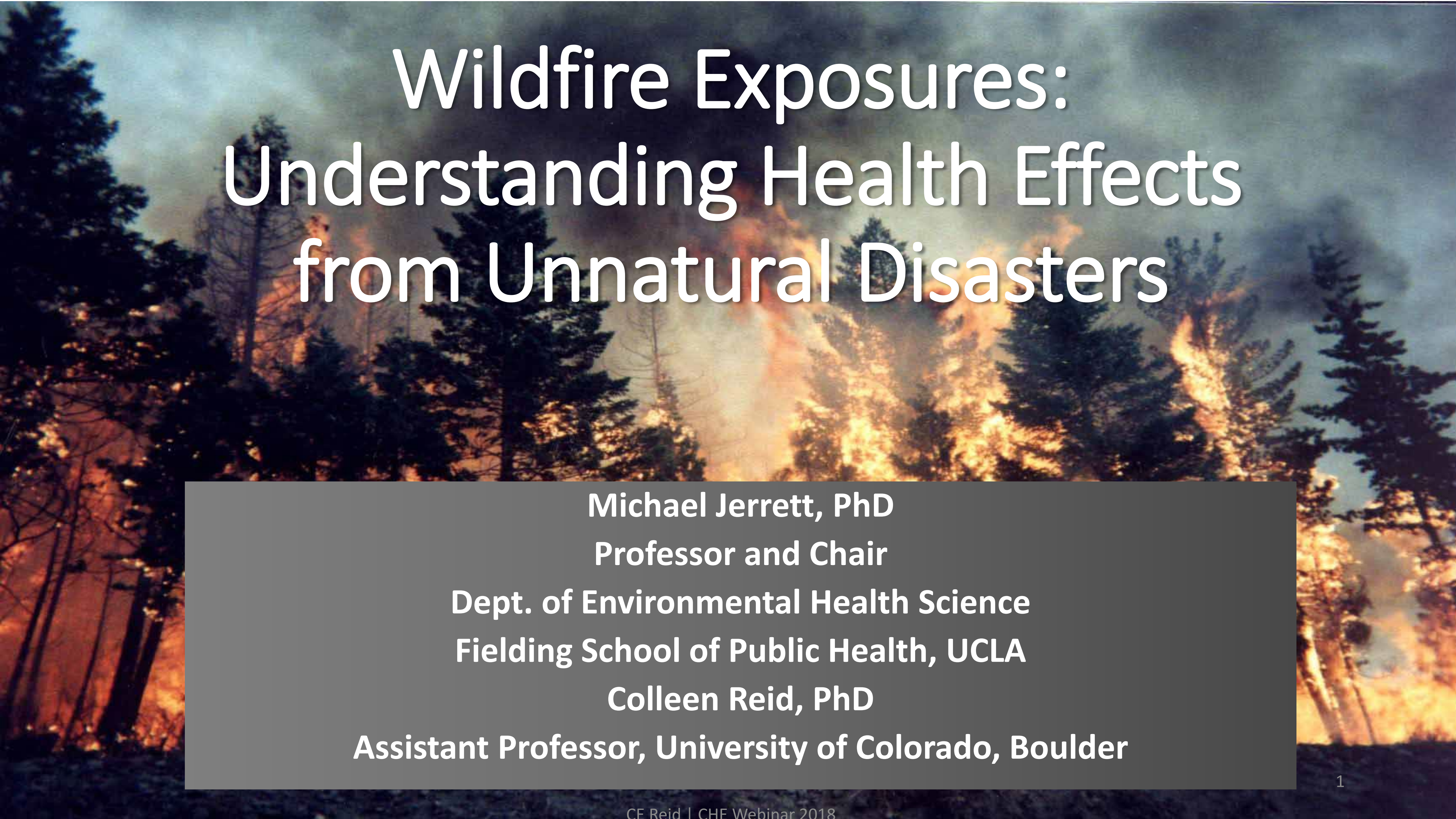
Wildfire Exposures: Understanding Health Effects from Unnatural Disasters



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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

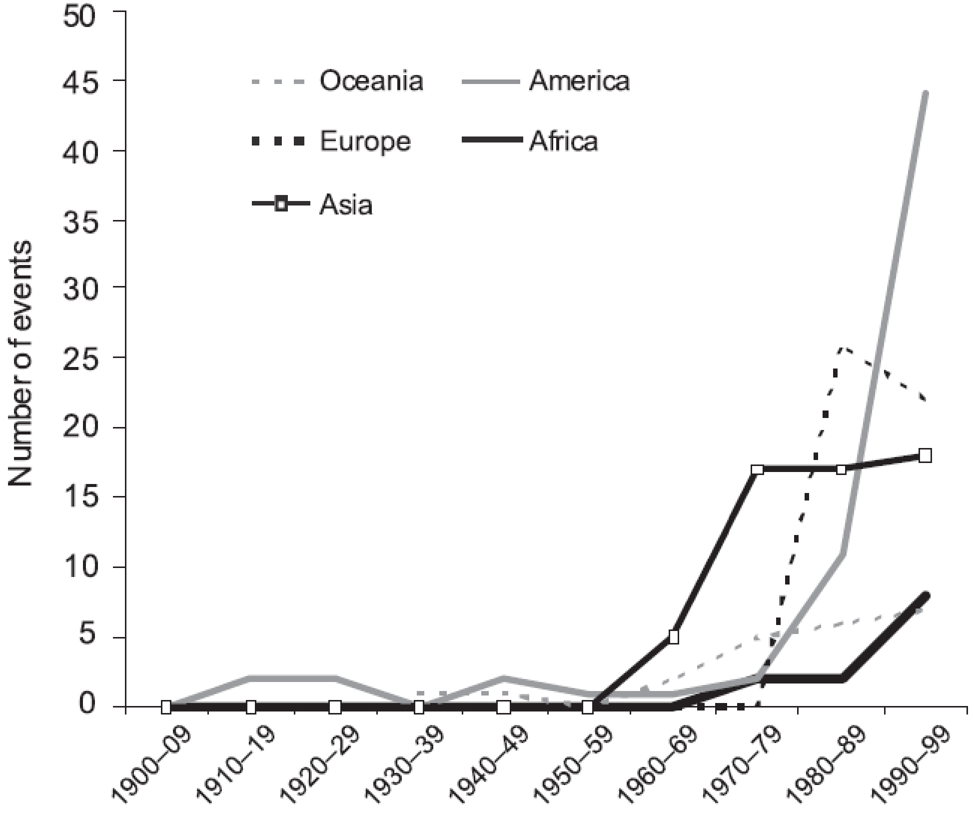
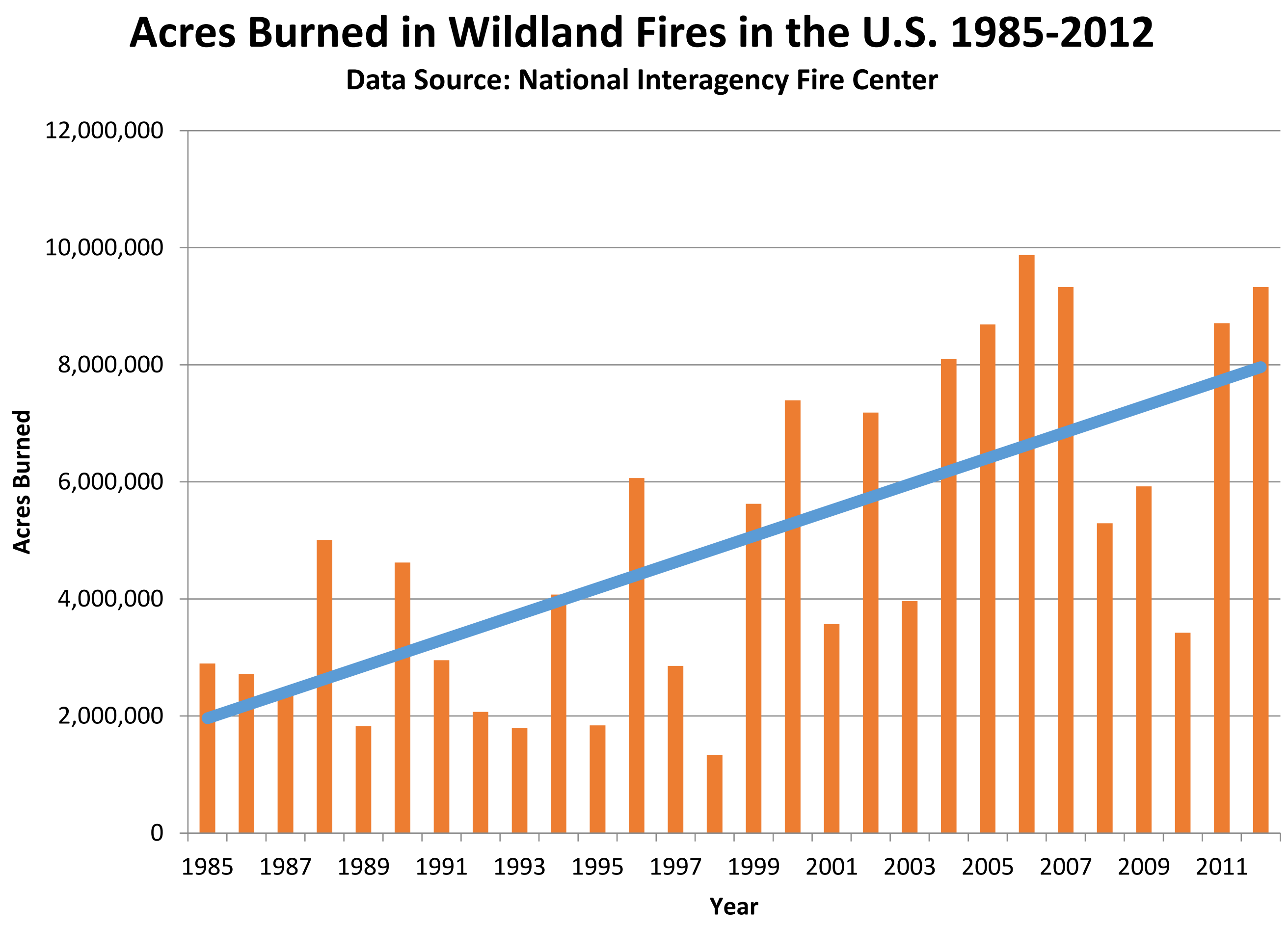


Figure 16.8. Number of Recorded Wild Fires by Continent and Decade in Twentieth Century (OFDA/CRED)

Millenium Ecosystem Assessment
2005


Acres Burned in Wildland Fires in the U.S. 1985-2012
Data Source: National Interagency Fire Center
Acres Burned
12,000,000
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
Year

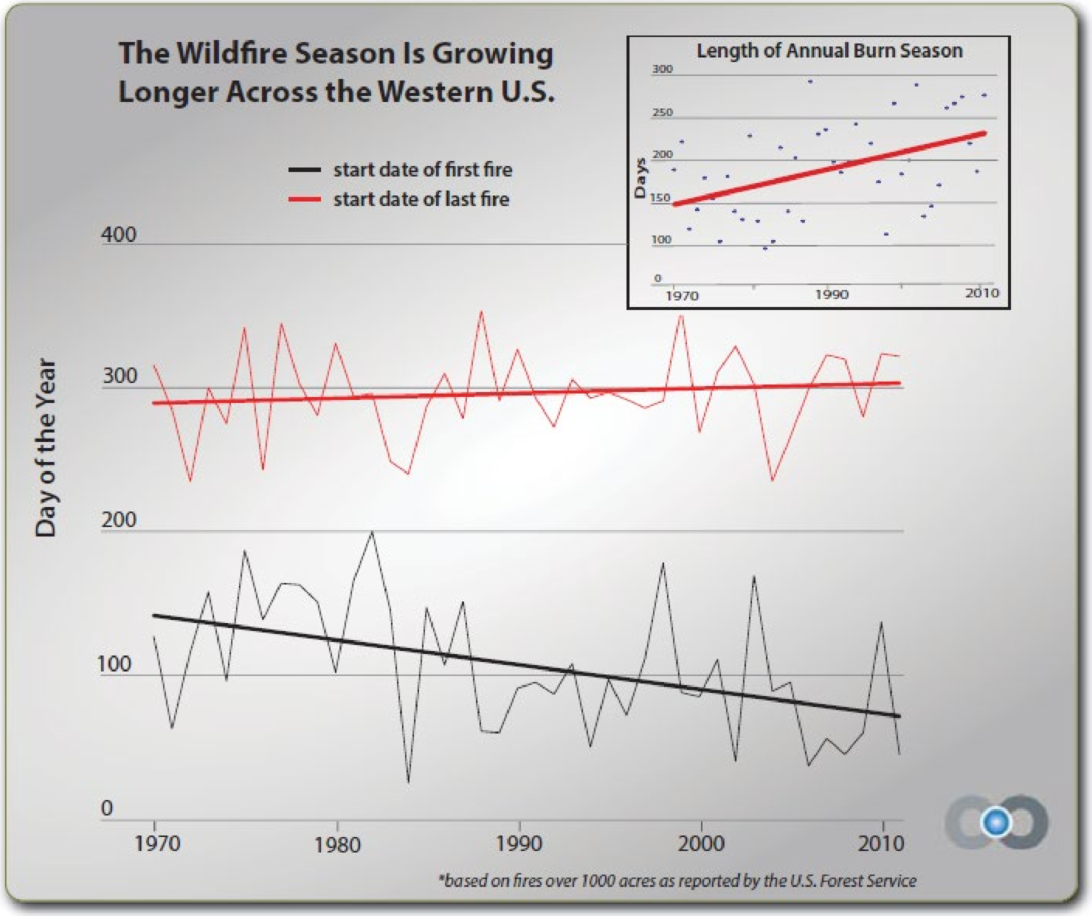
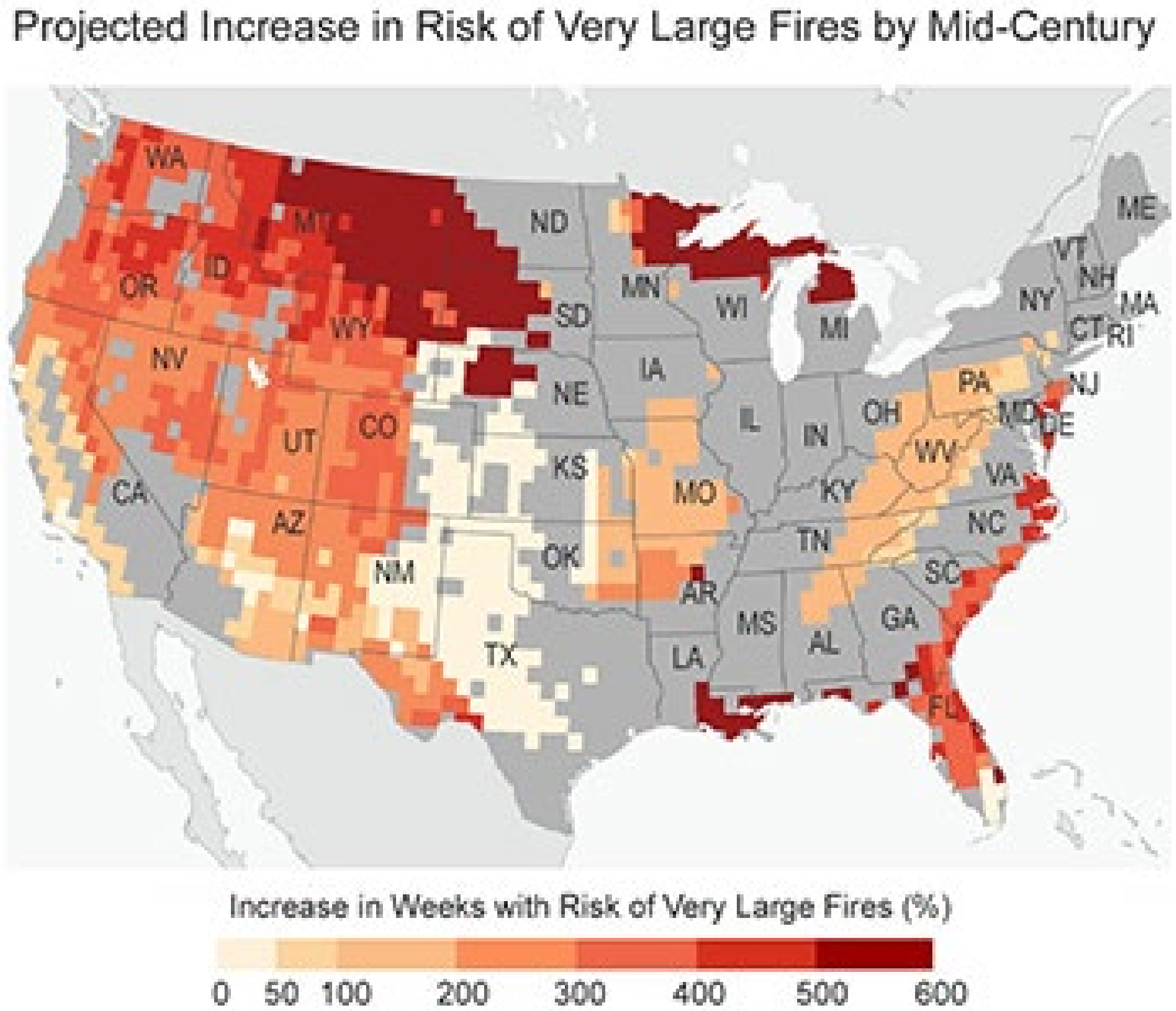


Figure 8. Across the West, the first wildfires of the year are starting earlier and the last fires are starting later than they were 40 years ago, which has extended the average wildfire season by about 75 days.

www.climatecentral.org

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 * 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

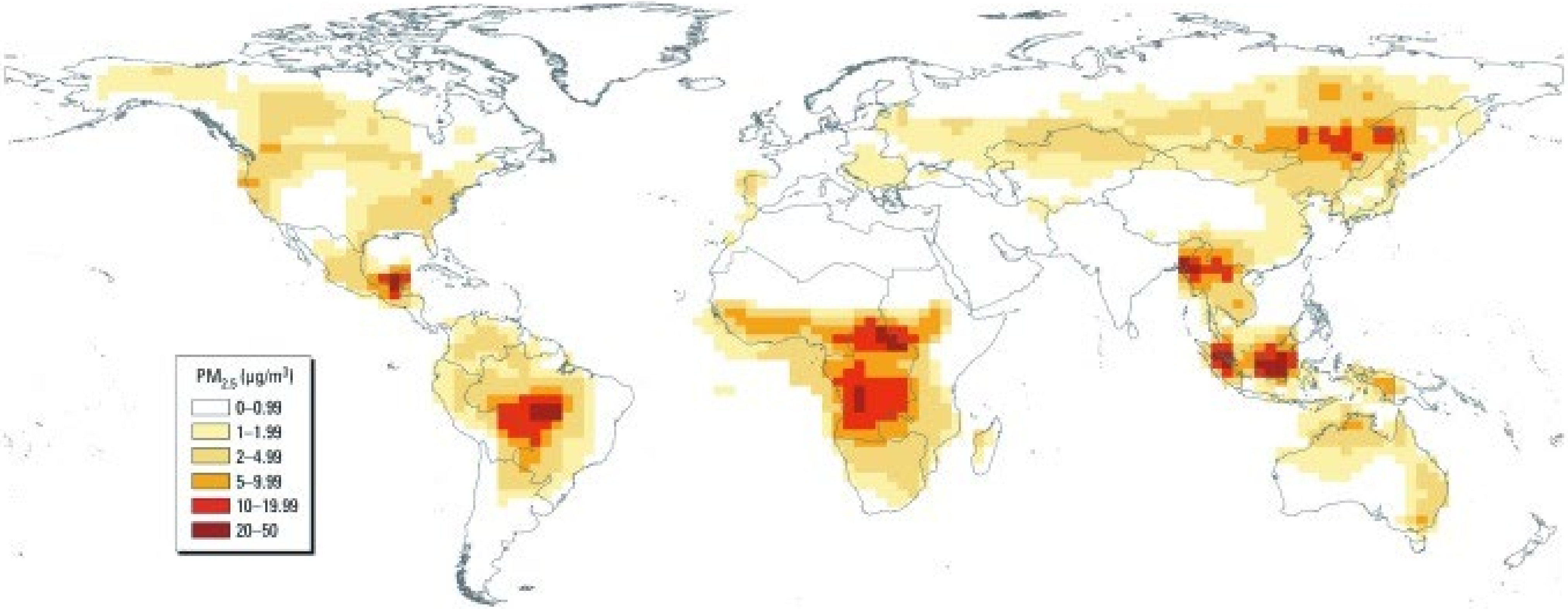
Tom Wordell, wildfire analyst, National Interagency Fire Center in Boise, Idaho:

"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."

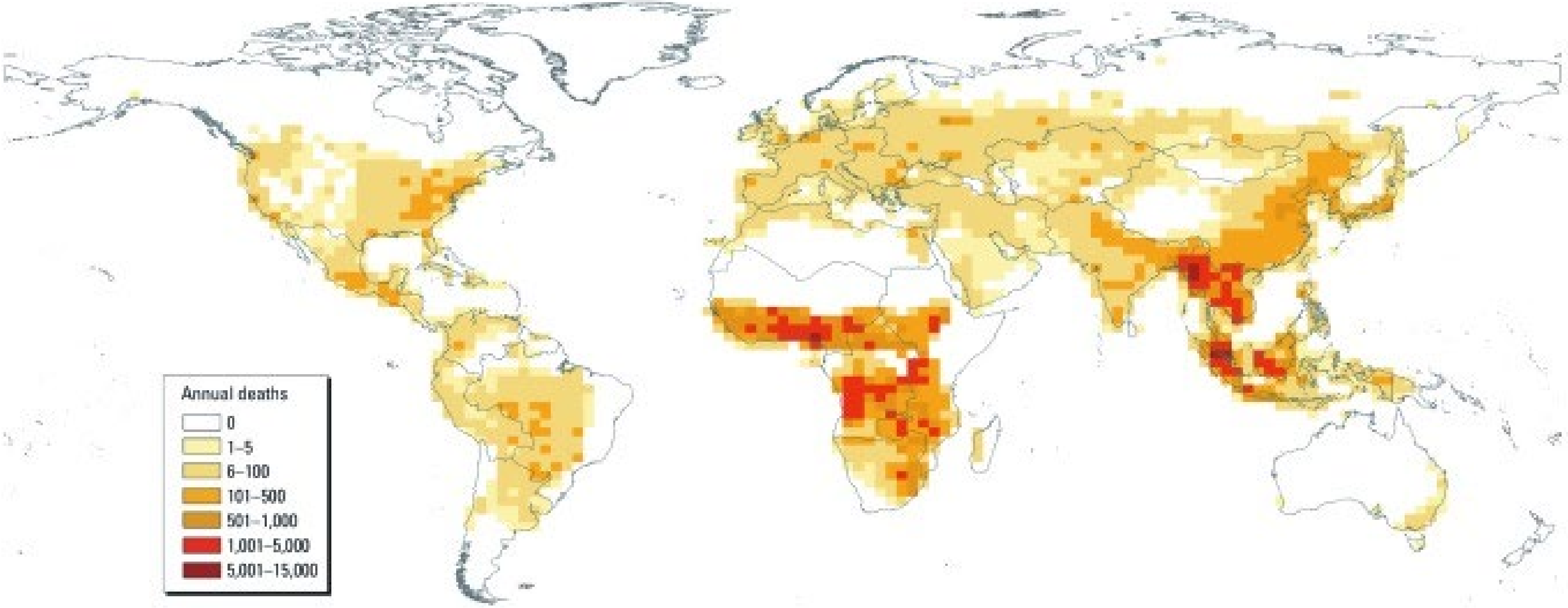
2 Key Implications:

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)



Source: Johnson et al. 2012

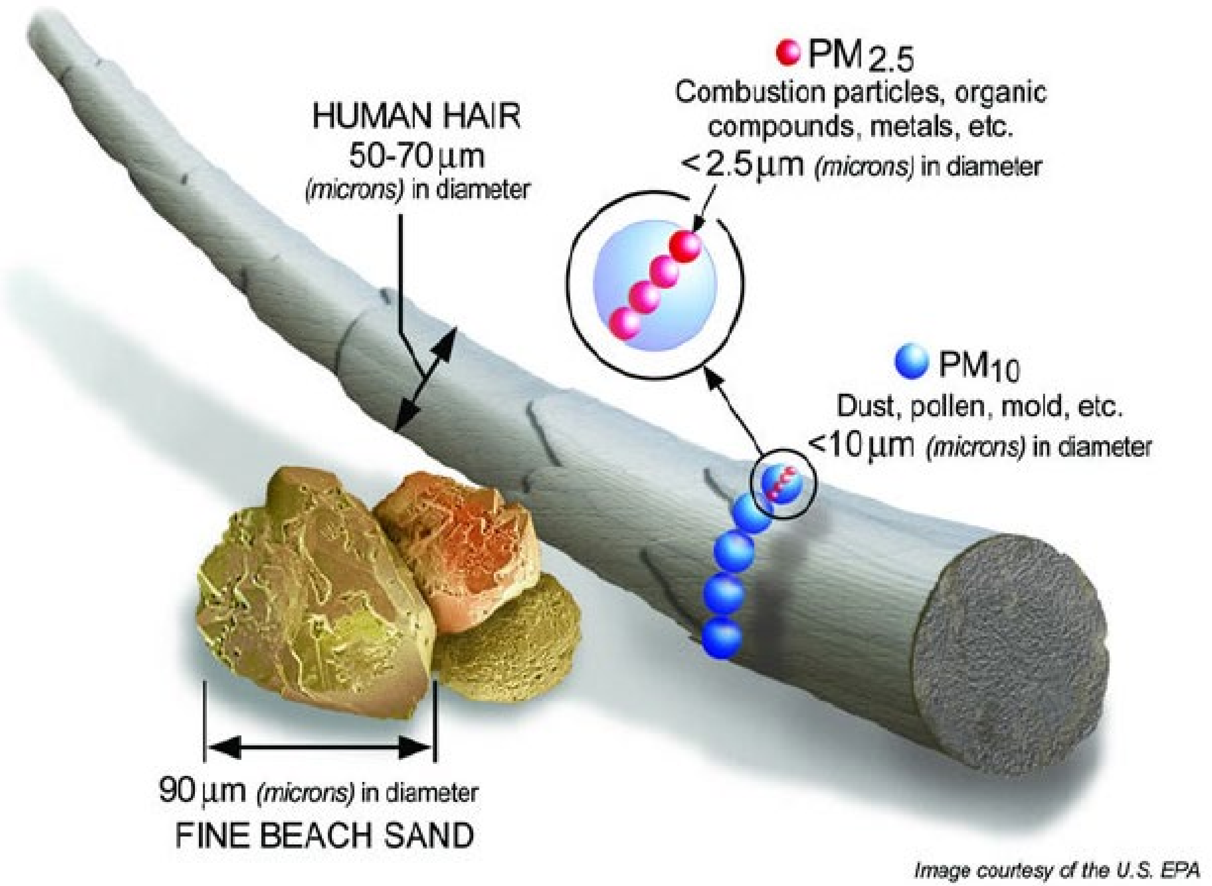
Emissions from Wildfires with Health Concerns

<u>Primary air pollutants</u>

- Carbon monoxide (CO)
- Nitrogen dioxide (NO_2)
- Polycyclic aromatic hydrocarbons (PAHs)
- Volatile organic compounds (VOCs)
- Particulate Matter (PM)

<u>Secondary air pollutants</u>

- Particulate Matter (PM)
- Ozone (O_3)



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

Environmental Science & Technology

Article

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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

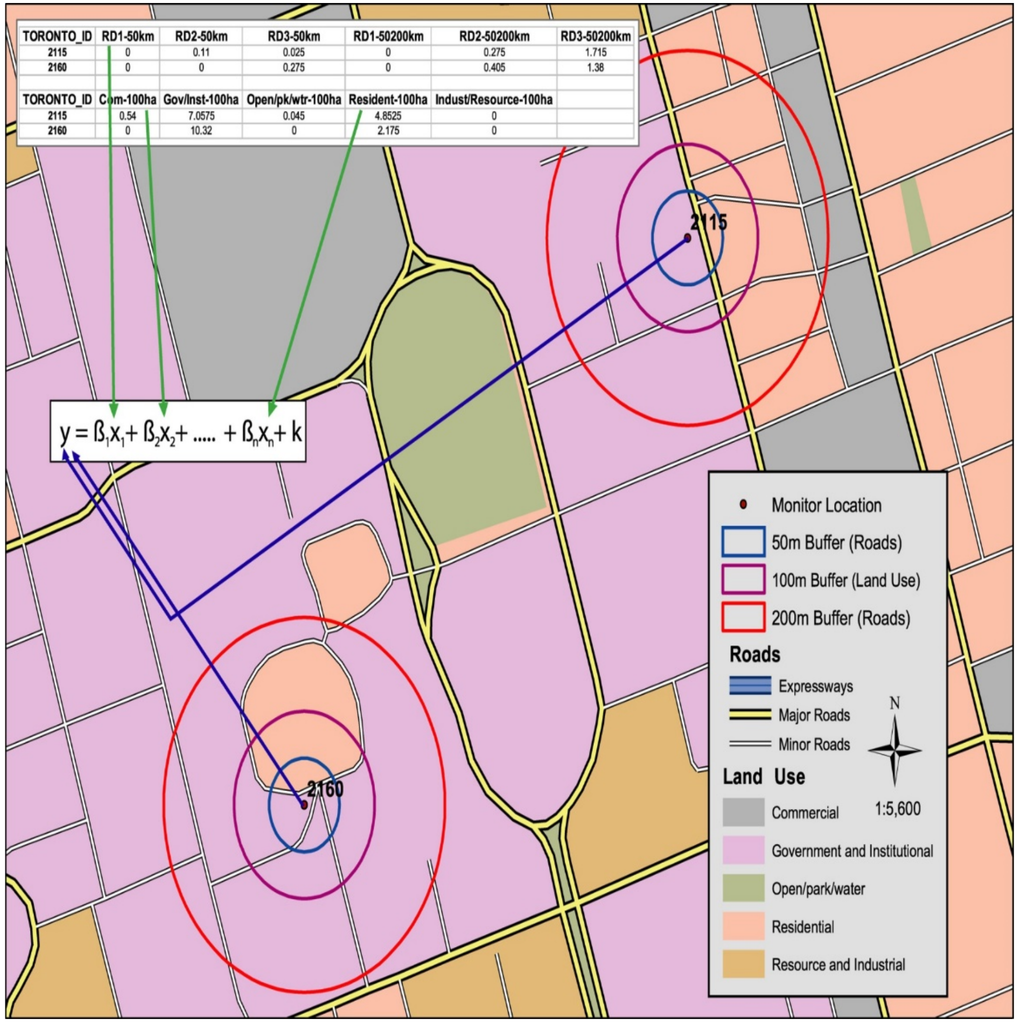
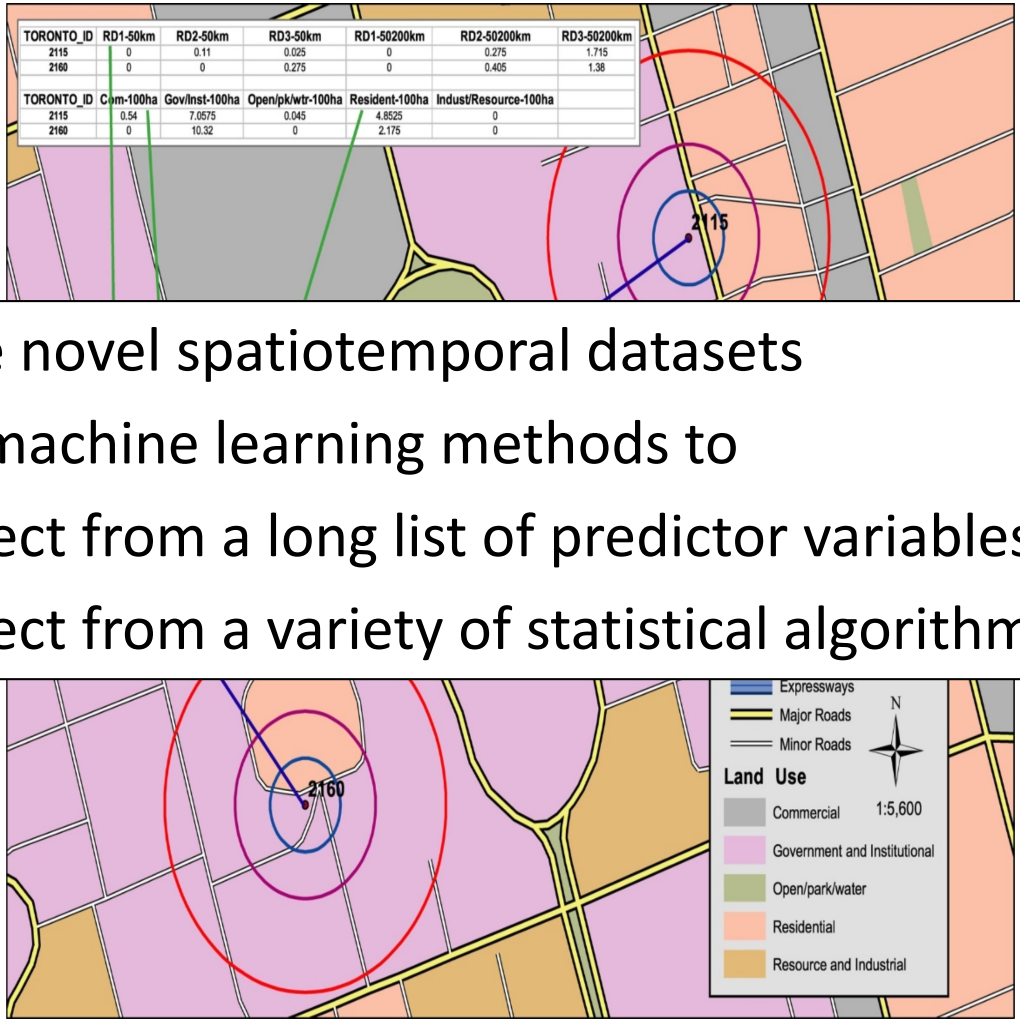


Image courtesy of Mike Jerrett

Methods – Adapt Land Use Regression Modeling with Machine Learning



TORONTO_ID	RD1-50km	RD2-50km	RD3-50km	RD1-50200km	RD2-50200km	RD3-50200km
2115	0	0.11	0.025	0	0.275	1.715
2160	0	0	0.275	0	0.405	1.38

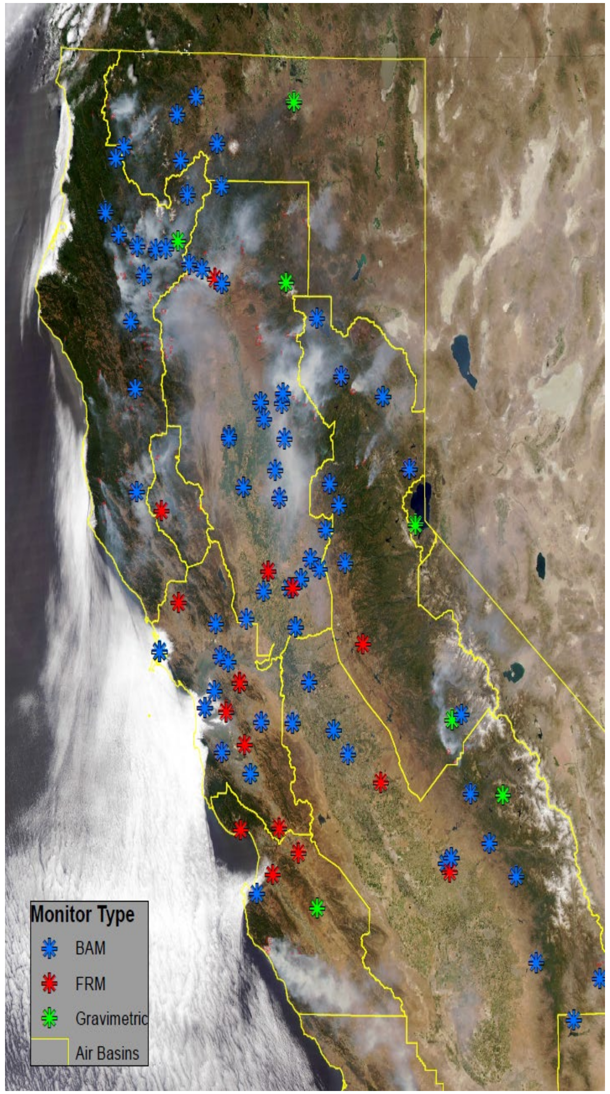
TORONTO_ID	Com-100ha	Gov/Inst-100ha	Open/pk/wtr-100ha	Resident-100ha	Indust/Resource-100ha
2115	0.54	7.0575	0.045	4.8525	0
2160	0	10.32	0	2.175	0

- 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).



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

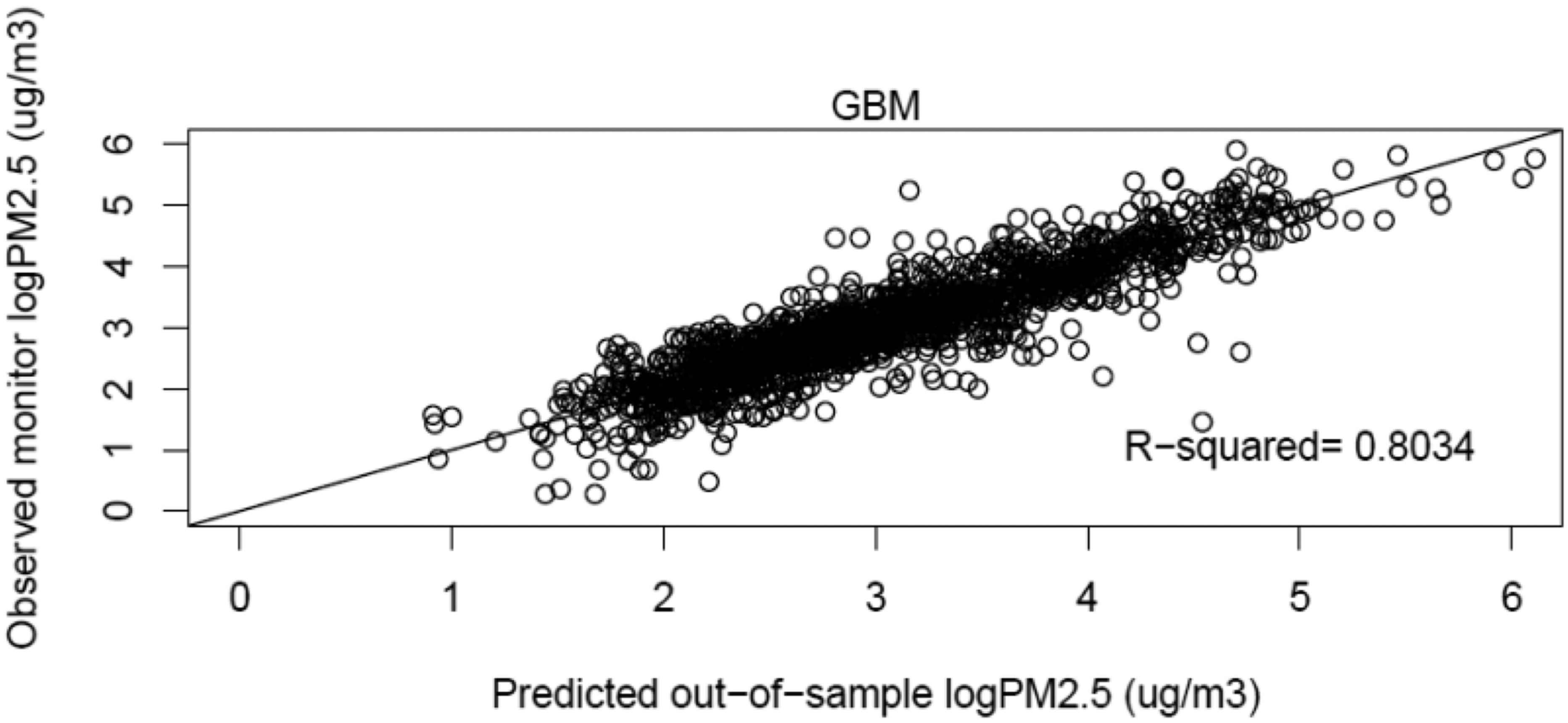
Statistical Algorithms

- 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

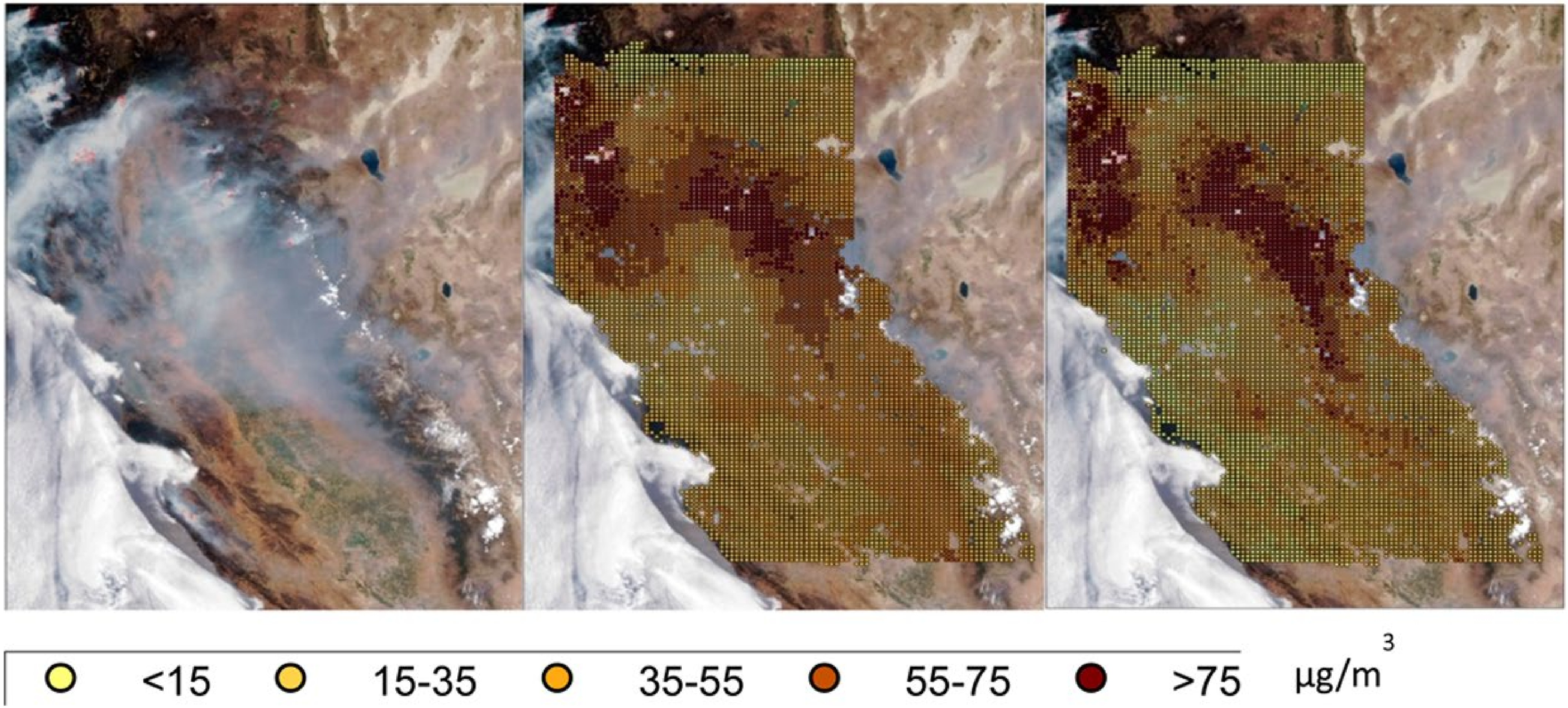
	model with smallest CV-RMSE for subsets of variables			model with fewer variables whose CV-RMSE was within 1.5% of the smallest CV-RMSE		
	CV-RMSE ($\mu g/m^3$)	CV-R^2	no. of variables selected	CV-RMSE ($\mu g/m^3$)	CV-R^2	no. of variables selected
random forest	1.513	0.796	20	1.521	0.790	14
bagged trees	1.687	0.672	27	1.696	0.665	15
generalized boosting model	1.489	0.803	29	1.495	0.799	13
elastic net regression	1.848	0.538	28	1.852	0.535	27
multivariate adaptive regression splines	1.642	0.701	28	1.648	0.696	26
lasso regression	1.821	0.558	28	1.834	0.548	23
support vector machines	1.556	0.761	16	1.561	0.758	15
gaussian processes	1.580	0.746	16	1.591	0.739	14
generalized linear model	1.821	0.558	29	1.834	0.549	23
K-nearest neighbors	2.030	0.387	2	2.044	0.374	1
generalized additive model	1.607	0.725	26	1.609	0.724	25

Observed on Predicted



GBM = Generalized Boosting Model; logPM2.5 = natural logarithm of the fine particulate matter concentration

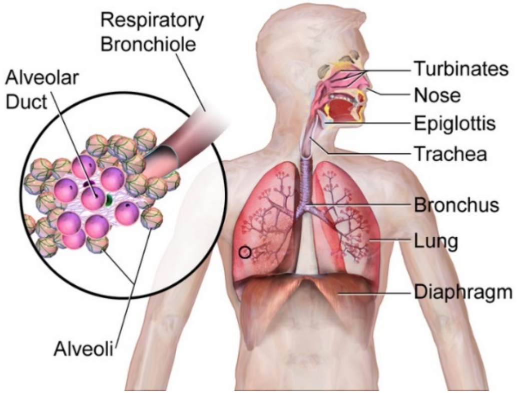
Predictions with Smoke Plume Shown



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

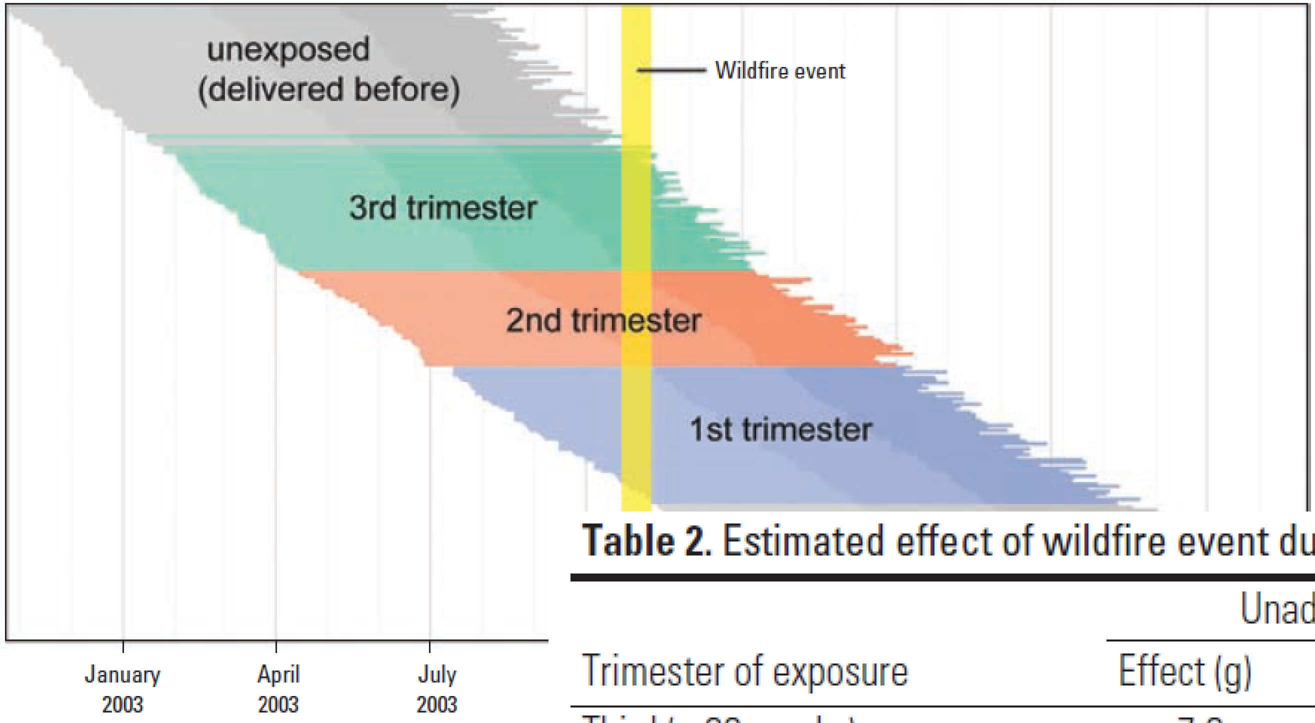


Figure 2. Schematic illustrating exposure as
lap between the wildfire event (yellow) an
clarity, gestational intervals are shown orde
from 2002–2004 is shown. Dates on the *x*-ax
seasonality.

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

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

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

Holstius et al. 2012 *EHP*

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

Photo credit: https://www.flickr.com/photos/kylewith/14435190829

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

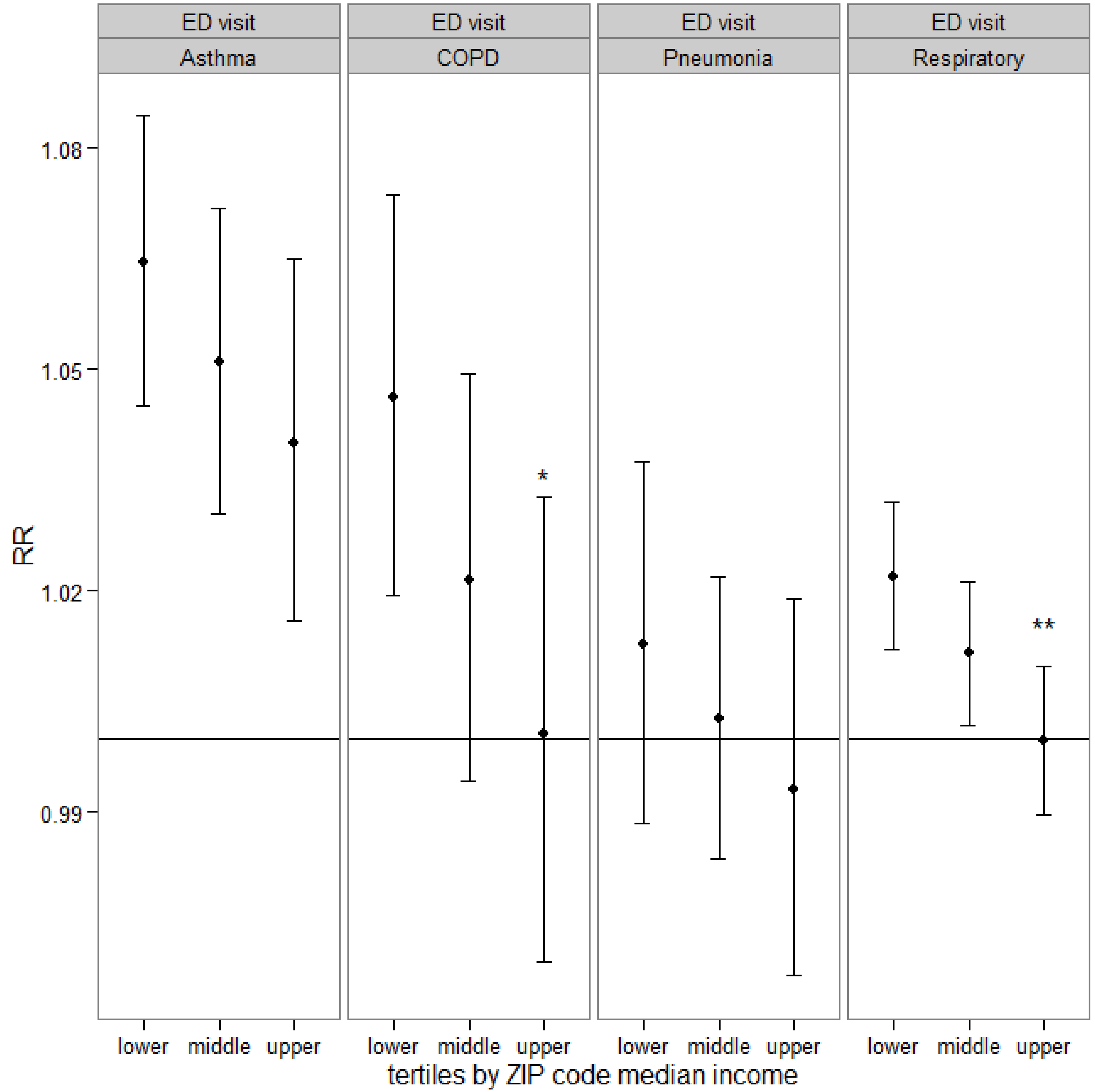
Reid et al. 2016 *EHP*

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)

Reid et al. 2016 *EHP*

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

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