Wildfire Exposures: Understanding Health Effects from Unnatural Disasters

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Why should we care about wildfire exposures?

Hill and Woosley Fire Complex Ventura, CA, 2018
Number of Fires Increased Everywhere over 20th Century

Figure 16.8. Number of Recorded Wild Fires by Continent and Decade in Twentieth Century (OFDA/CRED)
Acres Burned in Wildland Fires in the U.S. 1985-2012
Data Source: National Interagency Fire Center
Figure 8. Across the West, the first wildfires of the year are starting earlier and the last fires are starting later than they were 40 years ago, which has extended the average wildfire season by about 75 days.
Climate Change likely to Increase Risk of Wildfires

Source: adapted from Barbero et al. 2015
Wildfires Contribute to Carbon Release and Climate Change

- In California, forest lands which, as of 2014, represents 54% of total land area and contains 85% of the total carbon stocks

- But due to forest mismanagement, forests in CA actually release huge amounts of carbon

- $19.7 \times 10^6$ metric tons of carbon (MMTC) released 2012-2014
Fires are Bigger and Occurring at Urban-Wildland Interface
Fires are Bigger and Occurring at Urban-Wildland Interface
Implications of the Size and Location of Wildfires

Tom Wordell, wildfire analyst, National Interagency Fire Center in Boise, Idaho:

"I don't want to be callous, because many people are homeless and suffering, but if you live in a snake pit, you're going to get bit."

2 Key Implications:
1. More development in fire prone areas increases risk of fire due to human negligence
2. Greater human exposures to smoke, pollutants, and psychosocial stress
Wildfires and Crop Burning are Globally Significant
Estimates of the annual average (1997–2006) global mortality attributable to Wildfires (Total Burden 562,000)
Emissions from Wildfires with Health Concerns

Primary air pollutants

- Carbon monoxide (CO)
- Nitrogen dioxide (NO₂)
- Polycyclic aromatic hydrocarbons (PAHs)
- Volatile organic compounds (VOCs)
- Particulate Matter (PM)

Secondary air pollutants

- Particulate Matter (PM)
- Ozone (O₃)
Exposure Assessment Difficulties

• Sparse air pollutant monitoring network
  Many PM$_{2.5}$ monitors only measure every sixth or third day
• Leads to spatial and temporal averaging of exposure measurements
  • But, smoke plumes migrate quickly, changing exposures over smaller spatial and temporal scales
  • Many health effects studies likely have large measurement error bias
Spatiotemporal Prediction of Fine Particulate Matter During the 2008 Northern California Wildfires Using Machine Learning

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Methods – Adapt Land Use Regression Modeling with Machine Learning

Image courtesy of Mike Jerrett
Methods – Adapt Land Use Regression Modeling with Machine Learning

- Include novel spatiotemporal datasets
- Apply machine learning methods to
  - Select from a long list of predictor variables
  - Select from a variety of statistical algorithms

Image courtesy of Mike Jerrett
PM$_{2.5}$ Monitoring (2008 Wildfire Event)

• 121 PM$_{2.5}$ Monitors
  • Environmental Protection Agency (EPA), California Air Resources Board (CARB), US Forest Service (USFS)
  • 38 Federal Reference Method (FRM)
  • 16 other gravimetric
  • 67 Beta Attenuation Monitors (BAMs)

• Co-located Federal Equivalent Method (FEM) monitors agree with FRM (Pearson r values 0.94 – 1.00).
<table>
<thead>
<tr>
<th>Variables</th>
<th>Data Source</th>
<th>Temporal Resolution</th>
<th>Spatial Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM$_{2.5}$ from monitoring stations (N=112)</td>
<td>US EPA, California Air Resources Board, Air Districts, and US Forest Service</td>
<td>Daily or hourly</td>
<td></td>
</tr>
<tr>
<td><strong>Spatiotemporal Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GASP aerosol optical depth (AOD)</td>
<td>National Oceanic and Atmospheric Administration</td>
<td>Half-hourly, daylight 4 km</td>
<td>4 km</td>
</tr>
<tr>
<td>MODIS AOD</td>
<td>NASA</td>
<td>Twice daily</td>
<td>10 km</td>
</tr>
<tr>
<td>Local AOD</td>
<td>Sonoma Technology, Inc.</td>
<td>Daily</td>
<td>0.5 km</td>
</tr>
<tr>
<td>WRF-Chem PM$_{2.5}$ (µg/m$^3$)</td>
<td>National Center for Atmospheric Research</td>
<td>Hourly</td>
<td>12 km</td>
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<tr>
<td>Distance to nearest cluster of active fires (m)</td>
<td>Derived from USDA Forest Service Remote Sensing Applications Center</td>
<td>Daily</td>
<td></td>
</tr>
<tr>
<td>Counts of fires in nearest cluster / distance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative Humidity (%)</td>
<td>Rapid Update Cycle</td>
<td>Daily</td>
<td>13 km</td>
</tr>
<tr>
<td>Sea level pressure (Pa)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface pressure (Pa)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Planetary boundary layer height (m)</td>
<td></td>
<td></td>
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<tr>
<td>U-component of wind speed (m/s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V-component of wind speed (m/s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dew point temperature (K)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature at 2 m (K)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>Spatial Variables</strong></td>
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<td></td>
<td></td>
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<tr>
<td>X-coordinate (m)</td>
<td>U.S. Environmental Protection Agency Air Quality System</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y-coordinate (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counts of traffic within 1 km</td>
<td>Dynamap 2000, TeleAtlas</td>
<td>Annual</td>
<td>1 km</td>
</tr>
<tr>
<td>% of urban land use within 1km</td>
<td>2006 National Land Cover Database</td>
<td></td>
<td>1 km</td>
</tr>
<tr>
<td>% of agricultural land use within 1km</td>
<td>California Air Resources Board</td>
<td></td>
<td>1 km</td>
</tr>
<tr>
<td>% of vegetation land use within 1km</td>
<td>2006 National Land Cover Database</td>
<td></td>
<td>1 km</td>
</tr>
<tr>
<td>Any High intensity land use within 1km</td>
<td>2006 National Land Cover Database</td>
<td></td>
<td>1 km</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>National Elevation Dataset 2010</td>
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<tr>
<td>Binary indicator variables for air basin</td>
<td>California Air Resources Board</td>
<td>Air Basin</td>
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<tr>
<td>Population Density</td>
<td>U.S. Census 2000</td>
<td>Block Group</td>
<td></td>
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<tr>
<td><strong>Temporal Variables</strong></td>
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<td></td>
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</tr>
<tr>
<td>Julian Date</td>
<td></td>
<td>Daily</td>
<td></td>
</tr>
<tr>
<td>Weekend</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
Statistical Algorithms

- Random Forest
- Tree bagging
- Generalized Boosting Models (GBM)
- Generalized Linear Models (GLM)
- GLM with penalized maximum likelihood (glmnet)
- Multivariate adaptive regression splines (Earth)
- Lasso regression
- Ridge regression
- Support Vector Machines
- Gaussian Processes
- Generalized Additive Models (GAM)
- K nearest neighbors regression
### Table 2. CV-RMSE and CV-\( R^2 \) Values for the Best Model Across the 11 Algorithms

<table>
<thead>
<tr>
<th>Model</th>
<th>CV-RMSE (( \mu g/m^3 ))</th>
<th>CV-( R^2 )</th>
<th>No. of variables selected</th>
<th>Model with fewer variables whose CV-RMSE was within 1.5% of the smallest CV-RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>random forest</td>
<td>1.513</td>
<td>0.796</td>
<td>20</td>
<td>1.521</td>
</tr>
<tr>
<td>bagged trees</td>
<td>1.687</td>
<td>0.672</td>
<td>27</td>
<td>1.696</td>
</tr>
<tr>
<td>generalized boosting model</td>
<td>1.489</td>
<td>0.803</td>
<td>29</td>
<td>1.495</td>
</tr>
<tr>
<td>elastic net regression</td>
<td>1.848</td>
<td>0.538</td>
<td>28</td>
<td>1.852</td>
</tr>
<tr>
<td>multivariate adaptive regression splines</td>
<td>1.642</td>
<td>0.701</td>
<td>28</td>
<td>1.648</td>
</tr>
<tr>
<td>lasso regression</td>
<td>1.821</td>
<td>0.558</td>
<td>28</td>
<td>1.834</td>
</tr>
<tr>
<td>support vector machines</td>
<td>1.556</td>
<td>0.761</td>
<td>16</td>
<td>1.561</td>
</tr>
<tr>
<td>gaussian processes</td>
<td>1.580</td>
<td>0.746</td>
<td>16</td>
<td>1.591</td>
</tr>
<tr>
<td>generalized linear model</td>
<td>1.821</td>
<td>0.558</td>
<td>29</td>
<td>1.834</td>
</tr>
<tr>
<td>K-nearest neighbors</td>
<td>2.030</td>
<td>0.387</td>
<td>2</td>
<td>2.044</td>
</tr>
<tr>
<td>generalized additive model</td>
<td>1.607</td>
<td>0.725</td>
<td>26</td>
<td>1.609</td>
</tr>
</tbody>
</table>
Observed on Predicted

GBM = Generalized Boosting Model; logPM2.5 = natural logarithm of the fine particulate matter concentration
Predictions with Smoke Plume Shown

![Image showing predictions with smoke plume shown. The image contains satellite or aerial imagery with color-coded areas indicating different pollution levels: <15, 15-35, 35-55, 55-75, >75 μg/m³.](image-url)
Exposure Assessment

• Expensive and challenging

• Human mobility another critical factor as many people evacuate

• How do we automate modeling and get people to volunteer their geographic information during fires?
What are the health effects from exposure to wildfire smoke?

• Clear evidence of respiratory health effects

• Particularly for exacerbation of asthma, Chronic Obstructive Pulmonary Disease (COPD)

• But mostly null findings for cardiovascular outcomes

• Open question as to why a difference exists between the two outcomes (more from John Balmes soon)

Source: Reid et al. Critical review of health impacts of wildfire smoke exposure. Pending publication in *Environmental Health Perspectives*
Wildfire Smoke and Mortality

• Clear evidence of wildfire smoke impacts on all-cause mortality
  • But no clear evidence for specific causes of mortality such as respiratory or cardiovascular deaths
Fires effect on birth weight

Table 2. Estimated effect of wildfire event during gestation on birth weight (g), by trimester.

<table>
<thead>
<tr>
<th>Trimester of exposure</th>
<th>Effect (g)</th>
<th>95% CI</th>
<th>Adjusted model</th>
<th>Effect (g)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Third (≥29 weeks)</td>
<td>-7.9</td>
<td>(-12.8, -3.1)</td>
<td>-7.0</td>
<td>(-11.8, -2.2)</td>
<td></td>
</tr>
<tr>
<td>Second (17–28 weeks)</td>
<td>-17.1</td>
<td>(-21.9, -12.3)</td>
<td>-9.7</td>
<td>(-14.5, -4.8)</td>
<td></td>
</tr>
<tr>
<td>First (1–16 weeks)</td>
<td>-3.9</td>
<td>(-7.8, 0.0)</td>
<td>-3.3</td>
<td>(-7.2, 0.6)</td>
<td></td>
</tr>
<tr>
<td>Any trimester</td>
<td>-8.8</td>
<td>(-11.5, -6.1)</td>
<td>-6.1</td>
<td>(-8.7, -3.5)</td>
<td></td>
</tr>
</tbody>
</table>

Adjusted model includes terms for fetal sex, gestational age, parity, maternal age, maternal education, maternal race/ethnicity, secular trend, and season.
Mental Health

• Most studies of mental health with wildfires find evidence of various mental health impacts of wildfire smoke exposure including post traumatic stress disorder (PTSD), depression
  • Many of these studies are of populations that were not just exposed to smoke but also were evacuated or lost property or loved ones
  • Effects of “Solacetalgia” see Eisenman et al. 2015
  • Concerns about self-report of both exposure and health endpoints in many of these studies
Who is most vulnerable?

• Age
  • Some studies find older adults are more vulnerable
  • Some studies find younger adults are more vulnerable

• Pre-existing conditions
  • Only a few studies have looked at this with mixed results
  • But exacerbations of asthma and Chronic Obstructive Pulmonary Disease (COPD) are the clearest health findings for wildfire smoke

Reid et al. 2016 *EHP*
Who is most vulnerable?

• Socio-economic status (SES)
  • No differential effects by SES in British Columbia (Henderson et al. 2011)
  • More vulnerable in lower income areas found in studies in North Carolina (Rappold et al. 2012), California (Reid et al. 2016), and the western US (Liu et al. 2017)

• Race-ethnicity
  • Elderly Blacks had higher respiratory admissions associated with wildfires than elderly Whites in western US (Liu et al. 2017)
  • Indigenous Australians (Johnston et al. 2007; Hanigan et al. 2008)
Who is most vulnerable?
Uncertainties in the Evidence

- Why we have different findings for cardiovascular disease (CVD) that we see with “normal” air pollution?
- Who are the vulnerable populations?
- What other health endpoints related to smoke not yet studied (diabetes, hypertension)?
- What are the chronic health impacts of repeated exposures to wildfires – which is likely the new normal under likely climate change scenarios?
- What is the effectiveness of different public health interventions?
- What are health impacts of other air pollutants from wildfires not just PM (e.g. ozone)?
- How do we assess mobility (e.g., evacuations) on exposures?
- How long do particles persist indoors and how do they transform into air toxics?
Acknowledgements

• Prof. Colleen Reid for sharing her slides

• Joint Fire Science Research Program and the Environmental Protective Agency STAR program for funding
References