information can be made useful for decision-making.

7. Acknowledgements

WESTAR, EPHTN (unless they are on the author's list)
585 PM_{2.5} data from the Uintah Basin were provided by Seth Lyman at Utah State University. [look over full documentation file to determine full list of acknowledgements]

8. Papers to cite/discuss in Introduction and/or Discussion

Westerling (2016b,a)

590 References

- Achtemeier, G., Brenner, J. D., Core, J. E., Ferguson, S. A., Hardy, C. C., Hermann, S. M., Jackson, B., Lahm, P., Leenhouts, B., Leuschen, T., Mutch, R. E., Ottmar, R. D., Peterson, Janice L. Reinhardt, T. R., Seamon, P., Wade, D., 2001. Smoke management guide for prescribed and wildland fires
595 2001 edition. National Wildfire Coordination Group, 1-226.
URL https://www.fs.fed.us/pnw/pubs/journals/pnw_2001_ottmar001.pdf
- AirFire Team, 2017. SmartFire Fire Information System. U.S. Forest Service, Pacific Northwest Research Station, Seattle, Washington, <https://www.airfire.org/smartfire/>.
600

- Bowman, D. M. J. S., Balch, J. K., Artaxo, P., Bond, W. J., Carlson, J. M.,
Cochrane, M. A., D’Antonio, C. M., DeFries, R. S., Doyle, J. C., Harrison,
S. P., Johnston, F. H., Keeley, J. E., Krawchuk, M. A., Kull, C. A., Marston,
J. B., Moritz, M. A., Prentice, I. C., Roos, C. I., Scott, A. C., Swetnam,
605 T. W., van der Werf, G. R., Pyne, S. J., 2009. Fire in the Earth System.
Science 324 (5926), 481–484.
URL <http://science.sciencemag.org/content/324/5926/481>
- Brokamp, C., Jandarov, R., Rao, M. B., LeMasters, G., Ryan, P., Feb. 2017.
Exposure assessment models for elemental components of particulate matter
610 in an urban environment: A comparison of regression and random forest
approaches. Atmospheric Environment 151, 1–11.
URL <http://dx.doi.org/10.1016/j.atmosenv.2016.11.066>
- Davies, M. M., van der Laan, M. J., May 2016. Optimal Spatial Prediction
Using Ensemble Machine Learning. The International Journal of Biostatistics
615 12 (1), 179–201.
- Dennison, P. E., Brewer, S. C., Arnold, J. D., Moritz, M. A., 2014. Large wildfire
trends in the western United States, 1984–2011. Geophysical Research Letters
41 (8), 2928–2933, 2014GL059576.
URL <http://dx.doi.org/10.1002/2014GL059576>
- 620 Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., Howard, S.,
2007. A Project for Monitoring Trends in Burn Severity. Fire Ecology 3 (1),
3–21.
URL [https://www.mtbs.gov/sites/default/files/inline-files/
Eidenshink-final.pdf](https://www.mtbs.gov/sites/default/files/inline-files/Eidenshink-final.pdf)
- 625 Federal Highway Administration, 2017, accessed November 7, 2017. The Na-
tional Highway Planning Network. [https://www.fhwa.dot.gov/planning/
processes/tools/nhpn/index.cfm](https://www.fhwa.dot.gov/planning/processes/tools/nhpn/index.cfm).
- FEMA, 2017, accessed November, 2017. Incident Status Summary (ICS 209).
<https://www.fema.gov/media-library/assets/documents/33539>.
- 630 French, N. H. F., McKenzie, D., Erickson, T., Koziol, B., Billmire, M., End-
sley, K. A., Scheinerman, N. K. Y., Jenkins, L., Miller, M. E., Ottmar, R.,
Prichard, S., 2014. Modeling Regional-Scale Wildland Fire Emissions with
the Wildland Fire Emissions Information System. Earth Interactions 18 (16),
1–26.
635 URL <https://doi.org/10.1175/EI-D-14-0002.1>
- Gan, R. W., Ford, B., Lassman, W., Pfister, G., Vaidyanathan, A., Fischer,
E., Volckens, J., Pierce, J. R., Magzamen, S., Mar. 2017. Comparison of
wildfire smoke estimation methods and associations with cardiopulmonary-
related hospital admissions. GeoHealth 1 (3), 122–136.

- 640 Giglio, L., Csiszar, I., Justice, C. O., 2006. Global distribution and seasonality
of active fires as observed with the Terra and Aqua Moderate Resolution
Imaging Spectroradiometer (MODIS) sensors. *Journal of Geophysical Re-*
search: Biogeosciences 111 (G2), g02016; [https://modis.gsfc.nasa.gov/](https://modis.gsfc.nasa.gov/data/dataproduct/mod14.php)
[data/dataproduct/mod14.php](https://modis.gsfc.nasa.gov/data/dataproduct/mod14.php).
645 URL <http://dx.doi.org/10.1029/2005JG000142>
- Haikerwal, A., Reisen, F., Sim, M. R., Abramson, M. J., Meyer, C. P., Johnston,
F. H., Dennekamp, M., 2015. Impact of smoke from prescribed burning: Is it a
public health concern? *Journal of the Air & Waste Management Association*
65 (5), 592–598, pMID: 25947317.
650 URL <http://dx.doi.org/10.1080/10962247.2015.1032445>
- Hall, D. K., Riggs, G. A., 2016. MODIS/Aqua Snow Cover Daily L3 Global
500m Grid, Version 6. NASA National Snow and Ice Data Center Distributed
Active Archive Center <http://dx.doi.org/10.5067/MODIS/MYD10A1.006>.
- Hawbaker, T. J., Vanderhoof, M. K., Beal, Y.-J., Takacs, J. D., Schmidt,
655 G. L., Falgout, J. T., Williams, B., Fairaux, N. M., Caldwell, M. K., Picotte,
J. J., Howard, S. M., Stitt, S., Dwyer, J. L., 2017. Mapping burned areas
using dense time-series of Landsat data. *Remote Sensing of Environment*
198 (Supplement C), 504 – 522.
URL [http://www.sciencedirect.com/science/article/pii/](http://www.sciencedirect.com/science/article/pii/S0034425717302857)
660 [S0034425717302857](http://www.sciencedirect.com/science/article/pii/S0034425717302857)
- Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J.,
Herold, N., Wickham, J., Megown, K., 2017. Completion of the 2011 National
Land Cover Database for the Conterminous United States Representing a
Decade of Land Cover Change Information. *Photogrammetric Engineering &*
665 *Remote Sensing* 81 (5), 345 – 354, <https://www.mrlc.gov/nlcd2011.php>.
- Keller, J. P., Chang, H. H., Strickland, M. J., Szpiro, A. A., May 2017. Measure-
ment Error Correction for Predicted Spatiotemporal Air Pollution Exposures.
Epidemiology 28 (3), 338–345.
- Kuhn, M., 2017. The caret Package: Classification and Regression Training.
670 <https://github.com/topepo/caret>.
- Liu, X., Huey, L. G., Yokelson, R. J., Selimovic, V., Simpson, I. J., Miller, M.,
Jimenez, J. L., Campuzano-Jost, P., Beyersdorf, A. J., Blake, D. R., Butter-
field, Z., Choi, Y., Crounse, J. D., Day, D. A., Diskin, G. S., Dubey, M. K.,
Fortner, E., Hanisco, T. F., Hu, W., King, L. E., Kleinman, L., Meinardi,
675 S., Mikoviny, T., Onasch, T. B., Palm, B. B., Peischl, J., Pollack, I. B., Ry-
erson, T. B., Sachse, G. W., Sedlacek, A. J., Shilling, J. E., Springston, S.,
St. Clair, J. M., Tanner, D. J., Teng, A. P., Wennberg, P. O., Wisthaler, A.,
Wolfe, G. M., 2017. Airborne measurements of western U.S. wildfire emissions:
Comparison with prescribed burning and air quality implications. *Journal of*
680 *Geophysical Research: Atmospheres* 122 (11), 6108–6129, 2016JD026315.
URL <http://dx.doi.org/10.1002/2016JD026315>

- Liu, Y., Sarnat, J. A., Kilaru, V., Jacob, D. J., Koutrakis, P., May 2005. Estimating ground-level PM_{2.5} in the eastern United States using satellite remote sensing. *Environ Sci Technol* 39 (9), 3269–78.
- 685 LP DAAC, 2017, accessed November 12, 2017. MCD64A1: MODIS/Terra and Aqua Burned Area Monthly L3 Global 500 m SIN Grid V006. https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd64a1_v006.
- Mayer, Z., 2017. caretEnsemble. <https://github.com/zachmayer/caretEnsemble>.
- 690
- McKenzie, D., French, N. H. F., Ottmar, R. D., 2012. National database for calculating fuel available to wildfires. *Eos, Transactions American Geophysical Union* 93 (6), 57–58.
URL <http://dx.doi.org/10.1029/2012E0060002>
- 695 Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., Jovi, D., Woollen, J., Rogers, E., Berbery, E. H., Ek, M. B., Fan, Y., Grumbine, R., Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., Shi, W., 2006. North American Regional Reanalysis. *Bulletin of the American Meteorological Society* 87 (3), 343–360.
- 700 URL <https://doi.org/10.1175/BAMS-87-3-343>
- MTRI, 2017 accessed November 7, 2017. Wildland Fire Emissions Information System. <http://wfeis.mtri.org/>.
- NASA, 2017, accessed November 2, 2017. What is the difference between dark target and deep blue? <https://darktarget.gsfc.nasa.gov/content/what-difference-between-dark-target-and-deep-blue>.
- 705
- NASA LAADS DAAC, 2017, accessed November 2, 2017a. MOD04_L2 - MODIS/Terra Aerosol 5-Min L2 Swath 10km. https://ladsweb.modaps.eosdis.nasa.gov/api/v1/productPage/product=MOD04_L2.
- NASA LAADS DAAC, 2017, accessed November 2, 2017b. MYD04_L2 - MODIS/Aqua Aerosol 5-Min L2 Swath 10km. https://ladsweb.modaps.eosdis.nasa.gov/api/v1/productPage/product=MYD04_L2.
- 710
- NCEP, 2005. NCEP North American Regional Reanalysis (NARR). <http://rda.ucar.edu/datasets/ds608.0/>.
- NOAA NCEI, 2017, accessed November 2, 2017. Satellite Data Access by Datasets. <https://www.ncdc.noaa.gov/data-access/satellite-data/satellite-data-access-datasets>.
- 715
- NOAA OSPO, 2017, accessed November 3, 2017. Hazard Mapping System Fire and Smoke Product. <http://www.ospo.noaa.gov/Products/land/hms.html>.

- 720 Ottmar, R. D., Sandberg, D. V., Riccardi, C. L., Prichard, S. J., 2007. An overview of the Fuel Characteristic Classification System Quantifying, classifying, and creating fuelbeds for resource planning. *Canadian Journal of Forest Research* 37 (12), 2383–2393.
URL <https://doi.org/10.1139/X07-077>
- 725 Pandey, G., Zhang, B., Jian, L., 2013. Predicting submicron air pollution indicators: a machine learning approach. *Environmental Science-Processes & Impacts* 15 (5), 996–1005.
URL <http://pubs.rsc.org/ezp-prod1.hul.harvard.edu/en/content/articlepdf/2013/em/c3em30890a>
- 730 Prichard, S. J., Ottmar, R. D., Anderson, G. A., 2009. Consume 3.0 user’s guide. USDA Forest Service Pacific Wildland Fire Sciences Laboratory Rep., 239.
URL https://www.fs.fed.us/pnw/fera/research/smoke/consume/consume30_users_guide.pdf
- 735 R Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, <https://www.R-project.org/>.
- Raffuse, S. M., Pryden, D. A., Sullivan, D. C., Larkin, N. K., Strand, T., Solomon, R., 2009. SMARTFIRE Algorithm Description. Sonoma Technology, Inc. and US Forest Service, AirFire Team, Pacific Northwest Research Laboratory, 9.
740 URL https://www.researchgate.net/profile/Sean_Raffuse/publication/267251248_SMARTFIRE_Algorithm_Description/links/5527ef060cf2e089a3a218f0.pdf
- 745 Ramboll Environ, 2017, accessed November 7, 2017. A multi-scale photochemical modeling system for gas and particulate air pollution. <http://www.camx.com/>.
- Reid, C. E., Jerrett, M., Petersen, M. L., Pfister, G. G., Morefield, P. E., Tager, I. B., Raffuse, S. M., Balmes, J. R., Mar. 2015. Spatiotemporal prediction
750 of fine particulate matter during the 2008 northern California wildfires using machine learning. *Environ Sci Technol* 49 (6), 3887–96.
URL <http://pubs.acs.org/doi/10.1021/es505846r>
- Reid, C. E., Jerrett, M., Tager, I. B., Petersen, M. L., Mann, J. K., Balmes, J. R., Oct. 2016. Differential respiratory health effects from the 2008 northern
755 California wildfires: A spatiotemporal approach. *Environ Res* 150, 227–35.
- Rolph, G., Stein, A., Stunder, B., 2017. Real-time Environmental Applications and Display sYstem: READY. *Environmental Modelling & Software* 95 (Supplement C), 210 – 228.
URL <http://www.sciencedirect.com/science/article/pii/S1364815217302360>
760

- Sayer, A. M., Hsu, N. C., Bettenhausen, C., Jeong, M.-J., 2013. Validation and uncertainty estimates for MODIS Collection 6 Deep Blue aerosol data. *Journal of Geophysical Research: Atmospheres* 118 (14), 7864–7872.
URL <http://dx.doi.org/10.1002/jgrd.50600>
- 765 Schoennagel, T., Balch, J. K., Brenkert-Smith, H., Dennison, P. E., Harvey, B. J., Krawchuk, M. A., Mietkiewicz, N., Morgan, P., Moritz, M. A., Rasker, R., Turner, M. G., Whitlock, C., 2017. Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences* 114 (18), 4582–4590.
770 URL <http://www.pnas.org/content/114/18/4582.abstract>
- Schroeder, W., Oliva, P., Giglio, L., Csiszar, I. A., 2014. The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sensing of Environment* 143 (Supplement C), 85 – 96.
URL <http://www.sciencedirect.com/science/article/pii/S0034425713004483>
775
- Schweizer, D. W., Cisneros, R., 2017. Forest fire policy: change conventional thinking of smoke management to prioritize long-term air quality and public health. *Air Quality, Atmosphere & Health* 10 (1), 33–36.
- Sneeuwjagt, R. J., Kline, T. S., Stephens, S. L., 2013. Opportunities for improved fire use and management in California: lessons from Western Australia. *Fire Ecology* 9 (2).
780
- Steel, Z. L., Safford, H. D., Viers, J. H., 2015. The fire frequency-severity relationship and the legacy of fire suppression in California forests. *Ecosphere* 6 (1), 1–23, art8.
785 URL <http://dx.doi.org/10.1890/ES14-00224.1>
- Stephens, S. L., Ruth, L. W., 2005. Federal Forest-Fire Policy in the United States. *Ecological Applications* 15 (2), 532–542.
URL <http://dx.doi.org/10.1890/04-0545>
- Torvela, T., Tissari, J., Sippula, O., Kaivosoja, T., Leskinen, J., Virn, A., Lhde, A., Jokiniemi, J., 2014. Effect of wood combustion conditions on the morphology of freshly emitted fine particles. *Atmospheric Environment* 87 (Supplement C), 65 – 76.
790 URL <http://www.sciencedirect.com/science/article/pii/S1352231014000454>
- 795 US EPA, 2017, accessed November 2, 2017a. AQS Memos - Technical Note on Reporting PM2.5 Continuous Monitoring and Speciation Data to the Air Quality System (AQS). <https://www.epa.gov/aqs/aqs-memos-technical-note-reporting-pm25-continuous-monitoring-and-speciation-data-air-quality>.
- US EPA, 2017, accessed November 2, 2017b. Outdoor Air Quality Data Download Daily Data. <https://www.epa.gov/outdoor-air-quality-data/download-daily-data>.
800

- US EPA, 2017, accessed November 2, 2017c. Parameters. <https://aqs.epa.gov/aqsweb/documents/codetables/parameters.html>.
- US EPA, 2017, accessed November 2, 2017d. PM 2.5 - Visibility (IMPROVE).
805 <https://www3.epa.gov/ttnamti1/visdata.html>.
- US EPA, 2017, accessed November 2, 2017e. Sampling Methods for All Parameters. https://aqs.epa.gov/aqsweb/documents/codetables/methods_all.html.
- US EPA, 2017, accessed November 9, 2017. Particulate Matter (PM2.5) Trends.
810 <https://www.epa.gov/air-trends/particulate-matter-pm25-trends#pmreg>.
- US EPA, 2017, accessed October 23, 2017. National Emissions Inventory (NEI). <https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei>.
- 815 US EPA, US Forest Service, US CDC, and California Air Resources Board, 2016. Wildfire Smoke: A Guide for Public Health Officials Revised July 2016. Tech. rep., https://www3.epa.gov/airnow/wildfire_may2016.pdf.
- US Forest Service Air Fire Team, 2017, accessed November 1, 2017. BlueSky Modeling Framework. <https://www.airfire.org/bluesky/>.
- 820 US National Weather Service, 2016, accessed November 2, 2017. National Weather Service Instruction 10-1605. <https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf>.
- US National Weather Service, 2017, accessed November 2, 2017a. Storm Events Database. <https://www.ncdc.noaa.gov/stormevents/>.
- 825 US National Weather Service, 2017, accessed November 2, 2017b. Storm Events Database: Database Details. <https://www.ncdc.noaa.gov/stormevents/details.jsp>.
- USGS, 2017, accessed November 6, 2017. About 3DEP Products and Services. https://nationalmap.gov/3DEP/3dep_prodserv.html.
- 830 van Donkelaar, A., Martin, R. V., Levy, R. C., da Silva, A. M., Krzyzanowski, M., Chubarova, N. E., Semutnikova, E., Cohen, A. J., Nov. 2011. Satellite-based estimates of ground-level fine particulate matter during extreme events: A case study of the Moscow fires in 2010. *Atmospheric Environment* 45 (34), 6225–6232.
- 835 URL <http://www.sciencedirect.com/science/article/pii/S135223101100851X>http://ac.els-cdn.com/S135223101100851X/1-s2.0-S135223101100851X-main.pdf?_tid=ecd8cc88-458d-11e3-90eb-00000aabb0f26&acdnat=1383596341_3fc7642a69ed4ac2c8b75e979619a1e5

- 840 Wang, W., Barker, D., Bray, J., Bruyere, C., Duda, M., Dudhia, J., Gill, D.,
Michalakes, J., 2007. Users Guide for Advanced Research WRF (ARW) Mod-
eling System Version 3. Mesoscale and Microscale Meteorology DivisionNa-
tional Center for Atmospheric Research (MMM-NCAR).
- 845 Westerling, A. L., 2016a. Correction to ‘increasing western us forest wildfire
activity: sensitivity to changes in the timing of spring’. *Philosophical Trans-
actions of the Royal Society of London B: Biological Sciences* 371 (1707).
URL [http://rstb.royalsocietypublishing.org/content/371/1707/
20160373](http://rstb.royalsocietypublishing.org/content/371/1707/20160373)
- 850 Westerling, A. L., Jun. 2016b. Increasing western US forest wildfire activity:
sensitivity to changes in the timing of spring. *Philos Trans R Soc Lond B
Biol Sci* 371 (1696), bibtex: westerling.increasing.2016.
URL [http://rstb.royalsocietypublishing.org/content/371/1696/
20150178](http://rstb.royalsocietypublishing.org/content/371/1696/20150178)
- 855 Western Regional Air Partnership, 2017, accessed November 7, 2017. WRAP
fets. <http://wrapfets.org/>.
- Whiteman, C. D., Hoch, S. W., Horel, J. D., Charland, A., 2014. Relationship
between particulate air pollution and meteorological variables in Utah’s Salt
Lake Valley. *Atmospheric Environment* 94 (Supplement C), 742 – 753.
URL [http://www.sciencedirect.com/science/article/pii/
860 S1352231014004580](http://www.sciencedirect.com/science/article/pii/S1352231014004580)
- Williamson, G. J., Bowman, D. M. J. S., Price, O. F., Henderson, S. B., John-
ston, F. H., 2016. A transdisciplinary approach to understanding the health
effects of wildfire and prescribed fire smoke regimes. *Environmental Research
Letters* 11 (12), 125009.
865 URL <http://stacks.iop.org/1748-9326/11/i=12/a=125009>
- WRAP, 2017, accessed November 7, 2017. Particulate Matter Deterministic &
Empirical Tagging & Assessment of Impacts on Levels. [https://pmdetail.
wraptools.org/](https://pmdetail.wraptools.org/).

9. PM2.5 Surface Paper Notes

870 9.1. *Papers published in Atmospheric Environment used as style example*

Need to go through these papers

- Brokamp et al. (2017) (partially done, done through abstract)

9.2. *Notes on Papers*

Put in Brokamp et al. (2017)