



# Wildfire Particulate Emissions and Respiratory Health under Climate Change Scenarios:

## Project overview and results

Presented by:

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**Michele Ginsberg**, MD San Diego County Health and Human Service Agency

**R. Chris Owen**, PhD U.S. EPA/OAR/OAQPS/AQAD

**Michael Billmire**, Michigan Tech Research Institute



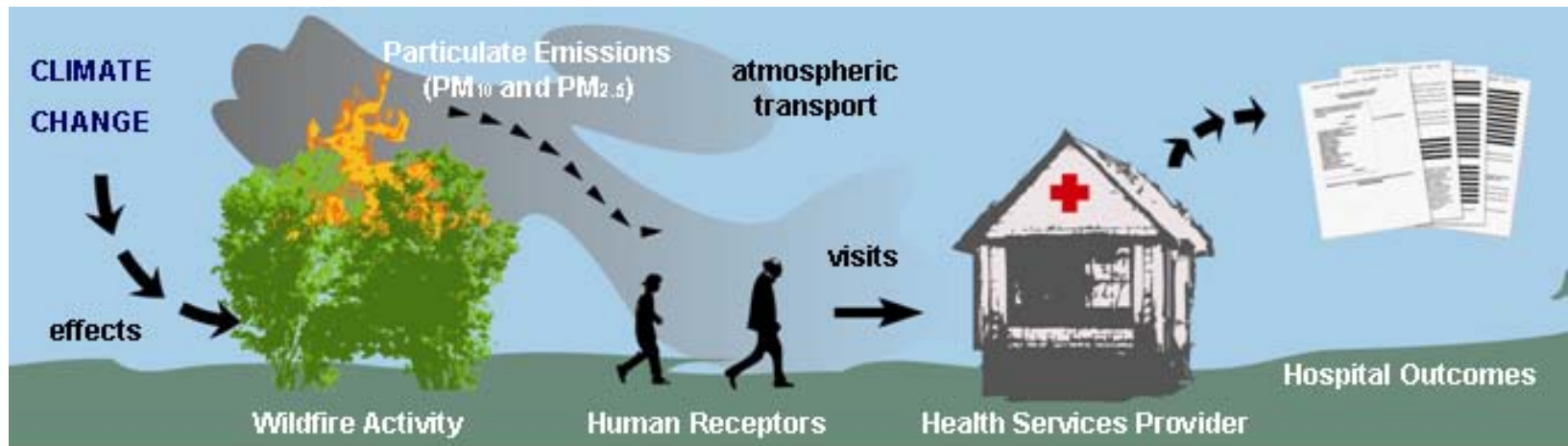
# Presentation Outline

- Introduction and Background
- Project methods and results
  - Emissions modeling – *Nancy French*
  - Atmospheric modeling – *R. Chris Owen*
  - Syndromic surveillance – *Dr. Michele Ginsberg*
  - Statistical modeling and results – *Michael Billmire*
  - Future fire occurrence modeling – *Nancy French*
- Summary of Project Outcomes
- Discussion



# Introduction: Purpose

- The goal of this research is to better understand how to approach forecasting and preparedness for fire-driven air pollution events.
- The project objectives are to develop methods to connect wildfire occurrence to health outcomes and to better understand how climate change will affect wildland fire air quality conditions detrimental to respiratory health.



# Introduction: Project team

## Principle Investigators

*Nancy HF French, PhD*, Michigan Tech Research Institute, nancy.french@mtu.edu

*Brian Thelen , PhD*, Michigan Tech Research Institute, brian.thelen@mtu.edu

## Research Team

### Michigan Tech Research Institute

*Benjamin W. Koziol*

*R. Chris Owen, PhD*

*Michael Billmire*

*Marlene Tyner*

*Tyler Erickson, PhD*

### Michigan Technological University

*Shiliang Wu, PhD*

*Y. Huang*

### San Diego County Health and Human Service Agency

*Michele Ginsberg, MD*

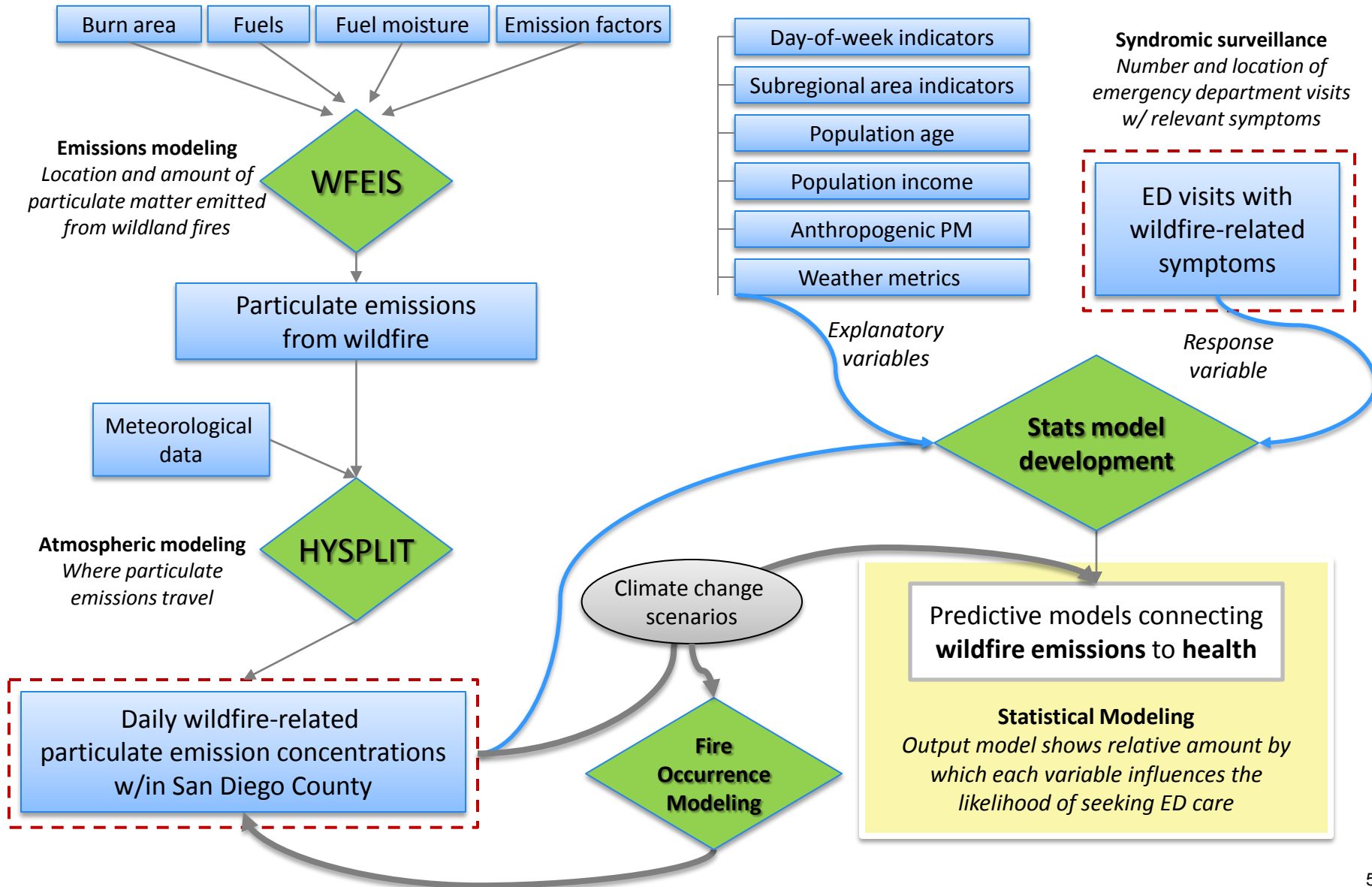
*Jeffrey Johnson*

### University of Maryland Department of Geographical Sciences

*Tatiana V. Loboda, PhD*

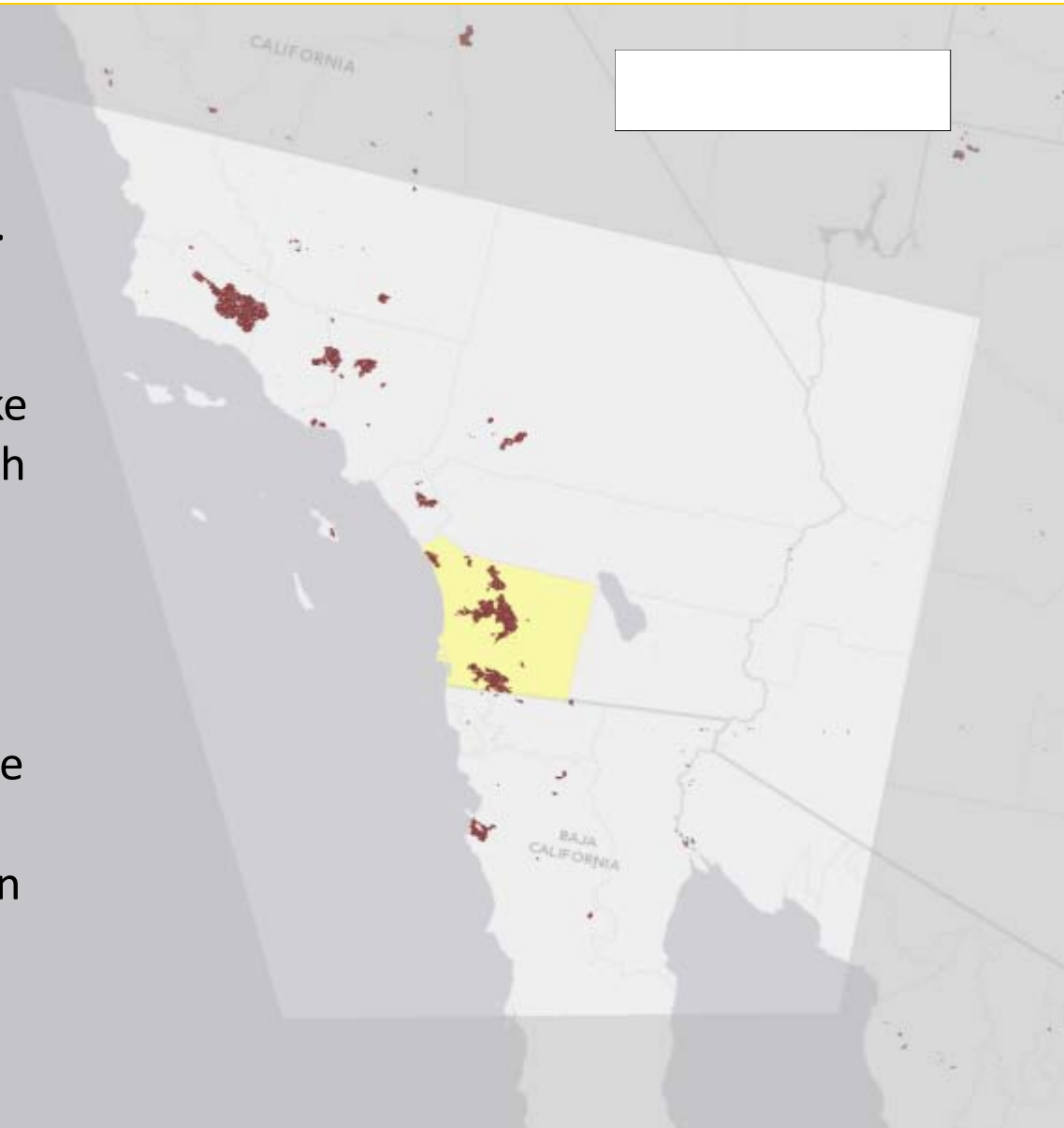
Funding provided by the **National Institute of Environmental Health Sciences**, a part of the **National Institute of Health**, under the NIEHS Interagency Working Group on Climate Change and Health Initiative

# Introduction: Methodology overview



# Introduction: Study area

- The study area shown was used to model the smoke impacting San Diego County.
- The comparison of the smoke concentration maps to health data is for San Diego County (highlighted in yellow)
- Future fire is modeled for the entire region to gauge the impacts of climate change on fire and health outcomes.





# Introduction: San Diego Wildland Fires

- Region within San Diego county is classified as a Mediterranean eco-climatic zone, with fire-prone chaparral shrublands and weather conducive to periodic burning.
- San Diego County experienced two catastrophic wildfire seasons in the past decade: October of 2003 and 2007
- Each firestorm burned approximately 13% of the county land area and each cost over \$41 million in fire suppression efforts and an estimated \$1.5 billion in damage

2007  
Approximately 515,000  
people evacuated  
Over 2,200 medical  
patients evacuated



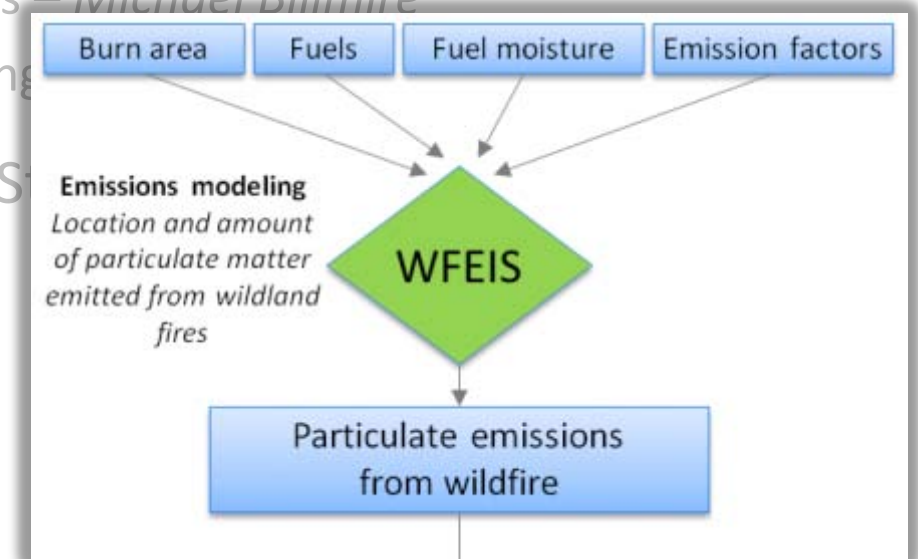
# Introduction: Main Outcomes

- Developed a coupled statistical and process-based model system that:
  - Demonstrates an end-to-end methodology for generating reasonable estimates of wildland fire particulate matter concentrations and effects on respiratory health,
  - Applicable at resolutions compatible with syndromic surveillance health information,
  - Model coefficients and functional estimates are specific to San Diego County, but the method has applicability to other regions and syndromic responses.
  - Model results show that at peak fire particulate concentrations the odds of a person seeking emergency care is increased by approximately 50% compared to non-fire conditions.
- Future fire model shows San Diego County should experience approximately two extreme fire seasons each decade by 2040, similar to the present.
- Demonstrated the value of syndromic surveillance data collection and analysis capabilities that are rapidly being developed across the US.
- Promoted collaboration between public health and environmental modeling communities to better understand determinants of health during a disaster.



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# Background: Particulate matter

- a.k.a. “**Total Suspended Particulates**” (TSP), fine particles suspended in gas or liquid (e.g., smoke, dust, allergens)
- For this study, we are concerned with respirable particulates, i.e., *particles with a diameter of less than 10  $\mu\text{m}$  and suspended in air*
- Association b/t exposure to PM and aggravation of heart and lung diseases
- Classified by particle size (US EPA):
  - **PM<sub>10</sub>** = “inhalable coarse particles”, diameter less than 10  $\mu\text{m}$
  - **PM<sub>2.5</sub>** = “fine particle pollution”, diameter less than 2.5  $\mu\text{m}$  (1/30 diameter of a human hair)
    - US EPA PM<sub>2.5</sub> 24-hour standard (2006): **35  $\mu\text{g}/\text{m}^3$**
    - Observed\* 24-hour PM<sub>2.5</sub> concentration, San Diego County 10-23-07: **179  $\mu\text{g}/\text{m}^3$**
- For this study, we modeled emissions of both classes, but combined the two for the statistical model (due to colinearity)

US EPA Particulate Matter standards information: <http://www.epa.gov/airquality/particlepollution/index.html>

\* California ARB site 2263, Escondido-E. Valley Parkway

# Wildland Fire Emissions Information System (WFEIS)

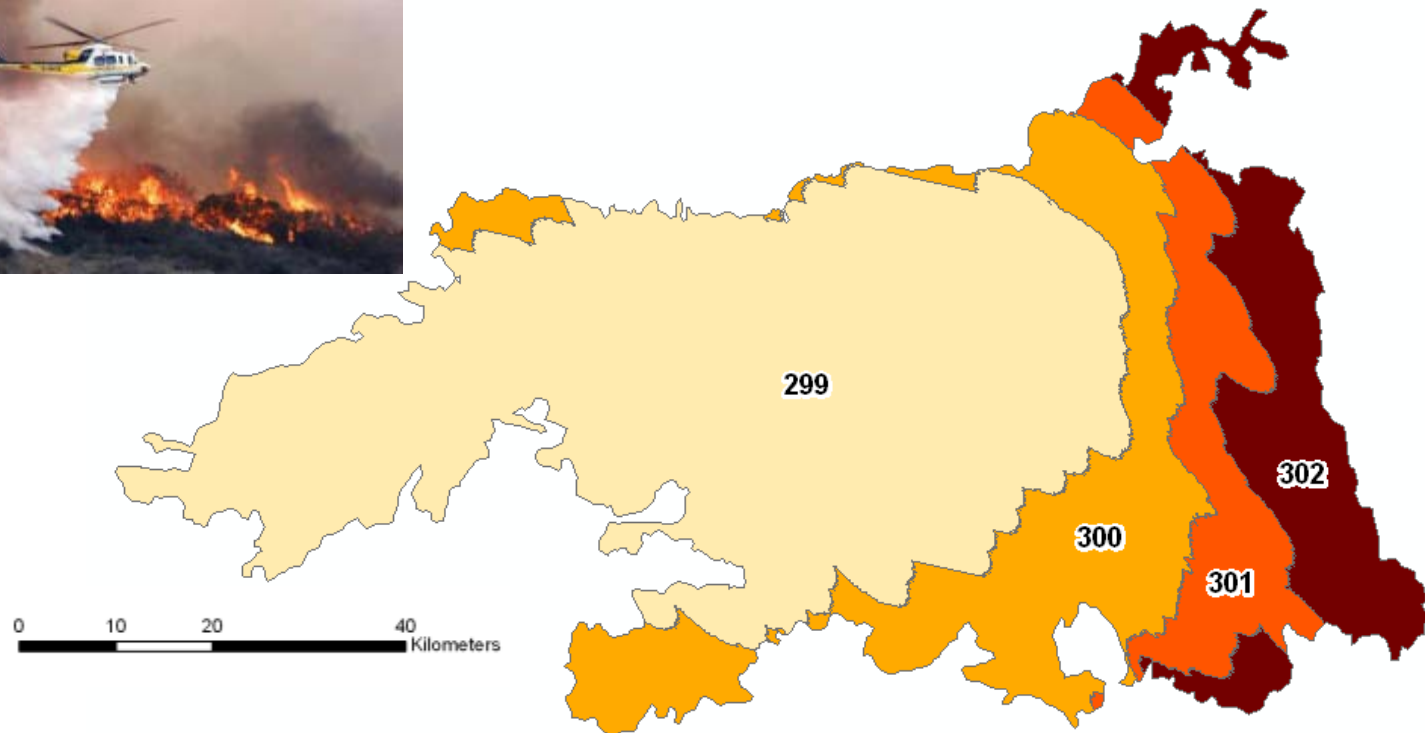
- Particulate emissions were calculated using the **Wildland Fire Emissions Information System (WFEIS)**, [wfeis.mtri.org](http://wfeis.mtri.org))
- Datasets used by WFEIS in this study:
  - Burn area : **Fire Progression Polygons**
    - Products developed from remote sensing<sup>1</sup> that uses surface reflectance, daily active fire detections, and land cover products to delineate daily burn area.
  - Vegetation Fuels : **Fuel Characteristic Classification System (FCCS)**<sup>2</sup>
    - Developed by the US Forest Service to provide a comprehensive description and quantification of fuel loadings across all strata of a cover type.
  - Emissions : **python-consume**
    - Developed by US Forest Service Fire and Environmental Research Applications (FERA) with assistance from MTRI, python-consume calculates fuel consumption and pollutant emissions from wildland fires based on fuel and environment conditions.

<sup>1</sup>Giglio, L. et al. 2009 Rem. Sens. Environ., 113(2), 408-420.

<sup>2</sup>McKenzie, D., French, N.H.F. and Ottmar, R.D. (2012), "National database for calculating fuel available to wildfires," EOS, 93, 57-58.

# Satellite-derived Fire Progression

- Example fire event in the fire progression dataset
  - developed from satellite fire detections & spatial analysis

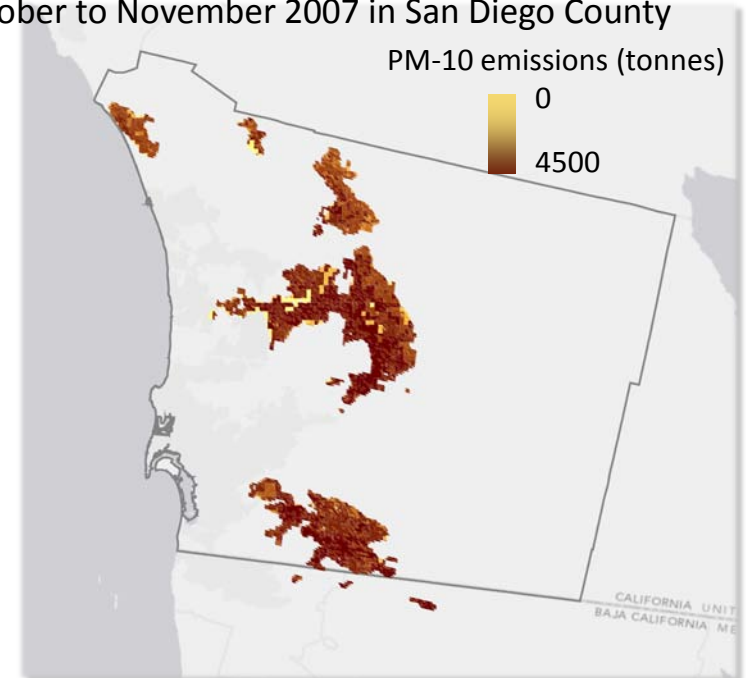
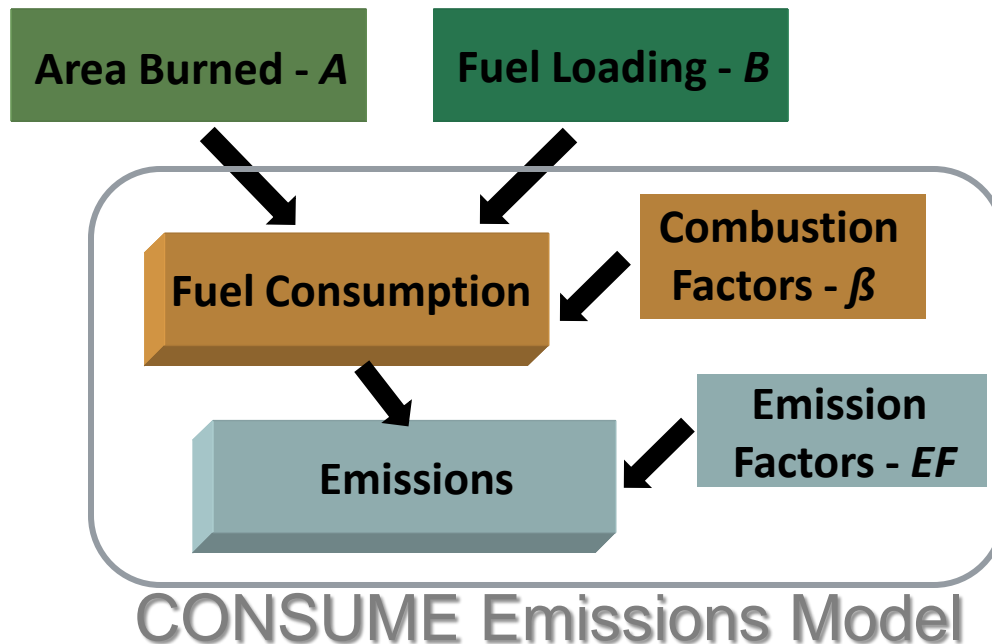


*2003 Cedar Fire: >260,000 acres burned in 4 days*

# Wildland Fire Emissions Information System (WFEIS)

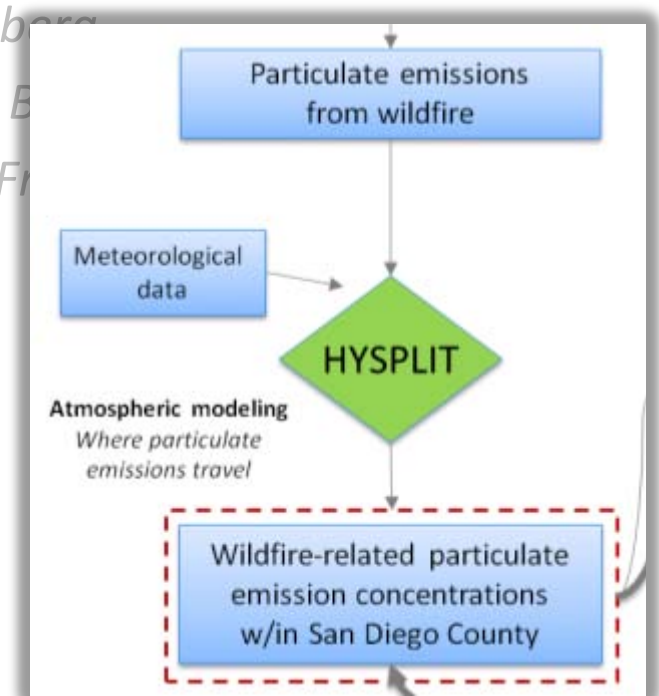
- The WFEIS process:
  - **Burn area data** is overlaid onto...
  - ...an underlying **vegetation fuels layer** (FCCS) to generate...
  - ...inputs for **python-consume** which calculates **PM-10 and PM-2.5 emissions** based on fuels and environmental inputs

Sample WFEIS output, showing PM-10 emissions from burn scars from October to November 2007 in San Diego County



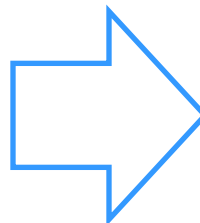
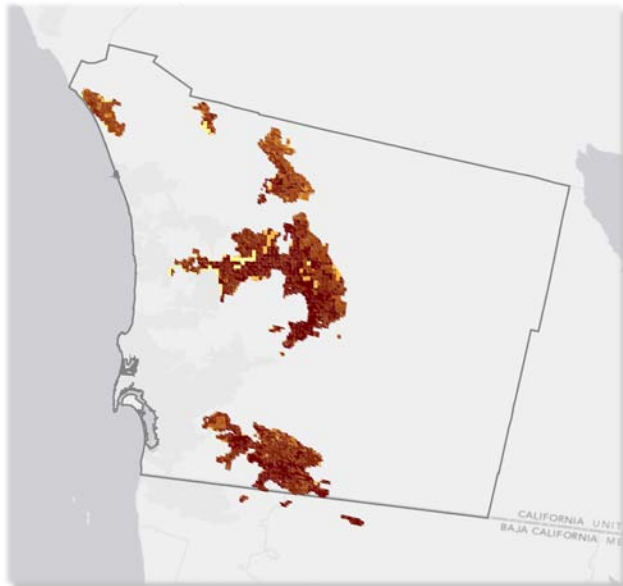
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# Fire emissions modeling → Atmospheric modeling

- Once emitted by wildland fire, PM does not stay put → diffuses, distributed by wind, etc.
- We use the HYSPLIT model to determine these atmospheric transport pathways
- WFEIS PM emissions are used as inputs to the HYSPLIT modeling system...



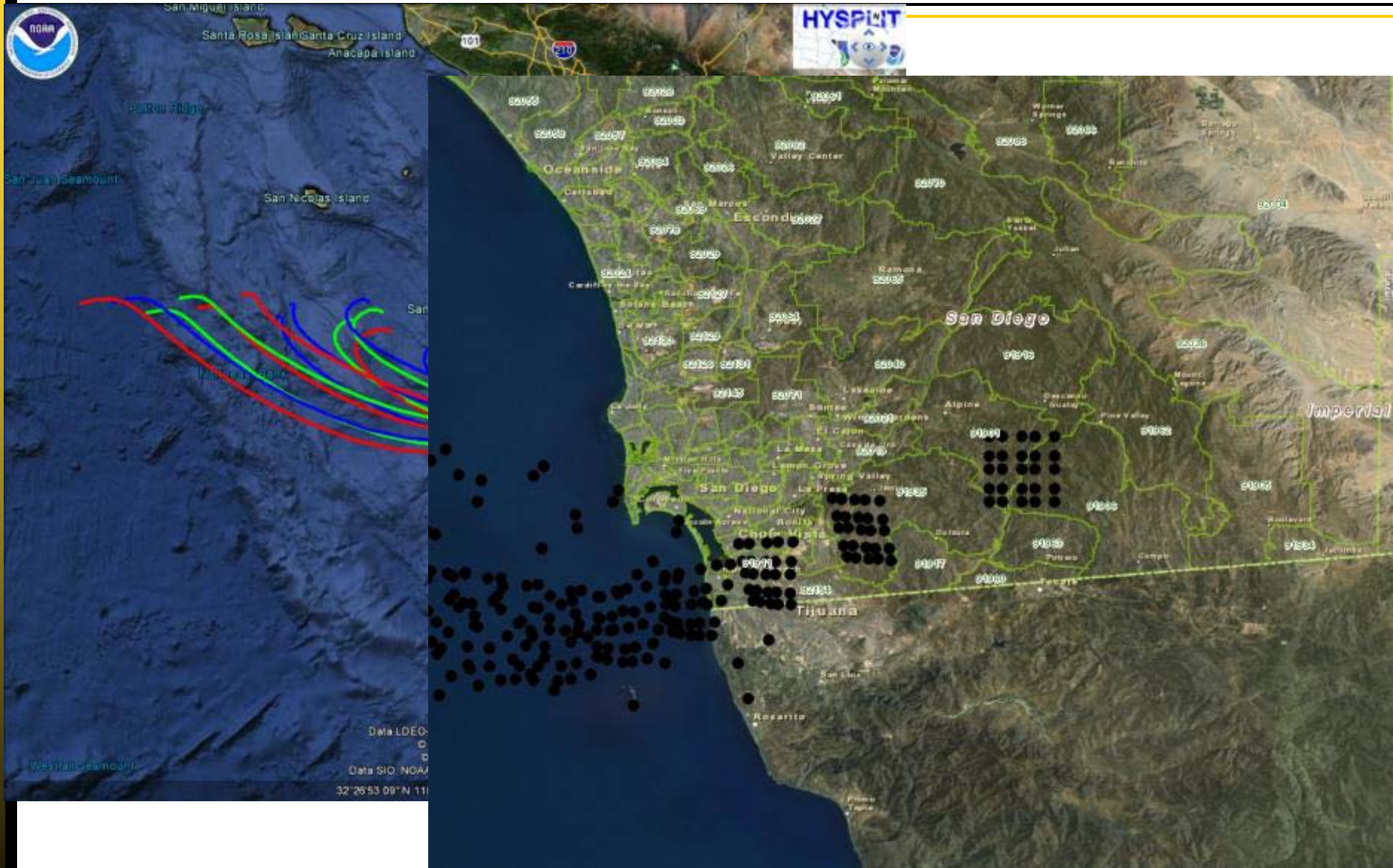
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1 1 24 1.0000 0.0100 0.0100
2 PM10
3 hy_2003-01-06_PM10_xxSB70.asc
4 1.05E-04 3.105E-04
21 344
22 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03
23 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03 9.789E-03
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28 7.252E+00 7.252E+00 7.252E+00 7.252E+00 7.252E+00 7.252E+00 7.252E+00 7.252E+00 7.252E+00
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43 1.309E+01 1.309E+01 1.309E+01 1.309E+01 1.309E+01 1.309E+01 1.309E+01 1.309E+01 1.309E+01
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48 257 281 -118.4300 33.3800
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50 4.387E+01 4.387E+01 4.387E+01 4.387E+01 4.387E+01 4.387E+01 4.387E+01 4.387E+01 4.387E+01
51
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# Atmospheric Transport Modeling

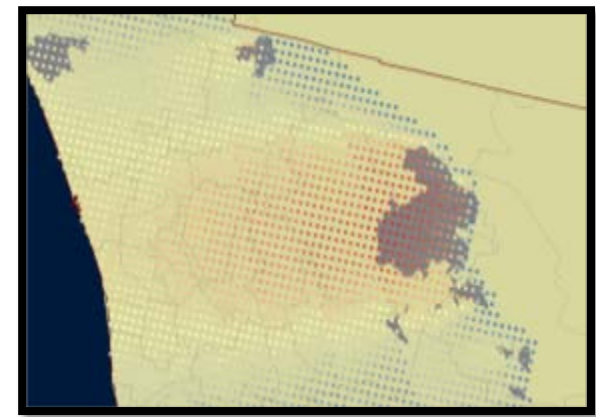
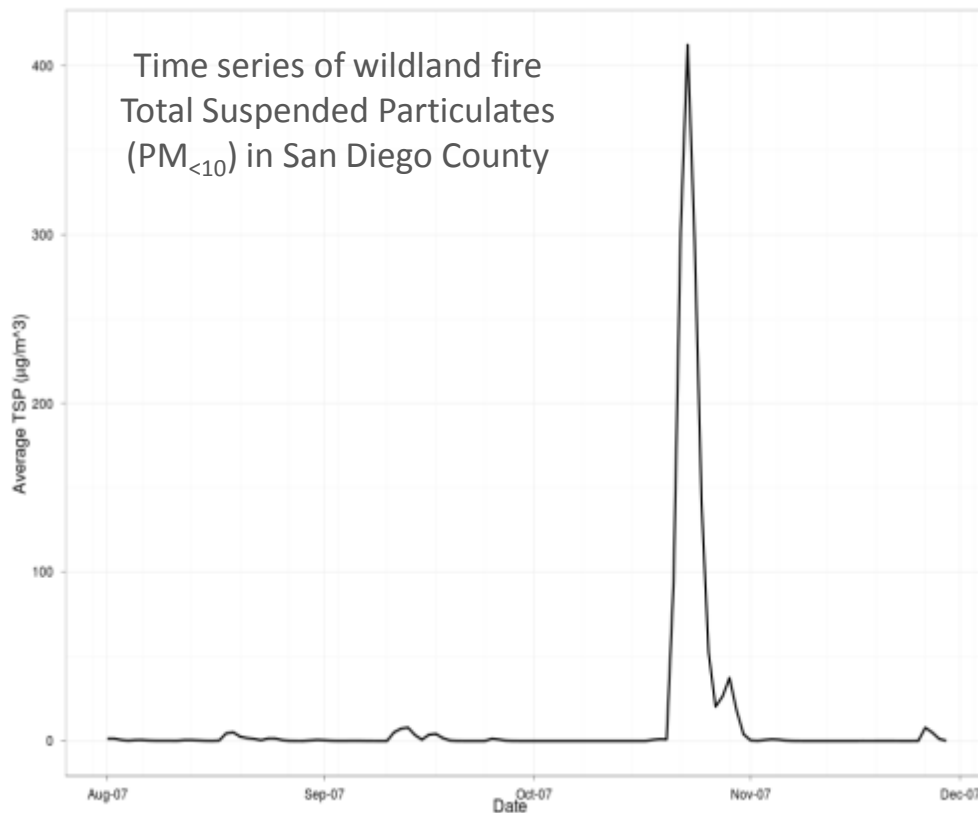
- HYSPLIT - **H**ybrid **S**ingle **P**article **L**agrangian **I**ntegrated **T**rajectory Model
  - Atmospheric transport model maintained by National Oceanic & Atmospheric Administration (NOAA)
  - Lagrangian models tracks small puffs or plumes of air
    - Each fire event is divided into hundreds of small plumes, which are dispersed by the model
    - Smoke plumes released at hourly intervals from daily emissions estimates
    - Smoke followed for a total of 3 days after emission
  - Smoke transport is driven by wind data on a 40km grid

# Atmospheric Transport Modeling



# Atmospheric Transport Modeling

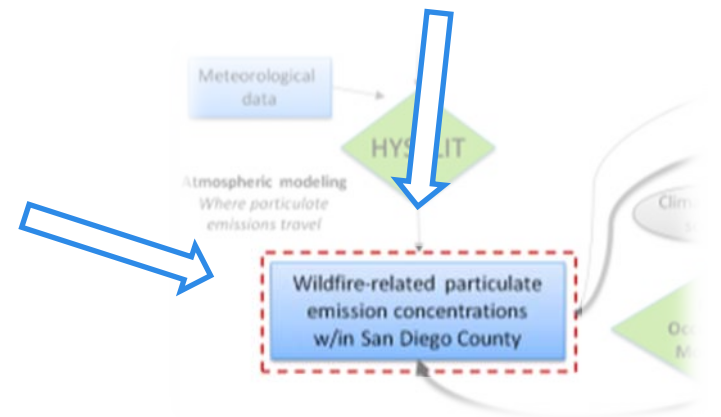
- Resulting plume grids were spatially aggregated to San Diego County and subregional areas



Modeled smoke conc. ( $\mu\text{g}/\text{m}^3$ )

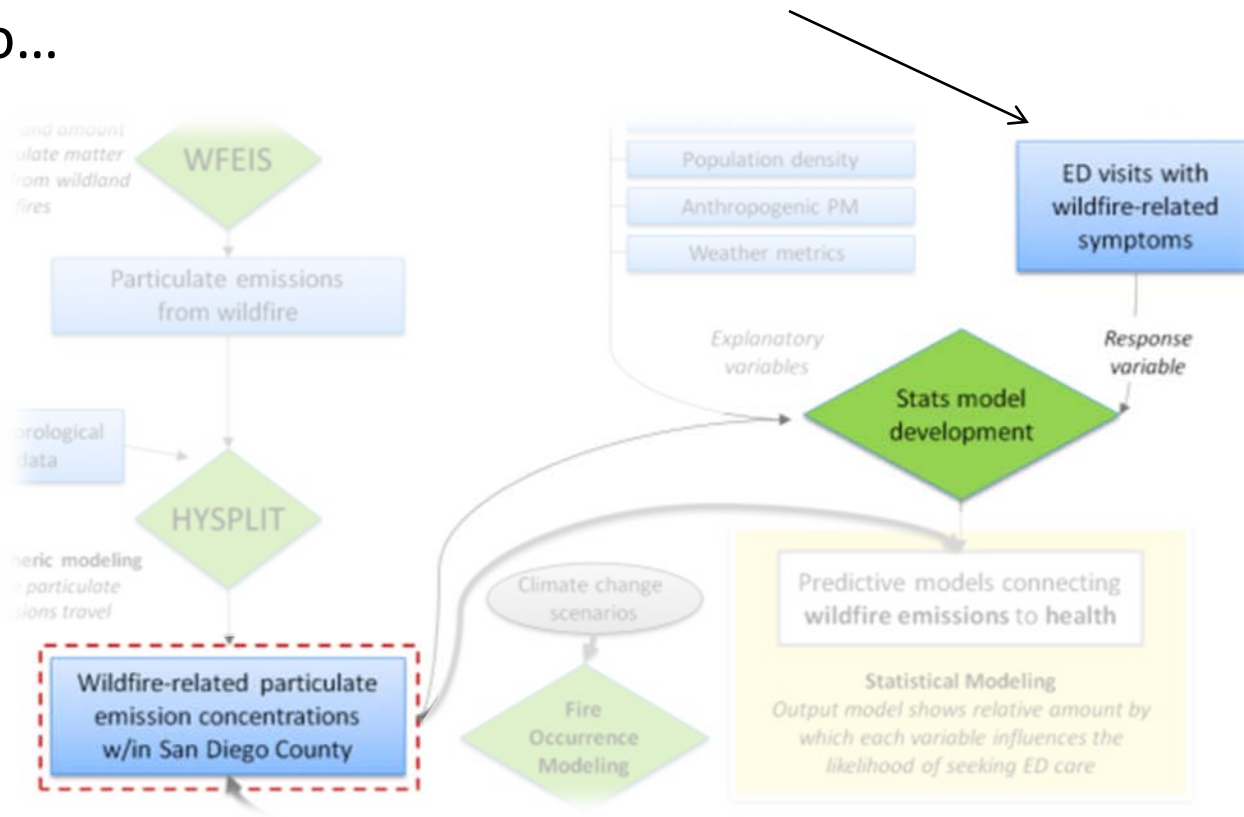
50
4
0

Zip code boundaries  
Burn area  
San Diego County boundary



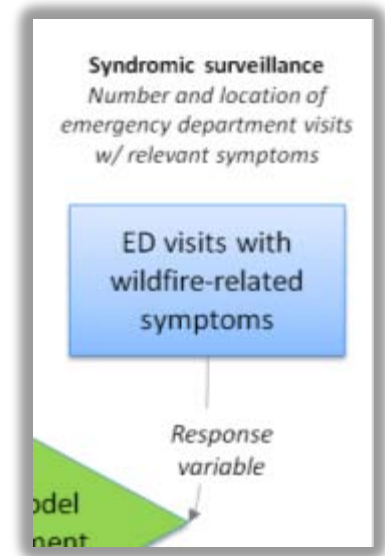
# Atmospheric Modeling

- Now that we have modeled **wildland fire-related particulate matter concentrations**, we can compare these values to **wildland fire-related health effects**, which leads us to...



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# Essential Public Health Services

- **Monitoring Community Health**
  - Reportable Conditions
  - Syndromic Surveillance
- **Public Health Surveillance**
  - Ongoing, systematic collection, analysis and interpretation of health-related data
  - Changes in data may indicate a disease outbreak or event that impacts health resources



# Syndromic Surveillance

- As real-time as possible
- Cover spectrum of illness – categorized
- De-Identified





# San Diego Sources

## 2003

- Pre-hospital transport
- 17 medical facilities – manual
- Air pollution control
- Medical Examiner
- Vital Records

## 2007

- Pre-hospital transport
- 10 medical hospitals – electronic
- 911
- Air pollution control
- Medical Examiner
- Vital Records

# Emergency Department Data

## ■ Data Collected Include:

- Date & Time of Visit
- Chief Complaint
- Mode of Arrival
- Age
- Zip Code
- Discharge Diagnosis
- Disposition

De-Identified Patient-Level Data



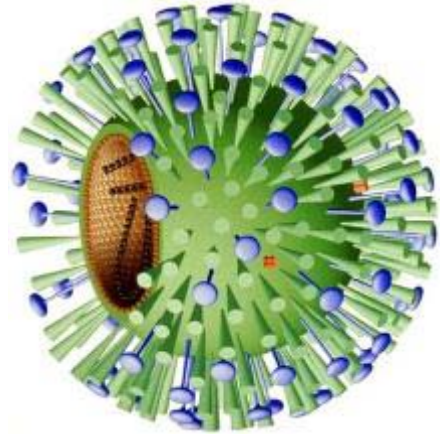
# Syndromic Surveillance

## ■ Core Syndrome Categories

- Abdominal Pain
- Altered Neurological (weakness, headache, seizure & bot-like)
- Bloody Diarrhea
- Botulism-Like
- Chest Pain
- Fever
- Influenza-Like-Illness
- Gastrointestinal (diarrhea, GI bleed, vomiting, nausea, & abdominal pain)
- Hazardous/Toxic
- Rash
- Respiratory (influenza-like-illness, cold, asthma, & respiratory with blood)

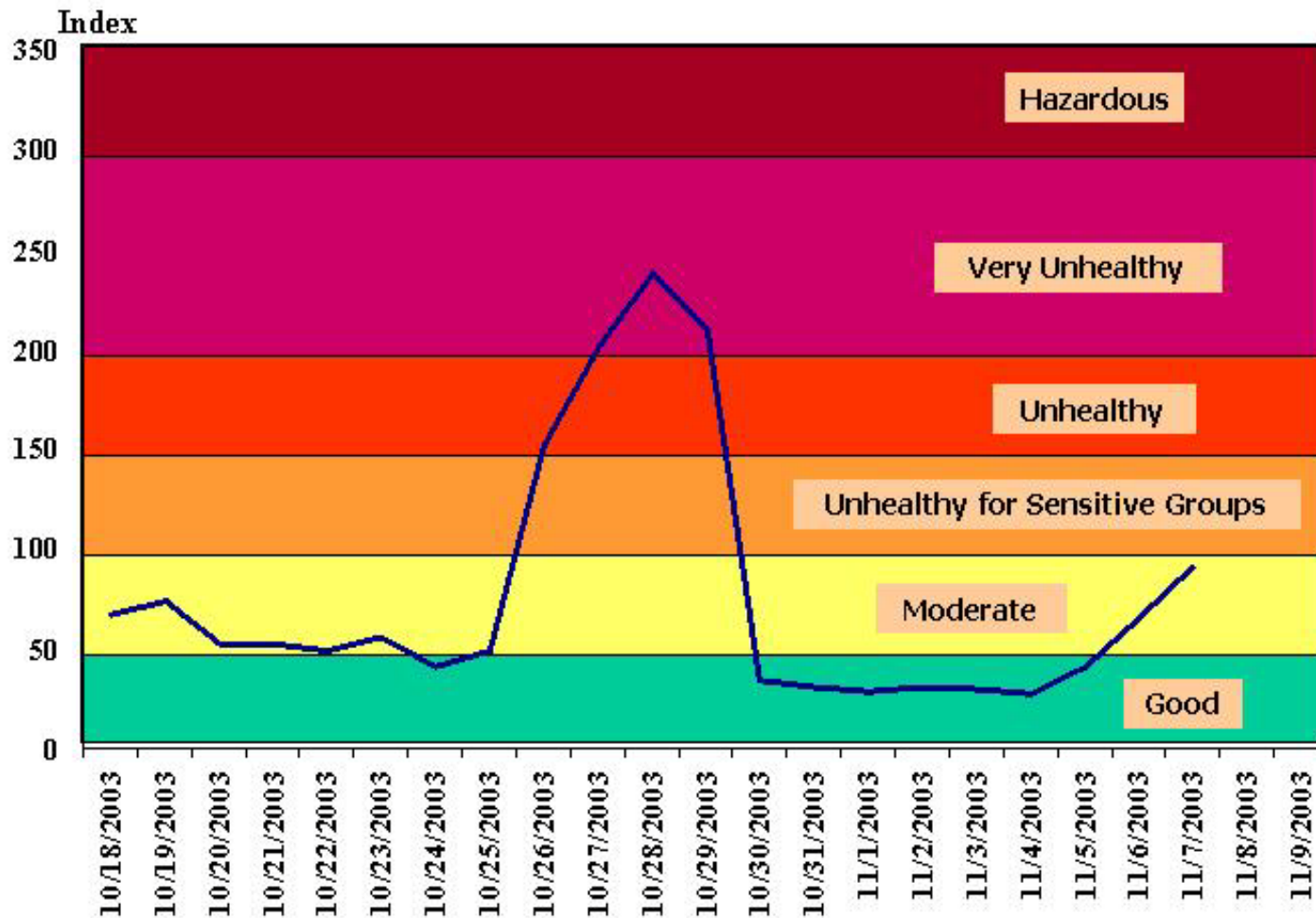
# Syndromic Surveillance

- GI Outbreaks – Shigella
- HAZ-Mat
  - Chemical Exposures
  - Carbon Monoxide
  - Chlorine
- Influenza Outbreaks



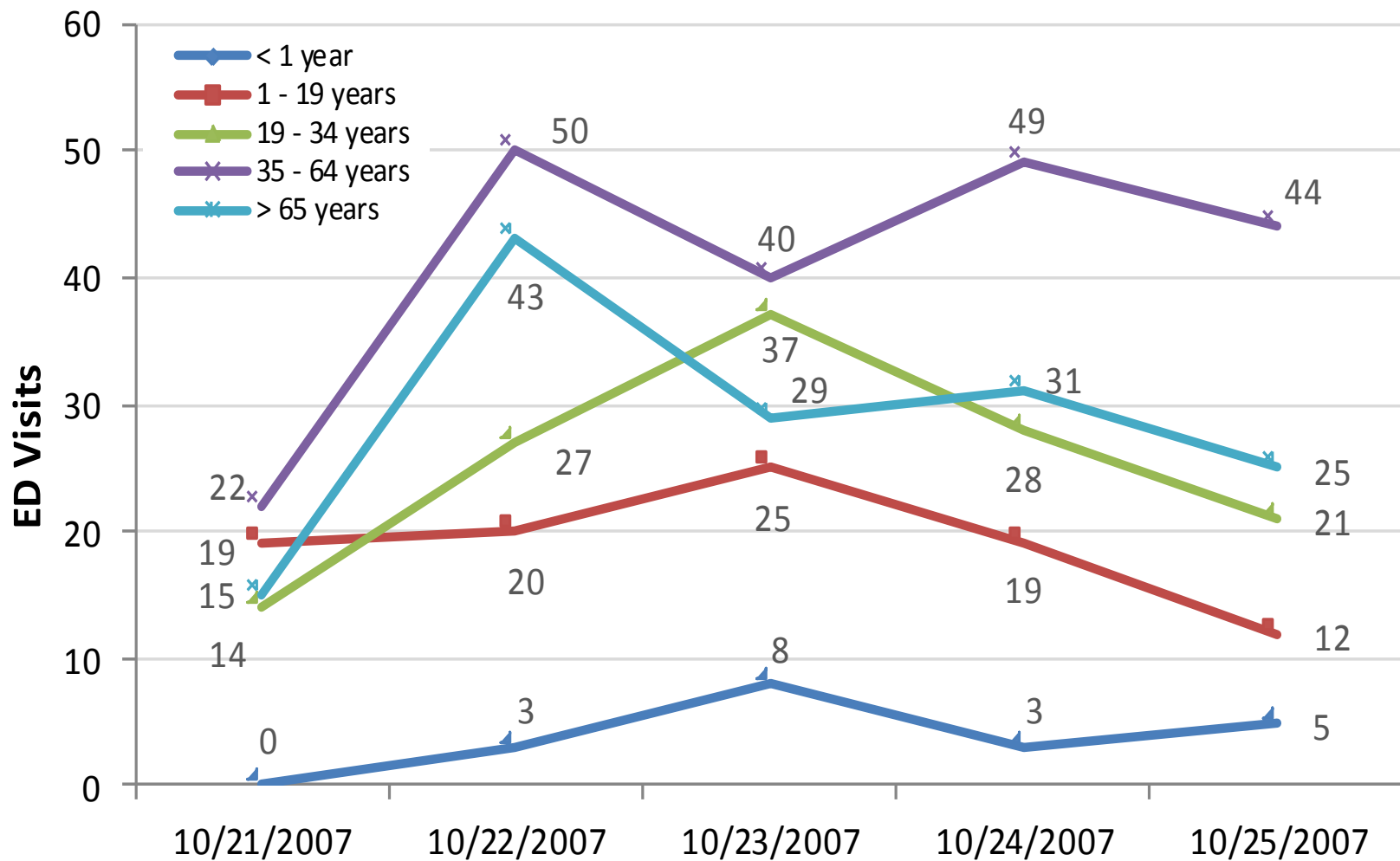
# San Diego Wild Fires: 2003 & 2007

## Air Quality Index For San Diego County

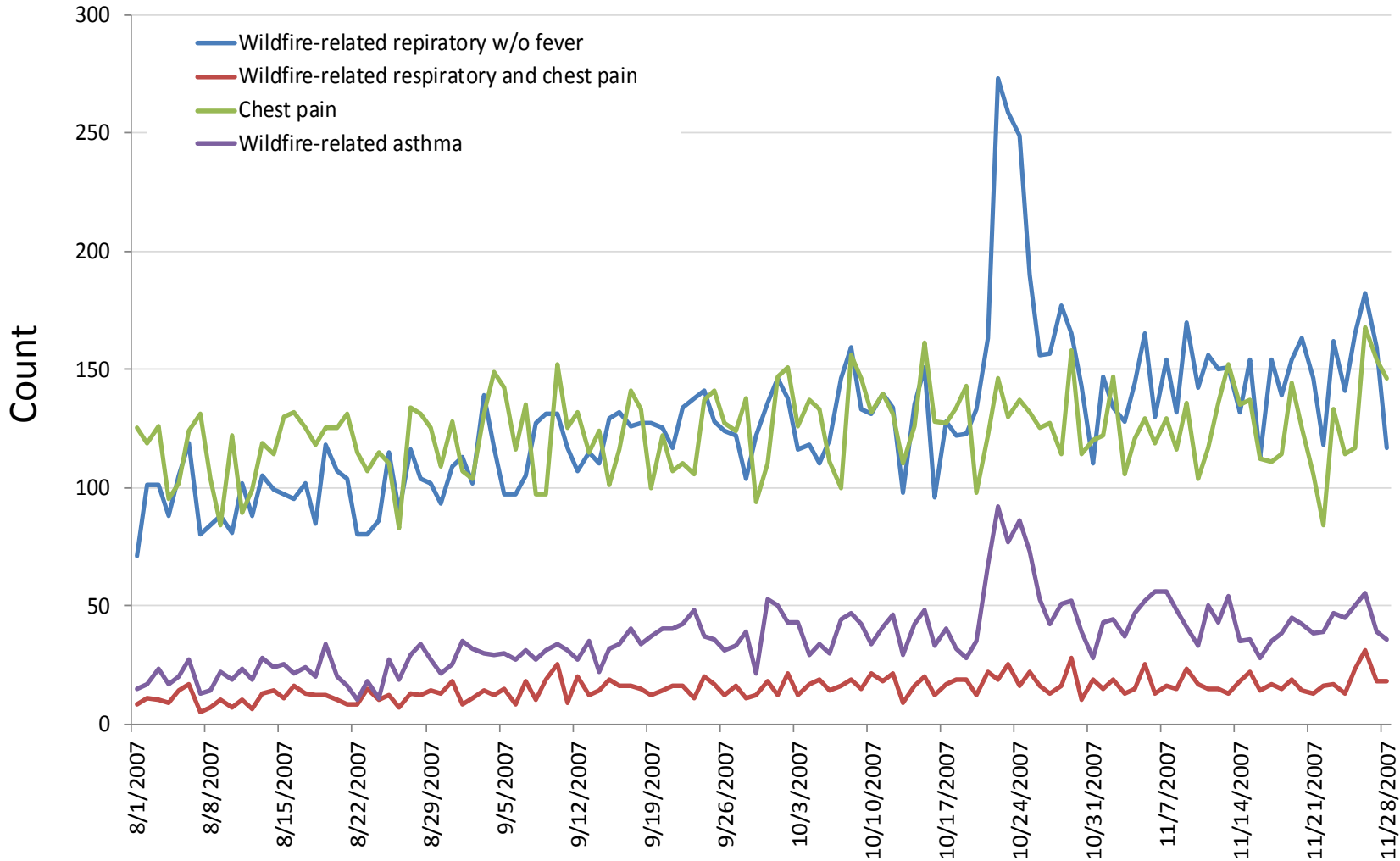


# Emergency Department Visits for Respiratory Symptoms by Age

## 10/21/2007 – 10/25/2007



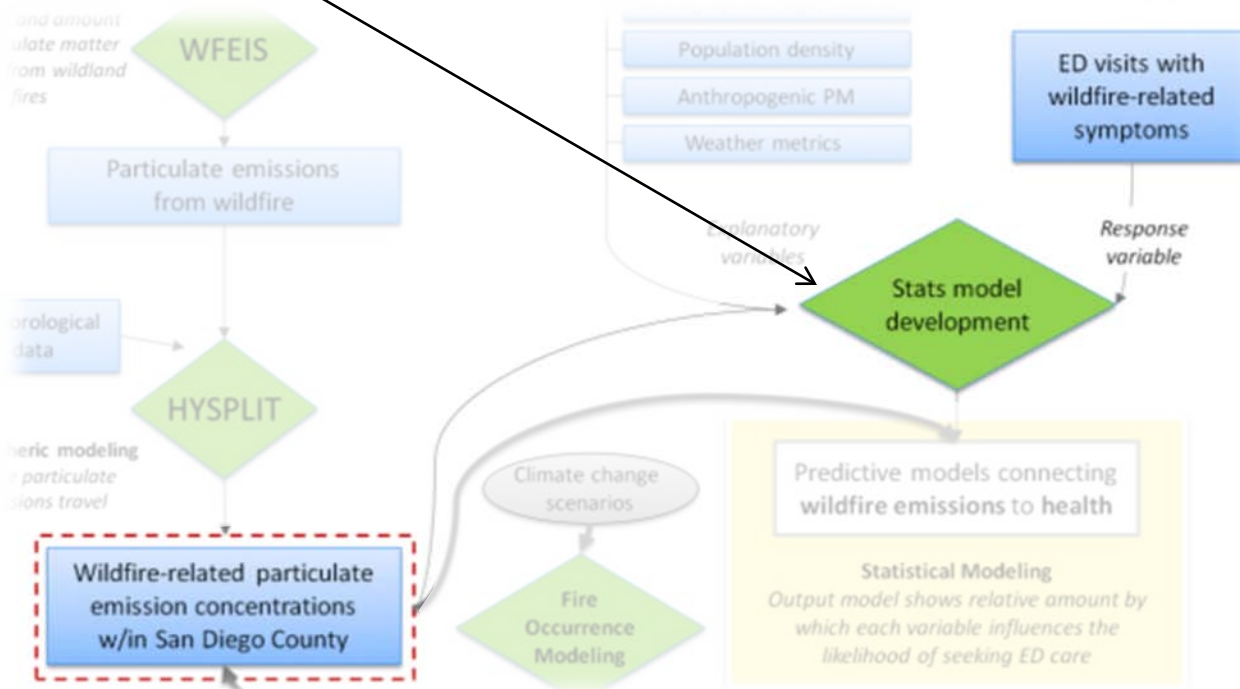
# 2007 Wildland Fire Impact – San Diego County





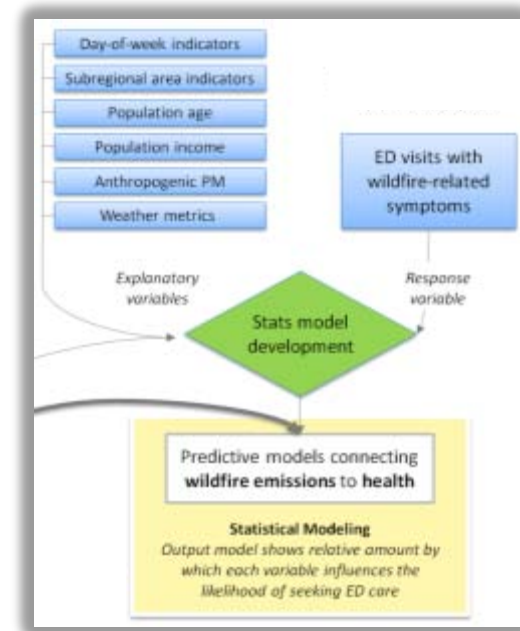
# Health Outcome Modeling

- Now that we have **wildland fire-related health effects**, we can combine with the **wildland fire-related particulate matter concentrations** to build our statistical model, which leads us to...



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# Statistical Modeling Outline

- Statistical approach, techniques, and diagnostics
- Application to our dataset
- Model results
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# Statistical Modeling Approach

- Response variable is  $X_{ij}$ , corresponding to number seeking emergency care, i.e., the number of recorded ED visits for day “i” from population “j” (dictated by spatial demographics). Modeled as a binomial random variable with probability  $p_{ij}$  and known total (population) number  $n_{ij}$ , where probability is assumed to follow logistical regression model of

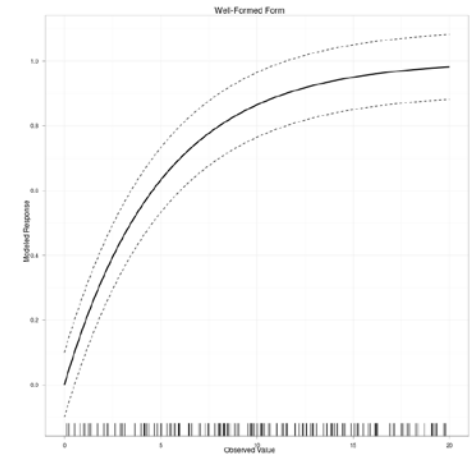
$$\text{logit}(p_{ij}) \equiv \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \sum_{k=1}^n \beta_k x_{ij} + \sum_{m=1}^n f_m(x_{ij})$$

- Response is modeled as an additive sum
  - Offset  $\beta_0$
  - Linear (parametric) terms with coefficients “ $\beta_1, \dots, \beta_n$ ”
  - Nonlinear (nonparametric) terms captured by functionals “ $f_1, \dots, f_n$ ”
- Coefficients and functional values, when back-transformed, are interpreted for their “additive effect on odds ratios” or **the relative amount with which they influence the likelihood of seeking ED care.**
- Generalized Additive Modeling (GAM) provided the statistical framework for fitting this model which takes the form of a nonlinear, binomial logistic regression

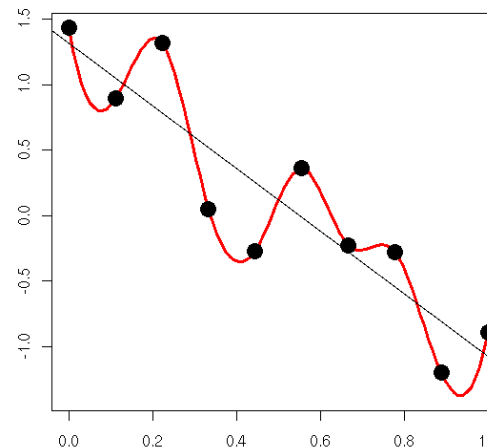
# Generalized Additive Modeling

- GAM is the general case of Generalized Linear Modeling which itself is the general case of normal linear regression.
- GAM allows for mixture of **parametric** and **nonparametric** model terms
- To avoid **overfitting** on non-parametric functionals, a technique called “**generalized cross-validation**” was used to automatically select an appropriate level of regularization or smoothing for the nonlinear terms -- a larger “lambda” dampens “wiggleness” (a technical term)

Example:  
Nonparametric relationship



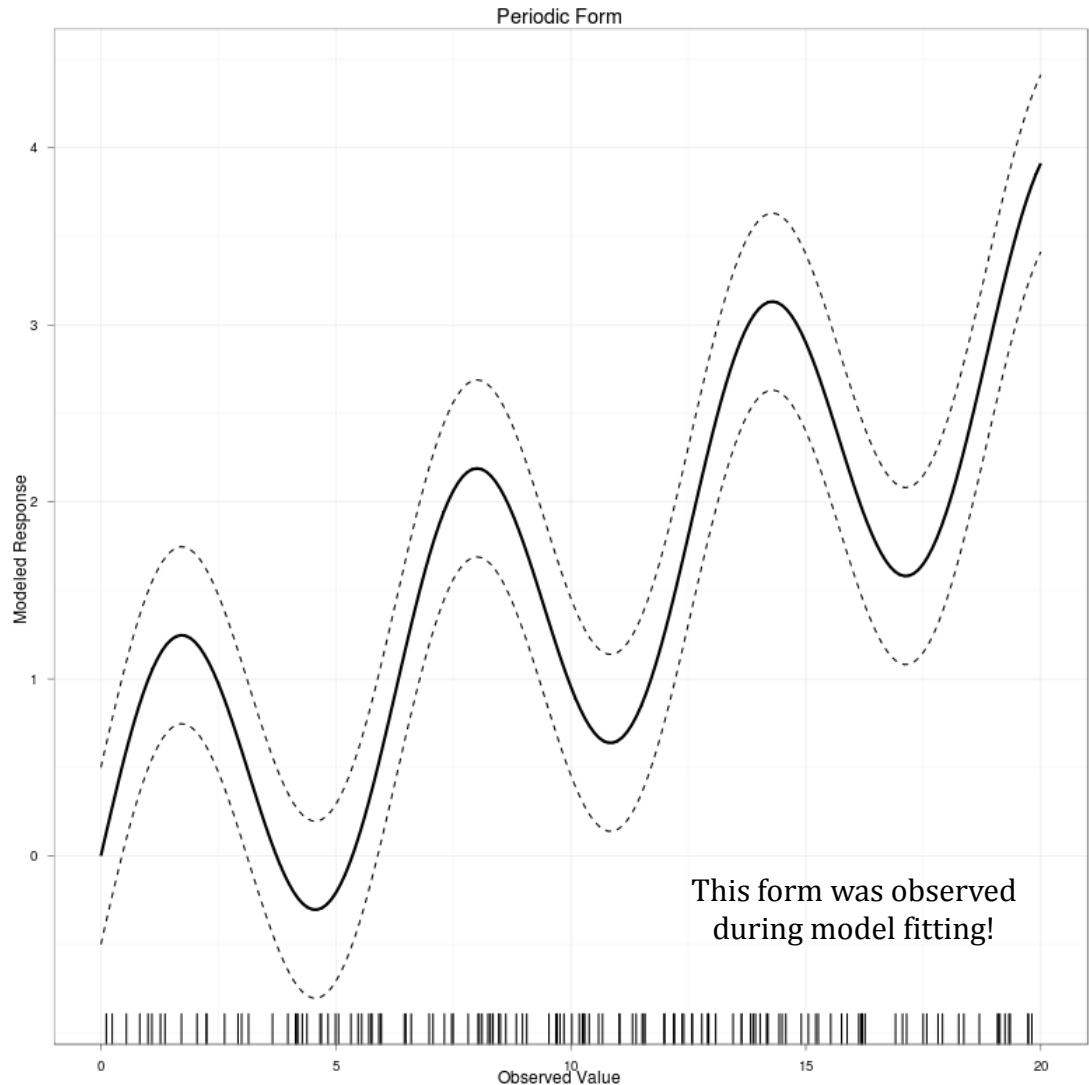
$$\min\left(\sum_{i=1}^n \{y_i - g(x_i)\}^2 + \lambda \int g''(x)^2 dx\right)$$



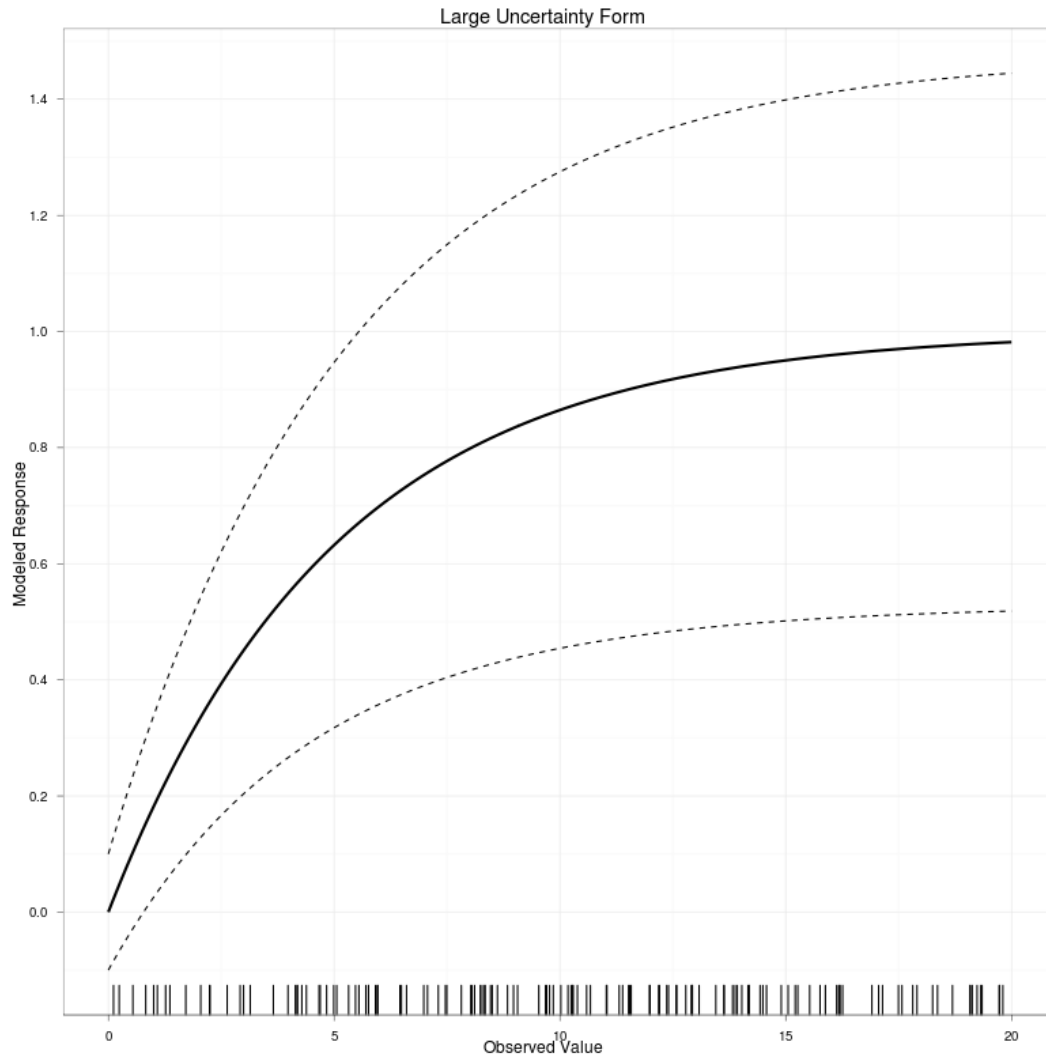
Example:  
Overfitting

# Cyclic + Trend? Really??

Unless there is a strong theoretical reason for this type of response, it would be best to search for additional sources of variation (working with an incomplete model)...



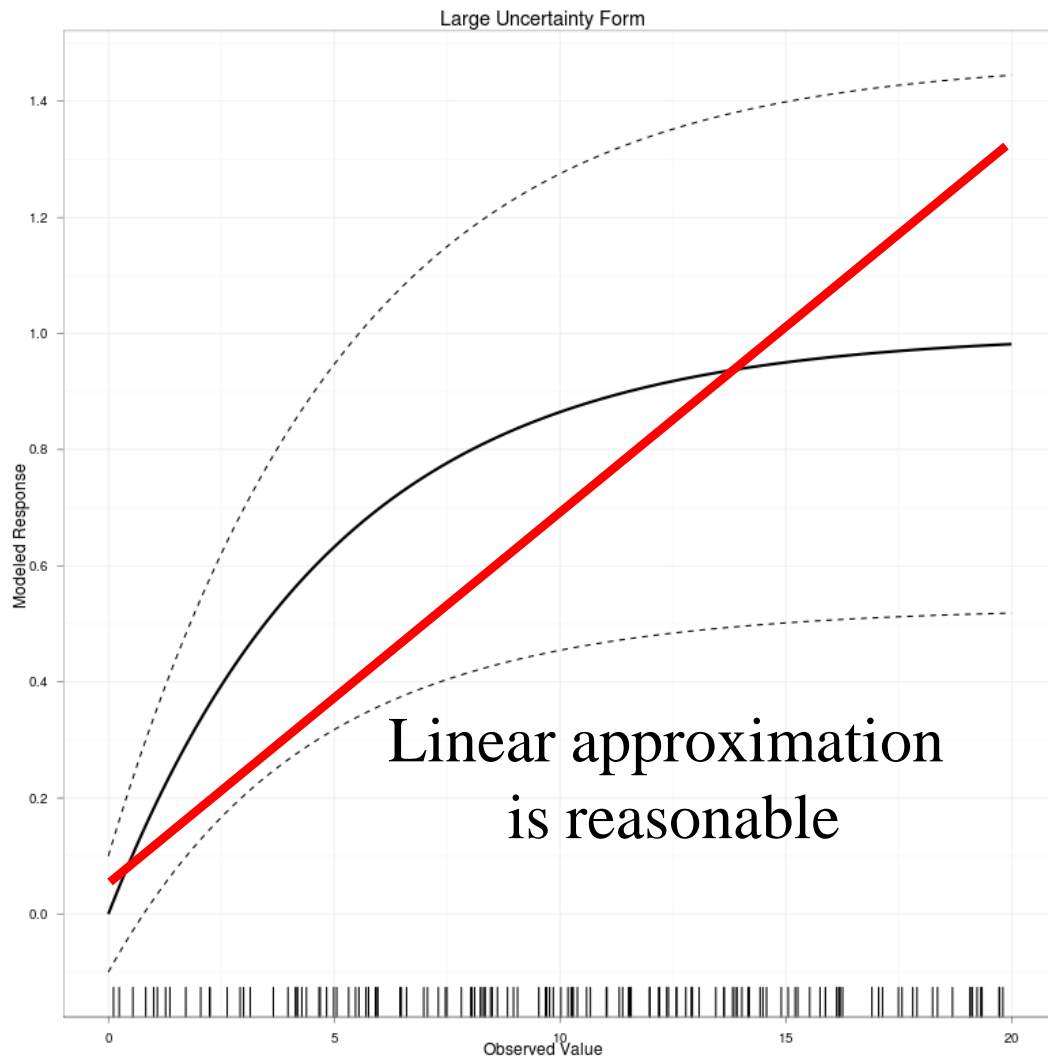
# Is the function linear within its uncertainty bounds?



Note how a linear function may be superimposed within the function's confidence bounds.

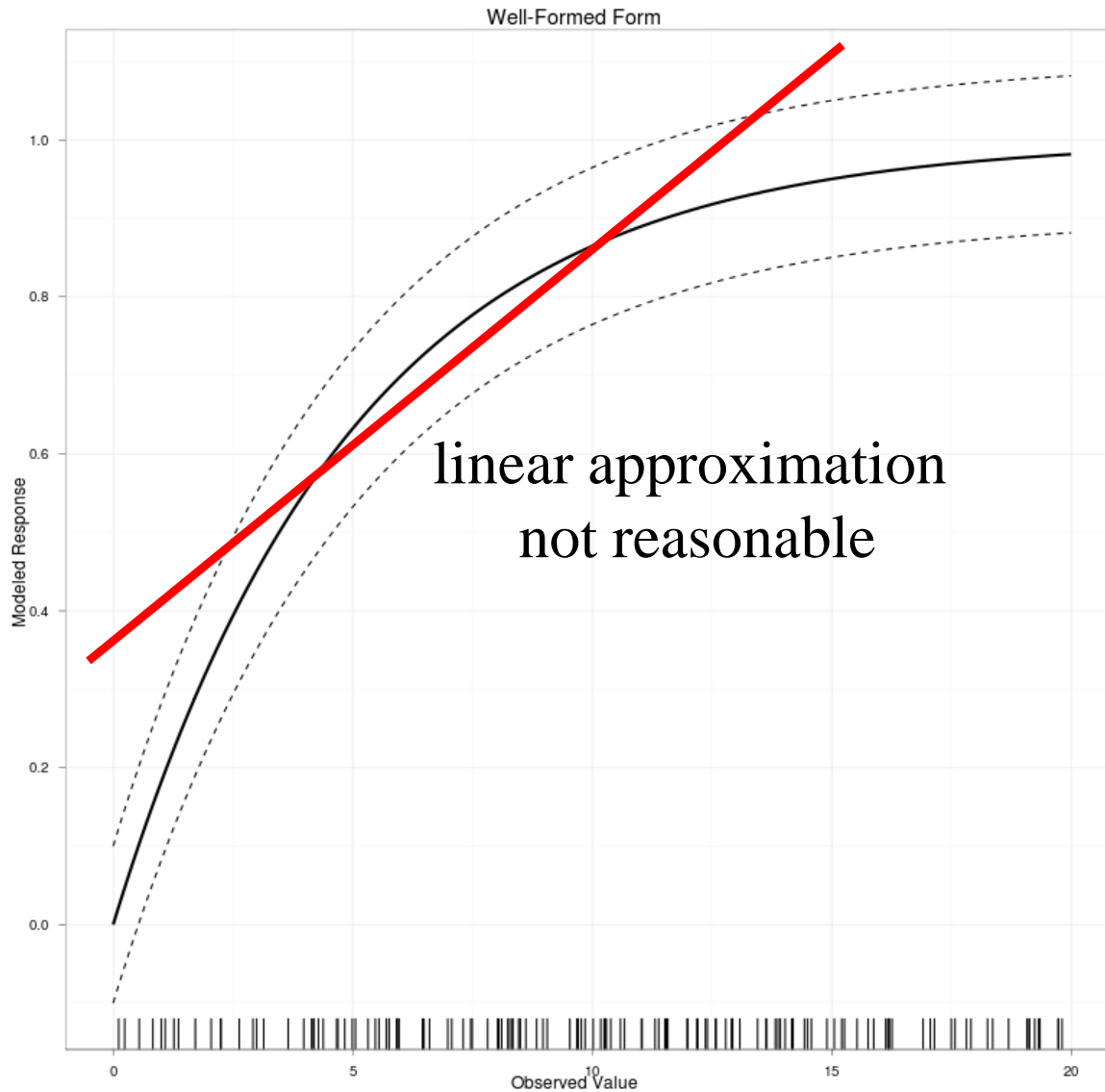


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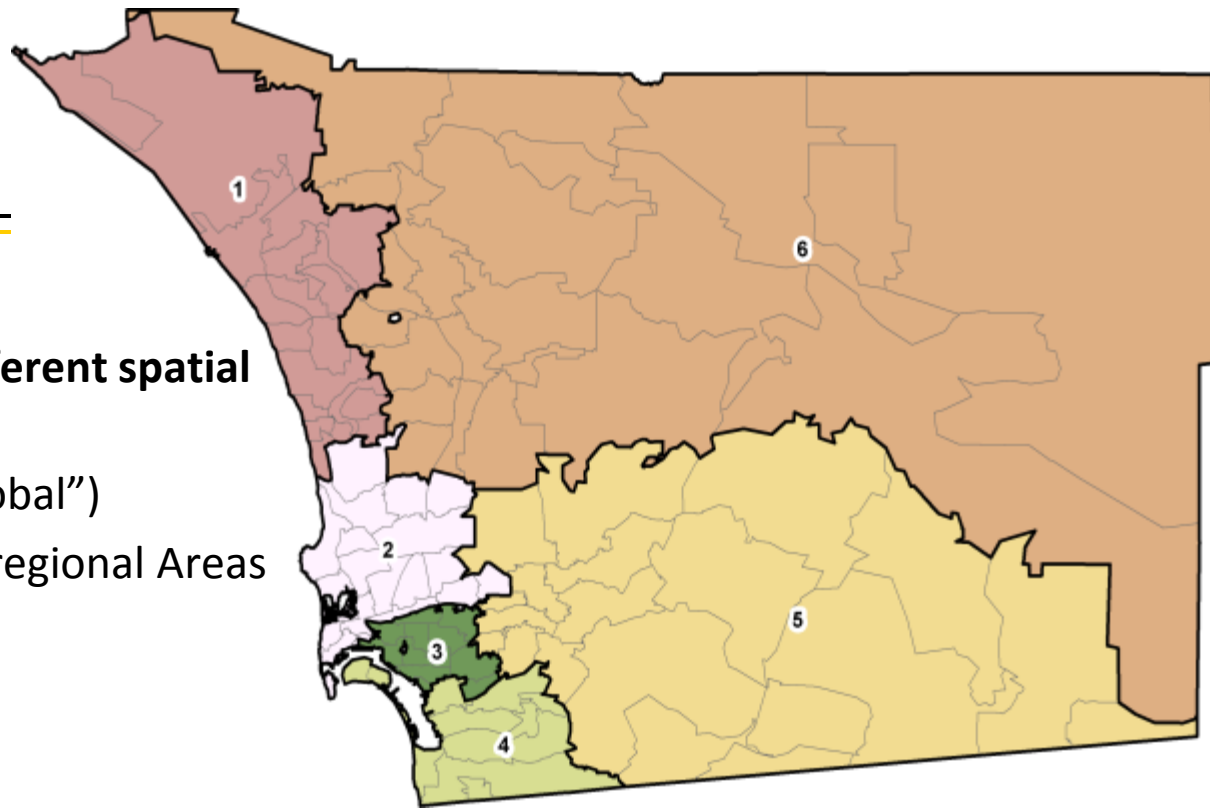
# Tight confidence bounds on a nonlinear function



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# Spatial Aggregation

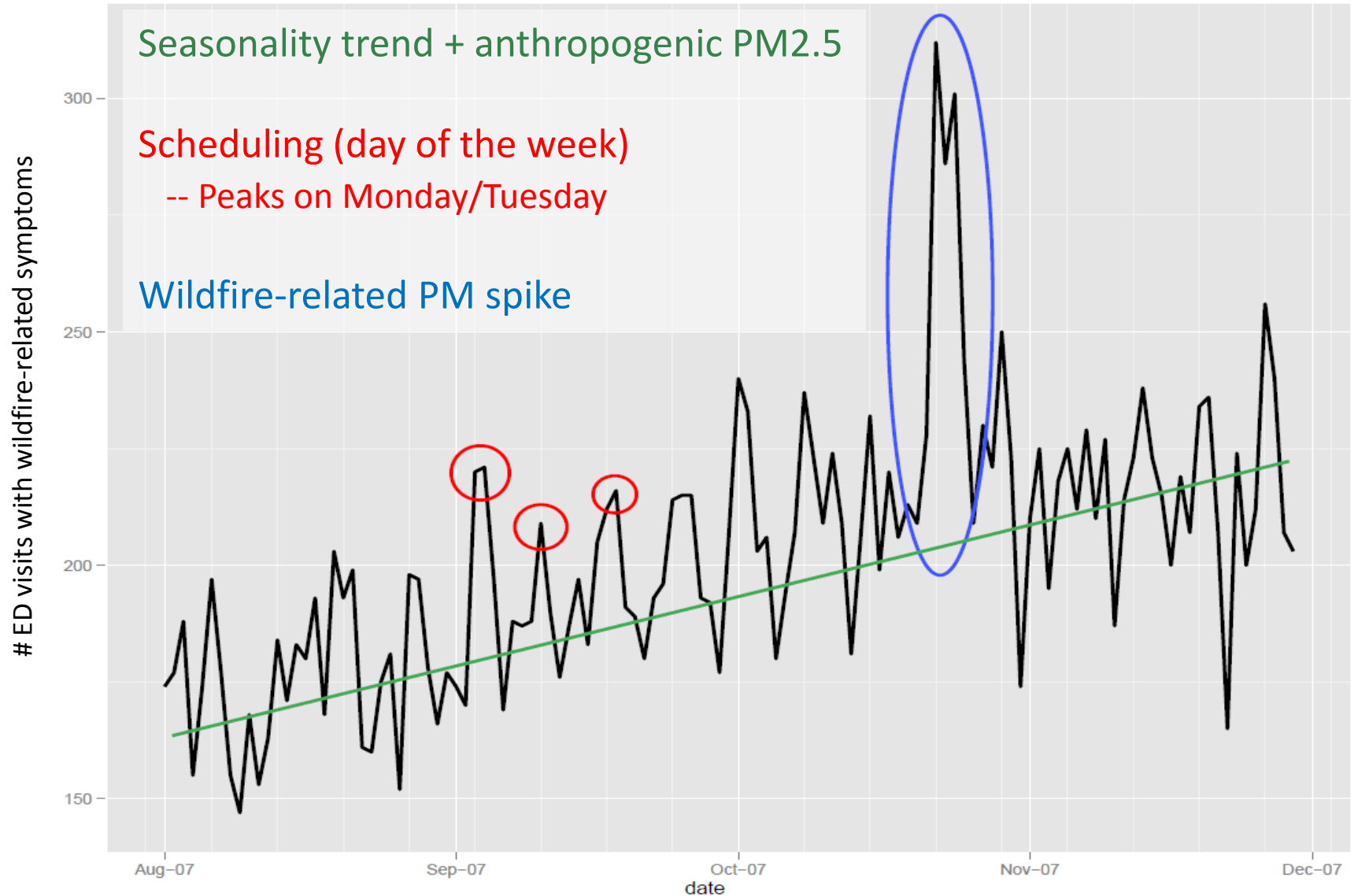


- **Two models were fit at different spatial aggregations:**
  1. San Diego County (“global”)
  2. San Diego County Subregional Areas

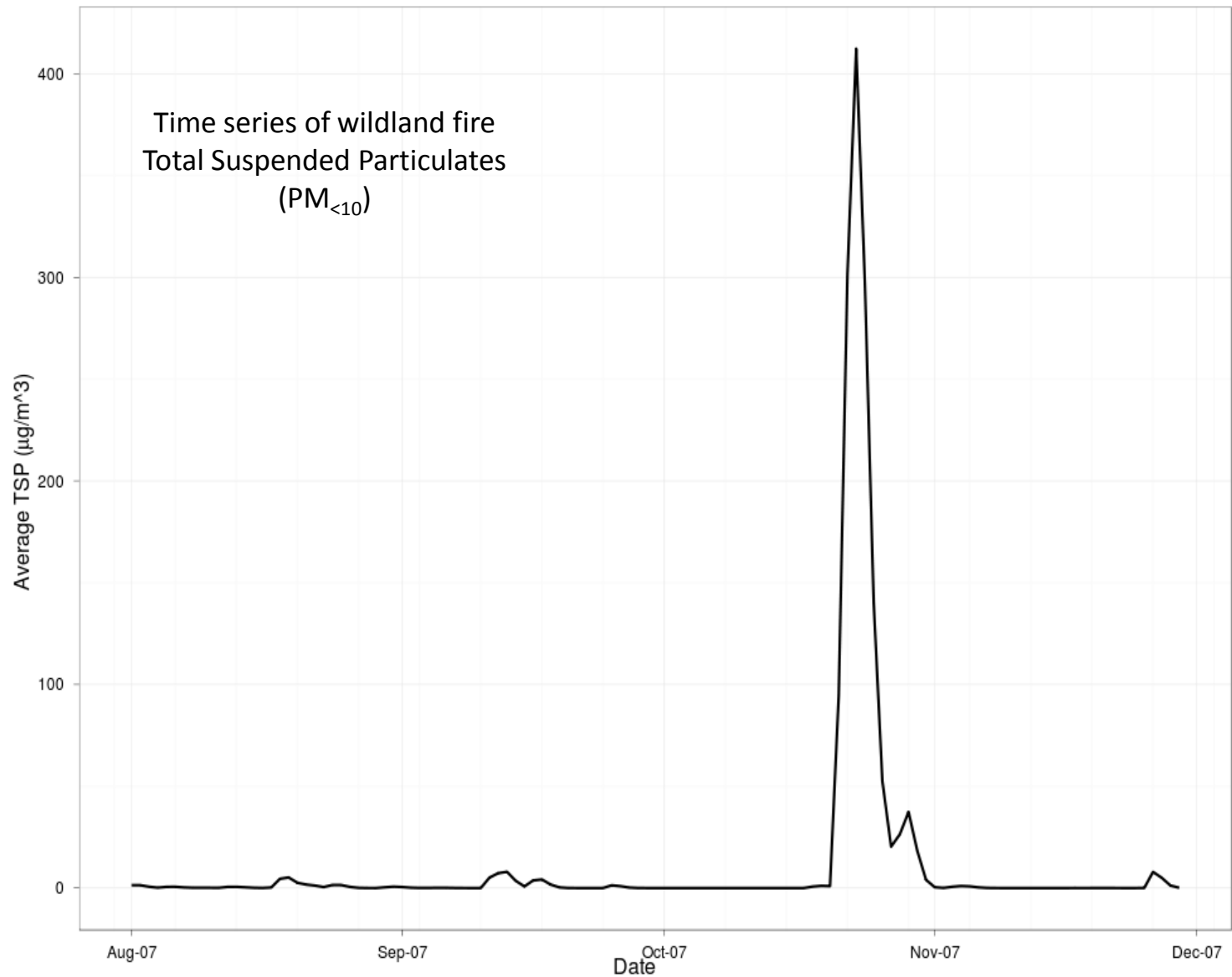
## **There are 4 reasons for this bi-level approach:**

1. The model at the level of San Diego County is easier to interpret having fewer model terms and serves as a heuristic.
2. Additional covariates can be included at the subregional area level to better capture spatial variability.
3. Coefficients and functions can be evaluated for stability between models.
4. Model differences inform appropriate levels of spatial aggregation and data demands for general applicability.

# San Diego County ED Visit Time Series



# San Diego County Modeled TSP Time Series



# Model/Variable Selection and Diagnostics

## ■ Explanatory variables tested

### – Continuous variables:

- Wildland fire  $PM_{<10}$  ← combined PM10 and PM2.5 due to “concurvity”
- Anthropogenic  $PM_{2.5}$
- Air temperature
- Relative humidity
- \*Population age (proportion of pop. within age brackets)
- \*Population income (proportion of pop. within income brackets)
- \*Elevation
- \*Population density
- \*Housing density

### – Binary variables:

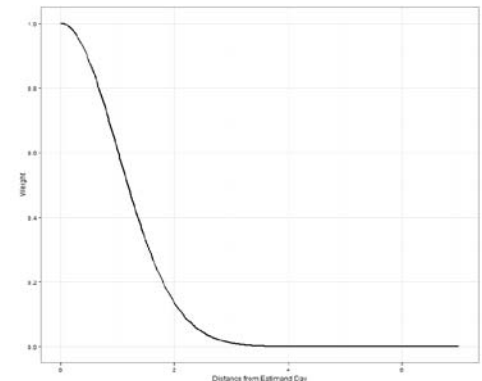
- Day-of-week indicators (e.g., “Is Monday”, “Is Tuesday”, etc.)
- \*Subregional area indicators (e.g., “Is SRA1”, “Is SRA2”, etc.)

\* Subregional area model only



# Model/Variable Selection and Diagnostics

- Observational data was stored in a relational database with the analysis performed in R v2.13 using the “mgcv” GAM-fitting package.
- Utilized standard backward variable selection
  - Standard iterative, remove one-at-time method
  - Nominal 5% significance level.
- Nonlinear vs. linear models were tested on all continuous variables
  - Nonlinear models selected based on stability, confidence interval criterion (required a curve or not), and “reasonability.”
  - Linear models selected for cases where nonlinear models were not required or appeared unstable - statistically justified
  - Utilized a bivariate interaction term for measures of relative humidity and temperature (i.e. weather).
- For particulate exposure, utilized a Gaussian-type weighting function
  - centered on the estimand day
  - standard deviation of one day.



# Statistical Modeling Outline

- Statistical approach, techniques, and diagnostics
- Application to our dataset
- **Model results**
- Model considerations

# Final Models

$$\text{logit}(p_{ij}) \equiv \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \sum_{k=1}^n \beta_k x_{ij} + \sum_{m=1}^n f_m(x_{ij})$$

*Wildland fire  $PM_{<10}$*

*$I_{Monday}$*

*$I_{Tuesday}$*

*\* $I_{SRA3}$*

*\* $I_{SRA6}$*

*\* $Age_{<24}$*

*\* $Income_{>50k}$*

*$s(\text{Anthropogenic}_{PM2.5})$   
 $te(\text{Temp}_{min}, RH_{mean})$*

## Tested but excluded:

- Other Weekday Offsets
- Other Weather Metrics
- \*Other SRA offsets
- \*Mean Elevation
- \*Housing Density
- \*Population Density

\* = Subregional Area Model Only

# Interpreting the Estimated Regression Terms

- Coefficients (or functions evaluated at observational values) are interpreted for their effect on log-odds or the logit-transformed response value. Transformations used for mathematical convenience!

- Odds is related to probability by:

$$Odds = \frac{Prob}{1 - Prob}$$

- For static values (e.g. indicator variables, SRA demographic proportions, model intercept) an example transformation using the Monday indicator variable from the San Diego County model:

$$\text{CHANGE IN ODDS} \longrightarrow 1.17 = e^{0.16} \longleftarrow \text{FITTED VALUE}$$

- For continuously varying data (e.g. fire TSP, weather), the predictor's value must be included to properly scale the odds effect (also applies to nonlinear predictors). Example transformation using maximum observed fire TSP concentration from the SRA model:

$$\text{CHANGE IN ODDS} \longrightarrow 1.70 = e^{587 * 0.0009} \longleftarrow \text{FITTED VALUE}$$

↑  
"OBSERVED" VALUE

# Model Results for Parametric Terms (Odds Effects)

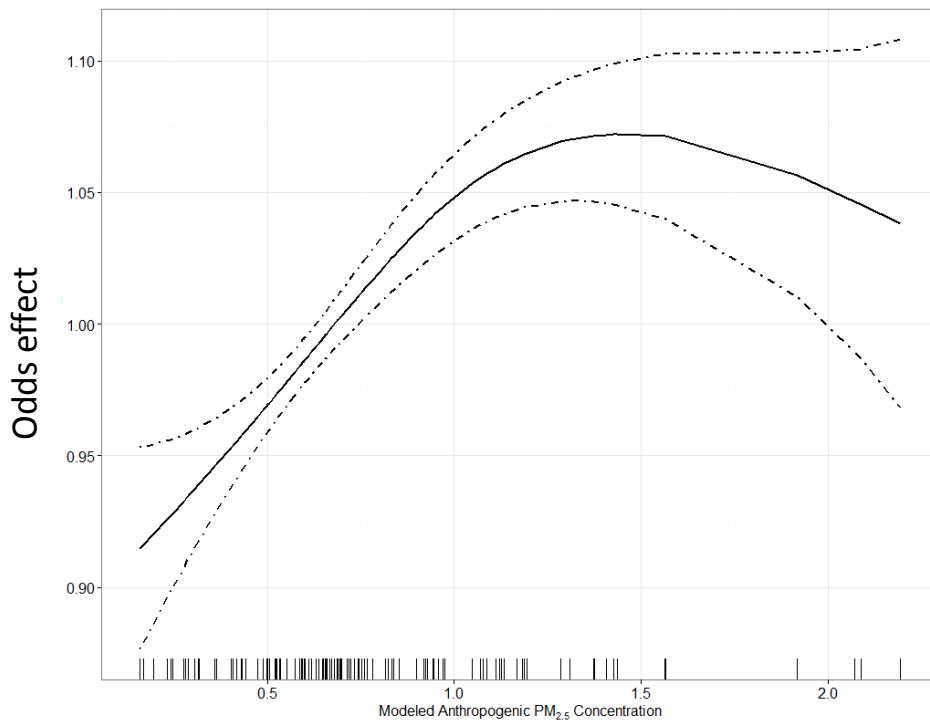
Term	San Diego County Model		Subregional Area Model	
	Observed Data Range	Estimated Odds Effect Range <sup>1</sup>	Observed Data Range	Estimated Odds Effect Range <sup>1</sup>
Adj. r-Squared	0.75		0.617	
Percent Deviance Explained	76%		75%	
Intercept	-9.45	7.9e-5	-7.87	3.8e-4
<i>Wildland fire PM<sub>&lt;10</sub></i>	0 - 412.31	1 - 1.43	0 - 623.47	1 - 1.72
<i>I</i> <sub>Monday</sub>	(0, 1)	(1, 1.17)	(0, 1)	(1, 1.17)
<i>I</i> <sub>Tuesday</sub>	(0, 1)	(1, 1.07)	(0, 1)	(1, 1.07)
<i>I</i> <sub>SRA3</sub>	NA	NA	(0, 1)	(1, 0.52)
<i>I</i> <sub>SRA6</sub>	NA	NA	(0, 1)	(1, 1.19)
<i>Income &gt;50k</i>	NA	NA	0.31 - 0.55	0.25 - 0.08
<i>Age &lt;24</i>	NA	NA	0.32 - 0.41	1.77 - 2.06

<sup>1</sup> GAM with binomial distribution and logit link

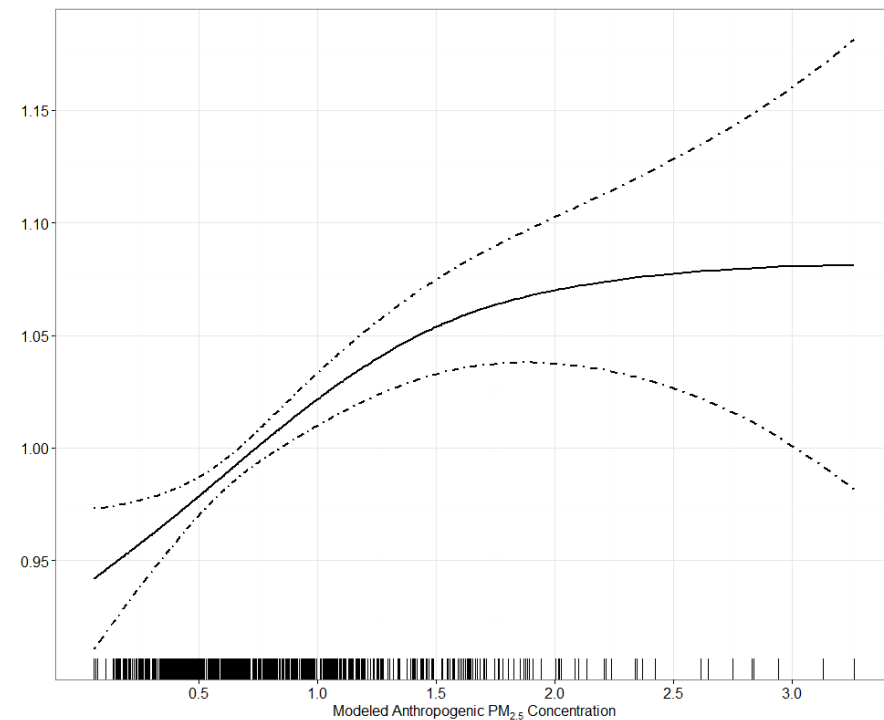
- All terms are significant at the 1% level ( $p < 0.01$ ).
- Maximum estimated effect on the odds of seeking ED care from *wildland fire PM<sub><10</sub>* is **43%** change for San Diego County model and **72%** change for the Subregional model (linear effect).

# Estimated Nonparametric Function for Anthropogenic PM<sub>2.5</sub> with Rugplots

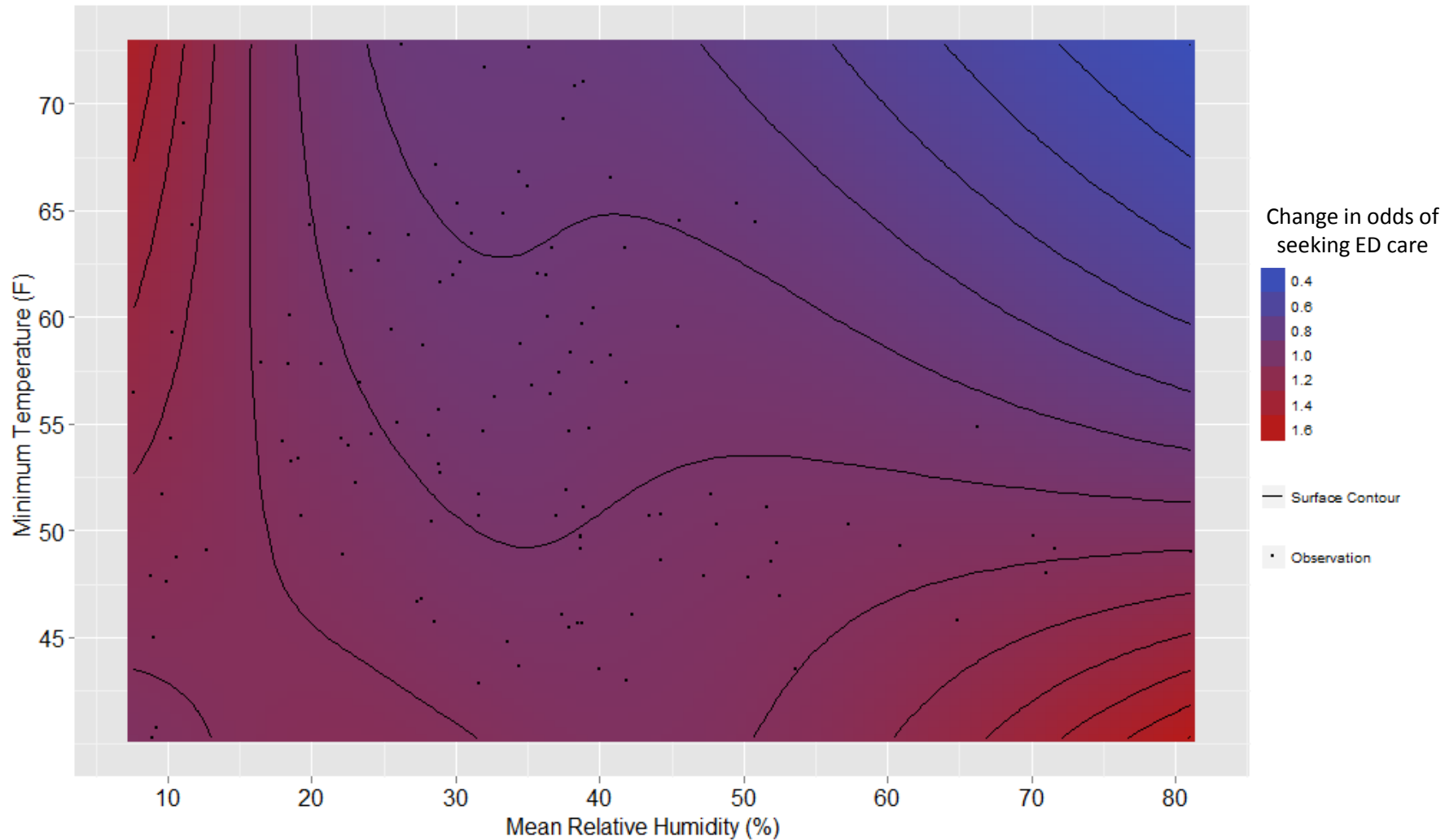
San Diego County (“global”) model



Subregional Area model

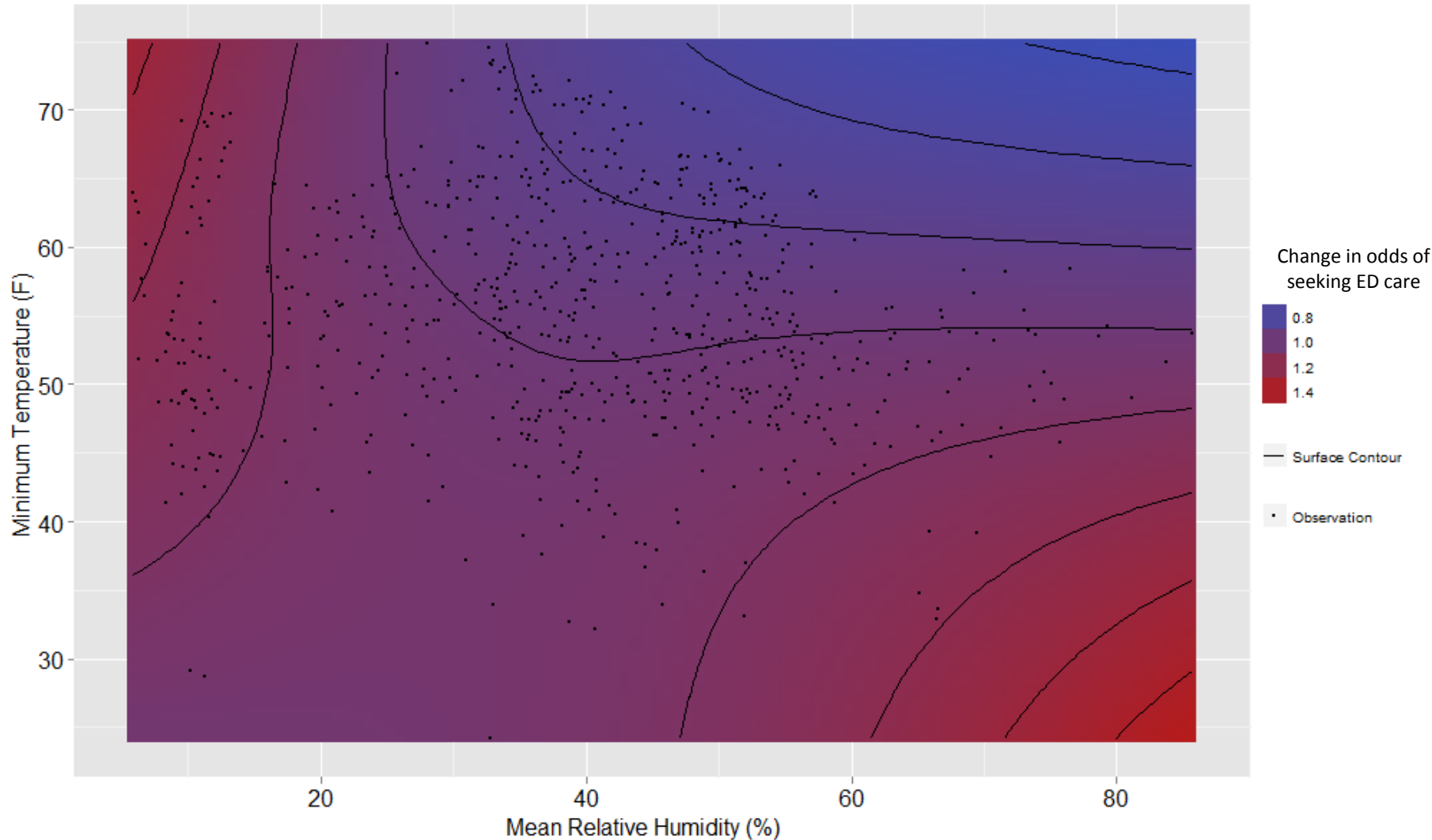


# Estimated Nonparametric Bivariate Function for Temperature/Humidity with Rugplots : San Diego Model

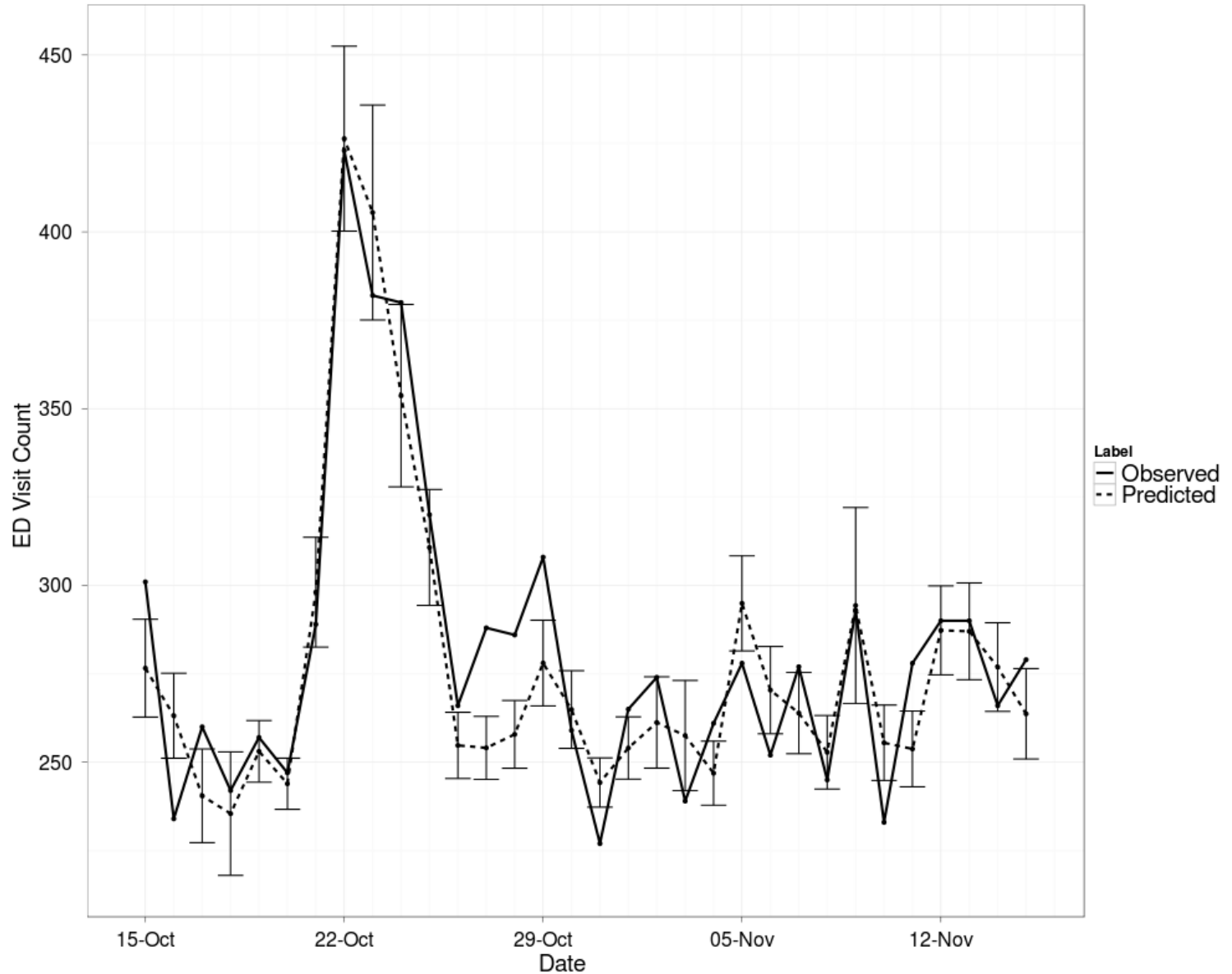




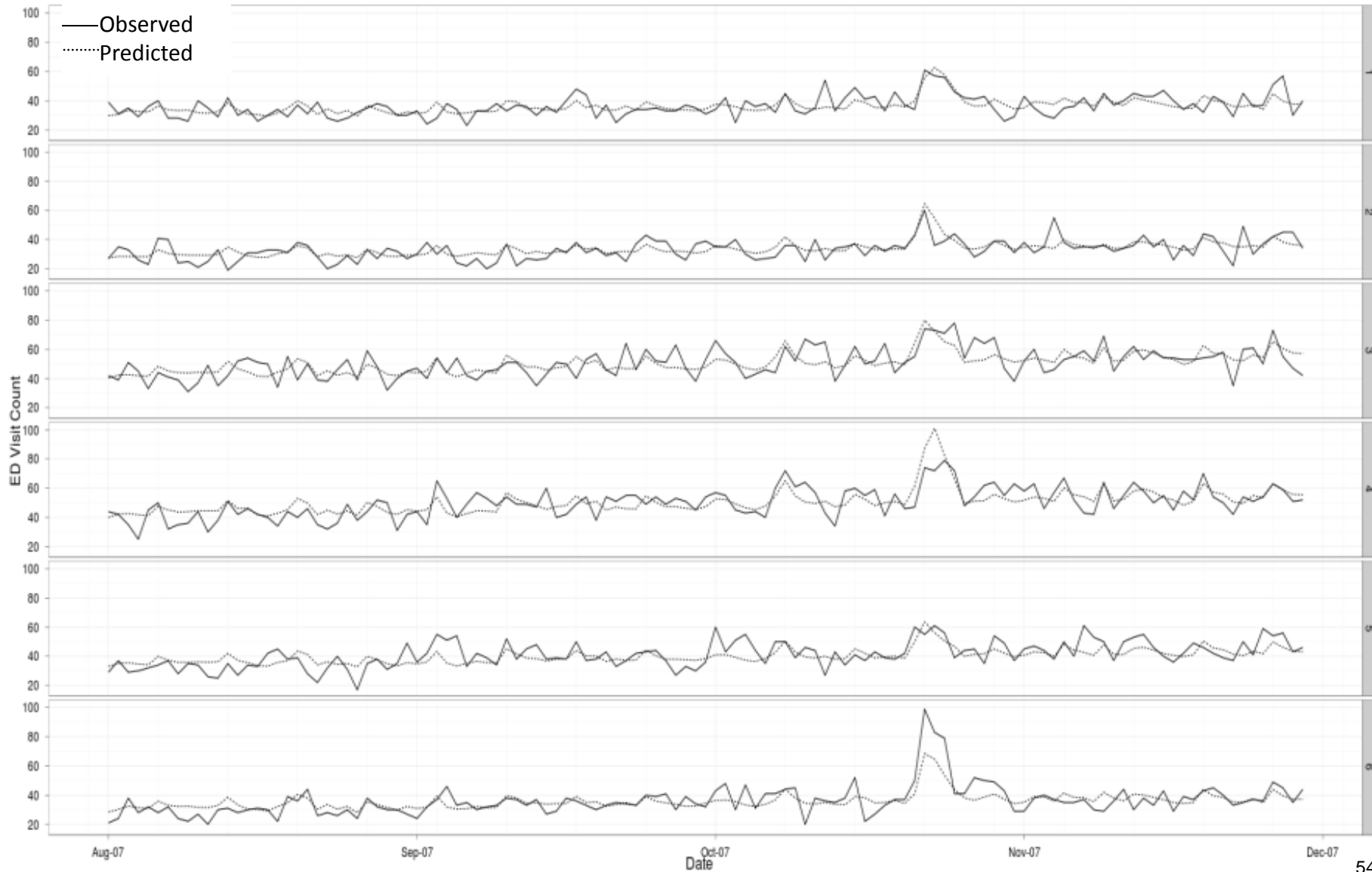
# Estimated Nonparametric Bivariate Function for Temperature/Humidity w Rugplots : Subreg Area Model



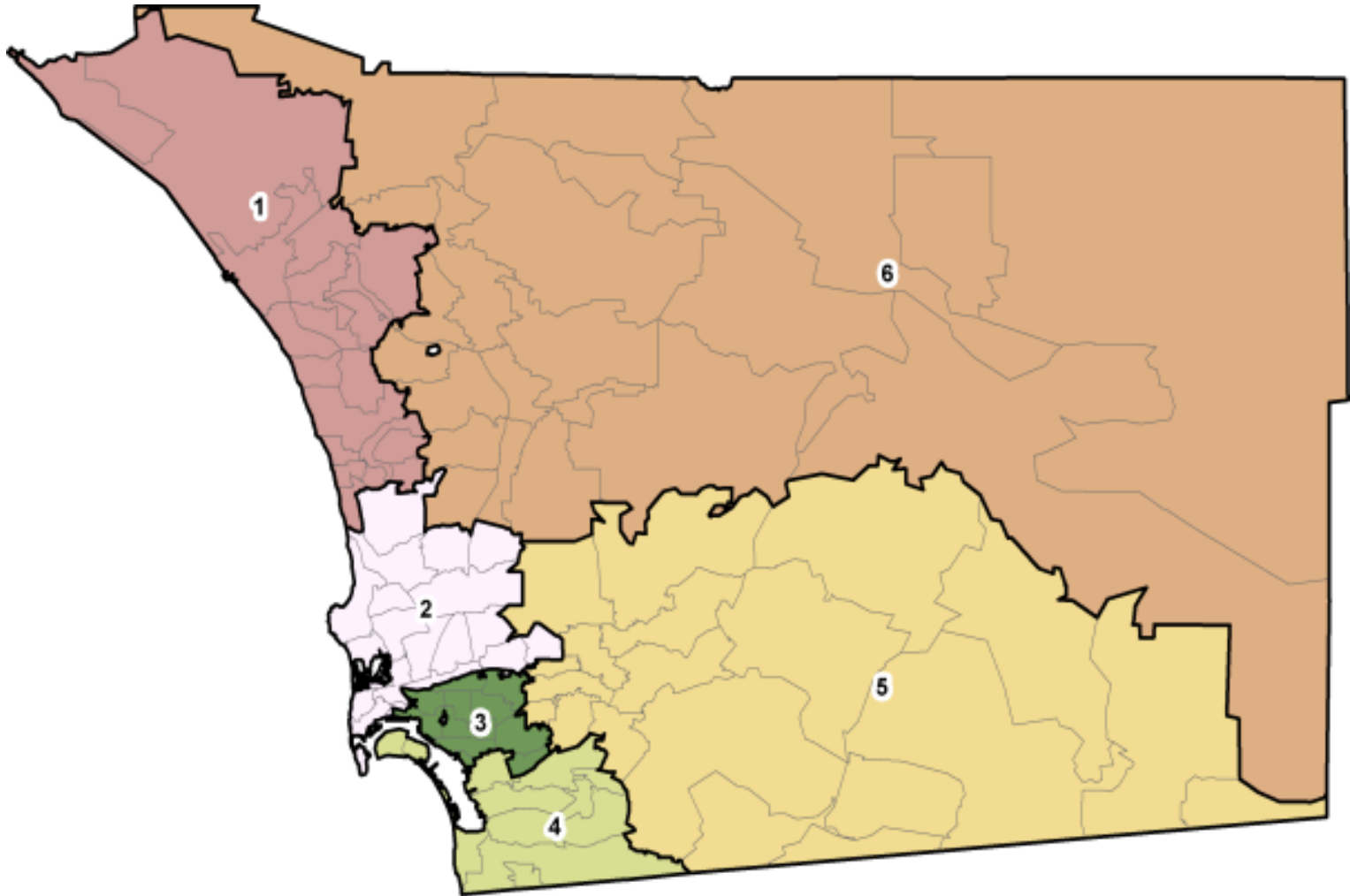
# Predicted-Observed San Diego County



# Predicted-Observed Subregional Areas



# Subregional areas



# Statistical Modeling Outline

- Statistical approach, techniques, and diagnostics
- Application to our dataset
- Model results
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# Model Considerations

- A simple cumulative exposure model was used that may not be applicable in all situations.
- Longer time series would allow these effects to become more measurable and significant.
- Other atmospheric irritants such as pollen and ozone may account for additional variability not captured by anthropogenic PM2.5 and weather. Wind velocities may also play a role.
- Extrapolation to responses under different burning scenarios (i.e. sustained for longer time period) is difficult considering the lack of definition for lagged and cumulative exposure effects in these data.

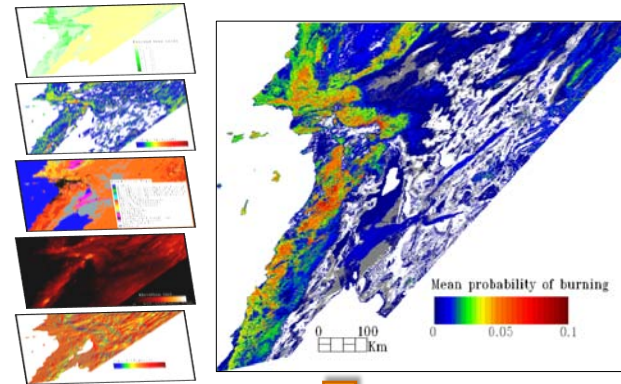
# Presentation Outline

- Introduction and Background
- Project methods and results
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# Modeling Future Fire Occurrences

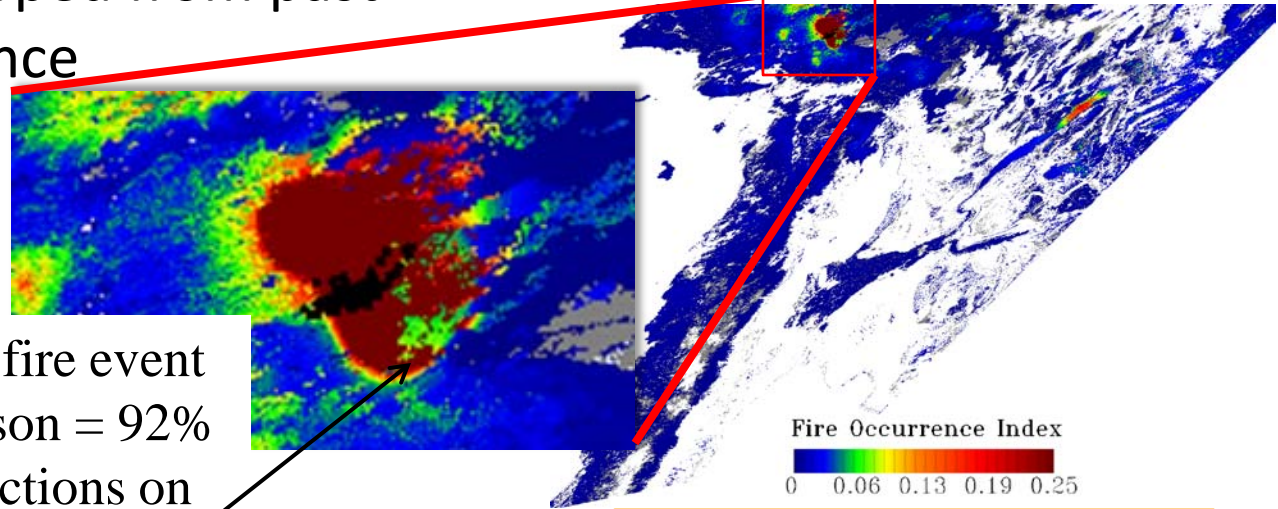
- **Fire Occurrence Index (FOI)** calculated daily from mapped Risk of Ignition (ROI), Potential Burning (PB), and Fire Weather (FW) developed from past fire occurrence

## Potential Burning



## Risk of Ignition

## Fire Weather



The largest fire event of 2010 season = 92% of fire detections on July 30, 2010 (black dots)

## FOI on July 30, 2010



# Modeling Future Fire Occurrences

**Canadian Fire Weather Index** was calculated for the study area

- Using weather variables produced by the Regional Climate Model (RegCM Version 4.1)<sup>1</sup> at 25 km cell-size
- Run under IPCC future climate scenarios
- For 2001-2040

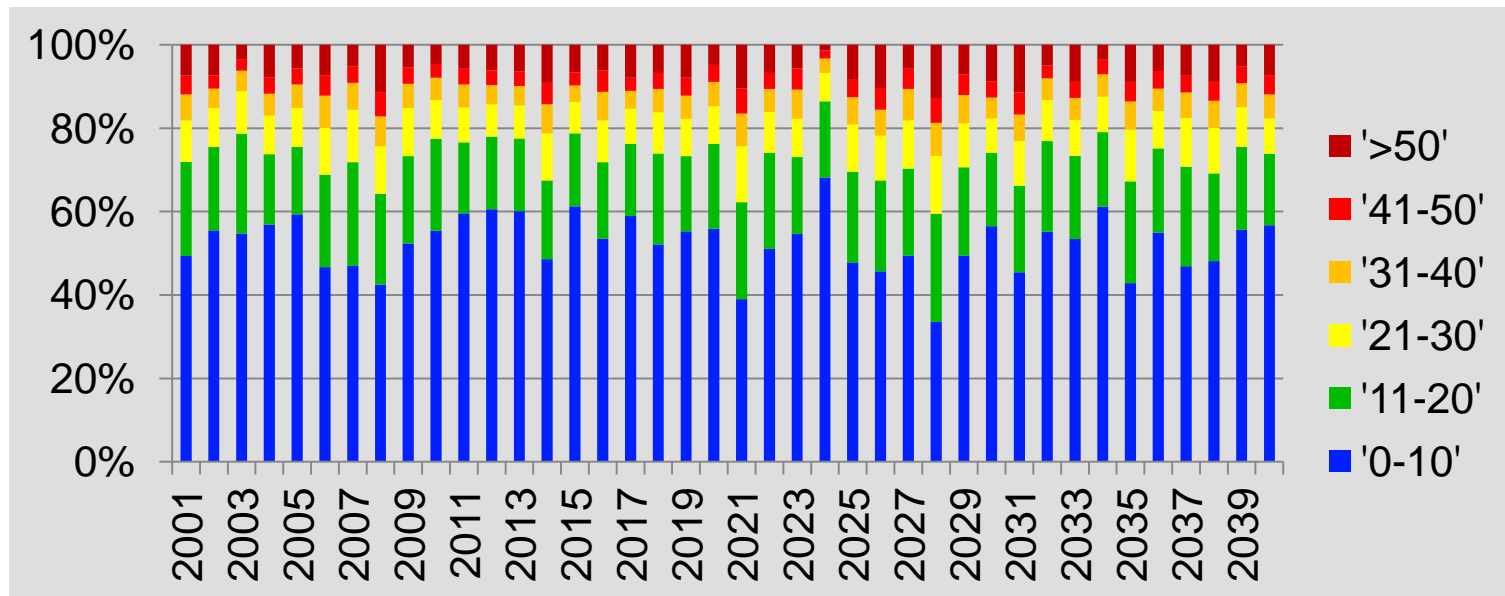
## **Result:**

- At the decadal scales the RegCM produced comparable conditions as those observed during 2001 – 2010
  - two years of elevated climatological fire danger in the 2000's
- Based on this finding we compared changes in RegCM-generated Fire Weather Index during 3 decades in the future (2011-2020, 2021-2030, and 2031-2040) to the simulated conditions during 2001-2010.

<sup>1</sup>Pal, J. S., et al. (2009), The ICTP RegCM3 and RegCNET: **Regional Climate Modeling for the Developing World**, *Bull. Amer. Meteor. Soc.*, **88**, 1395.

# Modeling Future Fire Occurrences

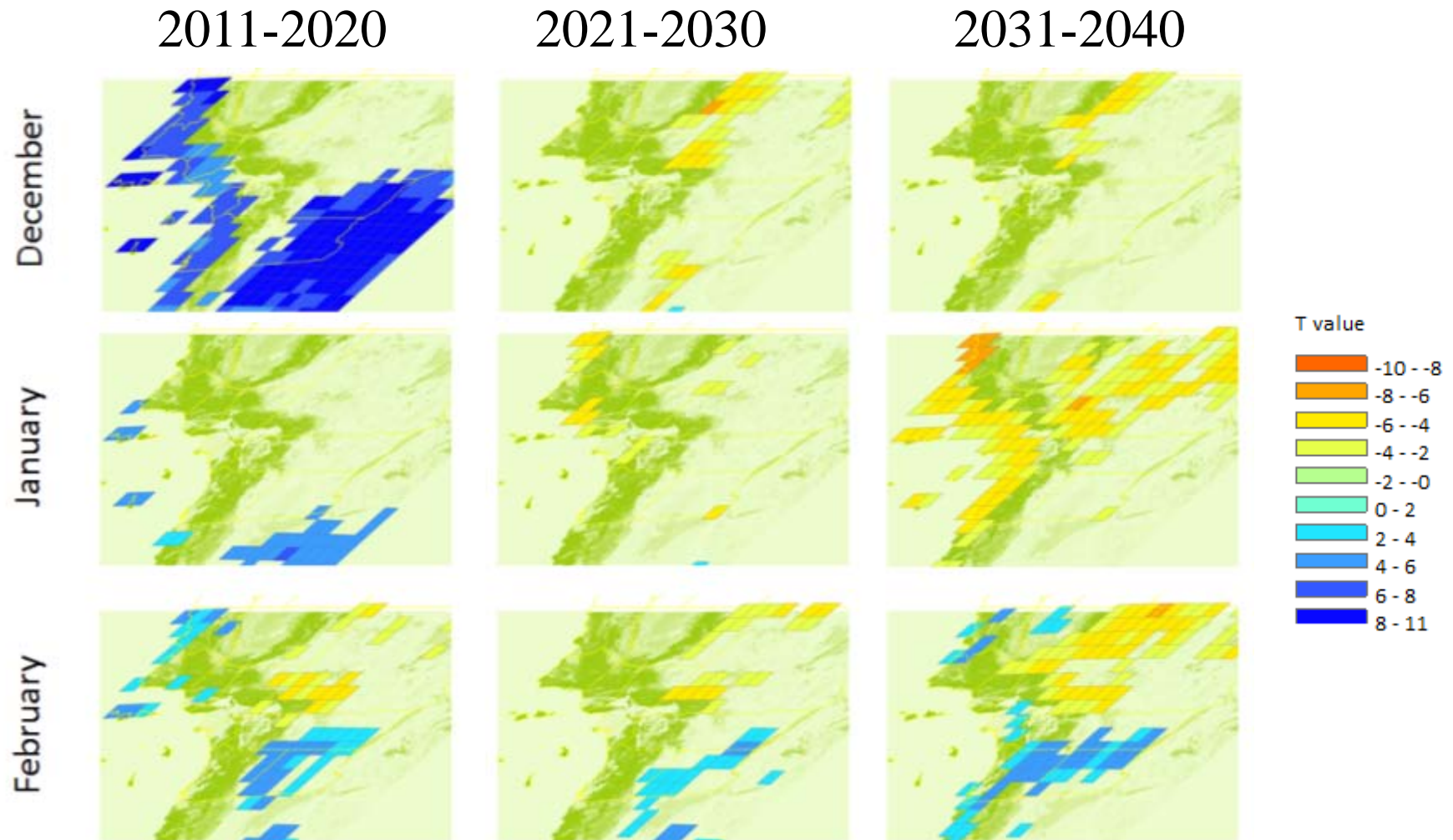
- Our results show it is likely that San Diego County will experience approximately two extreme fire seasons each decade by 2040. Similar to the present.



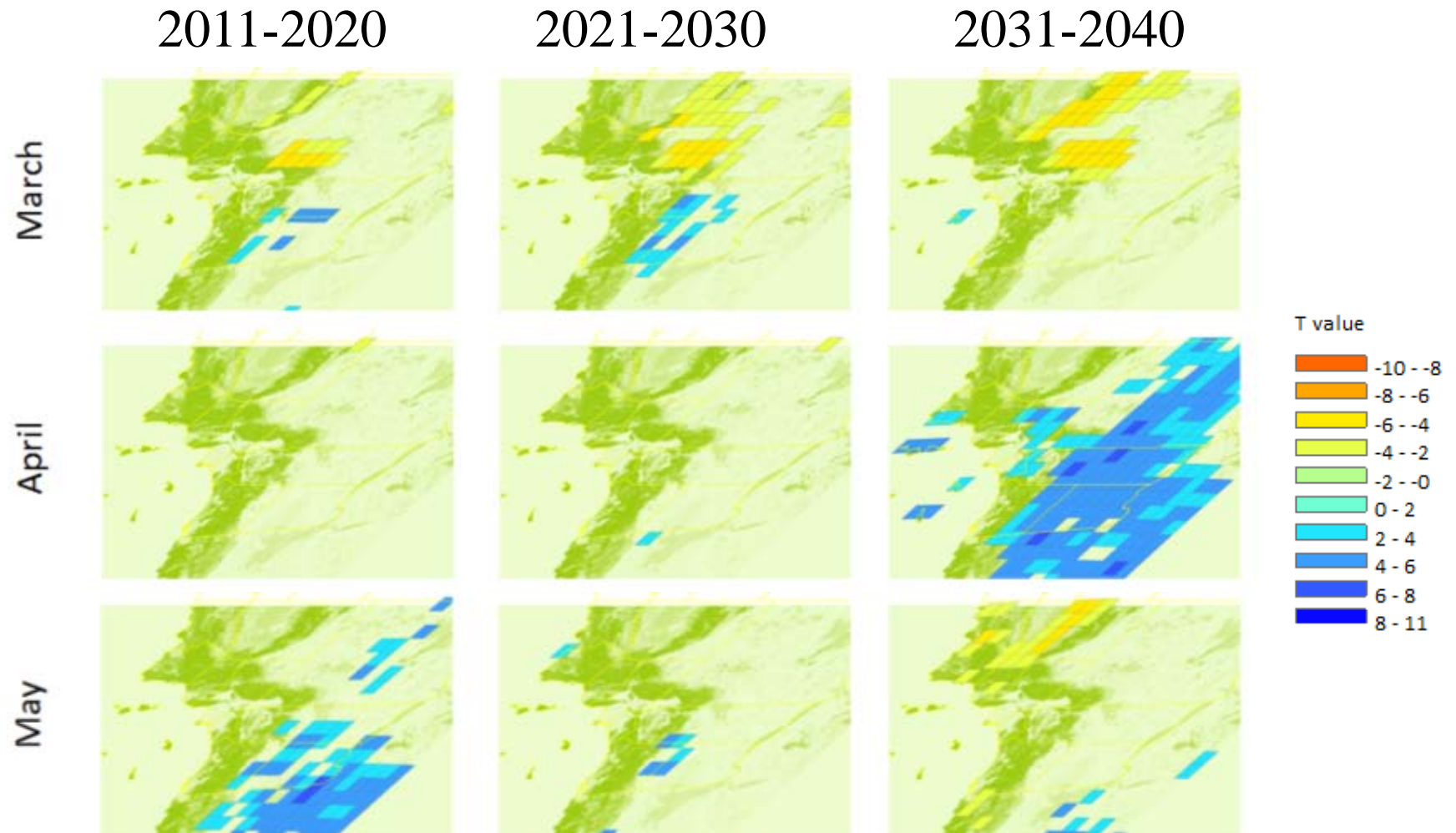
# Climate-induced changes in fire weather: methods

- Computed T-test values (*next slides*) to evaluate the differences in means of monthly FWI at the decadal scale.
  - e.g. all January fire weather index values over 2001-2010 (n = 310, 31 days in January multiplied by 10 years) were compared with all January values from 3 subsequent decades: 2011-2020, 2021-2030, and 2031-2040.
- Results with  $p < 0.001$  are spatially shown in the *next slides*.
  - T values show change as **base\_decade – new\_decade**, where base\_decade is 2001-2010 and new\_decade is 2011-2020, 2021-2030, or 2031-2040.
  - Thus **negative values imply an increase in overall fire danger** (expressed by FWI) (shown in green-red) and positive values show a reduction in the overall fire danger values (shown in blues).
- Background color (*next slides*) represents the range of Potential for Burning layer from the FOM with darker green indicating higher potential.

# Spatial and temporal patterns of climate-driven changes in fire weather: winter

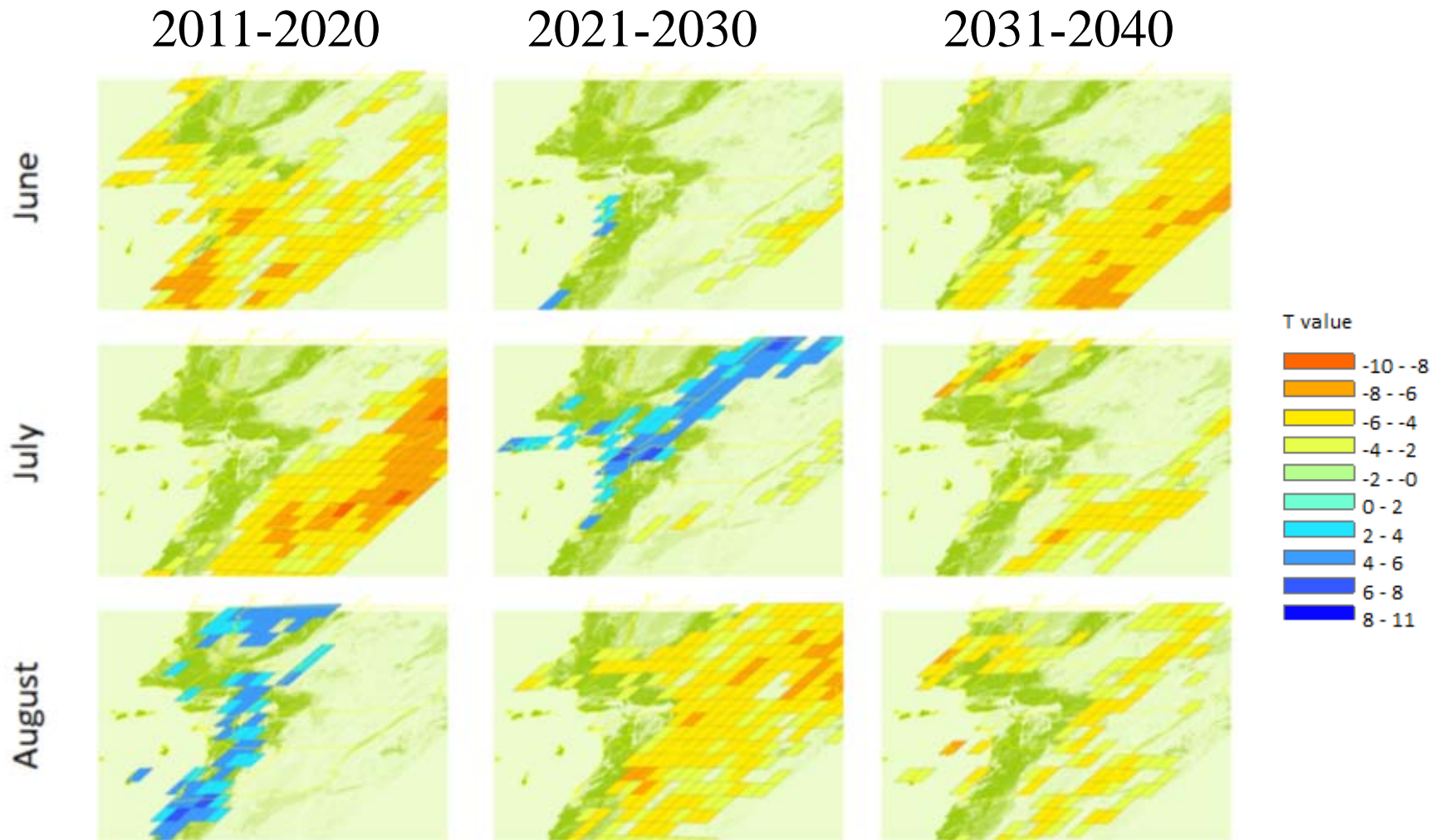


# Spatial and temporal patterns of climate-driven changes in fire weather: spring

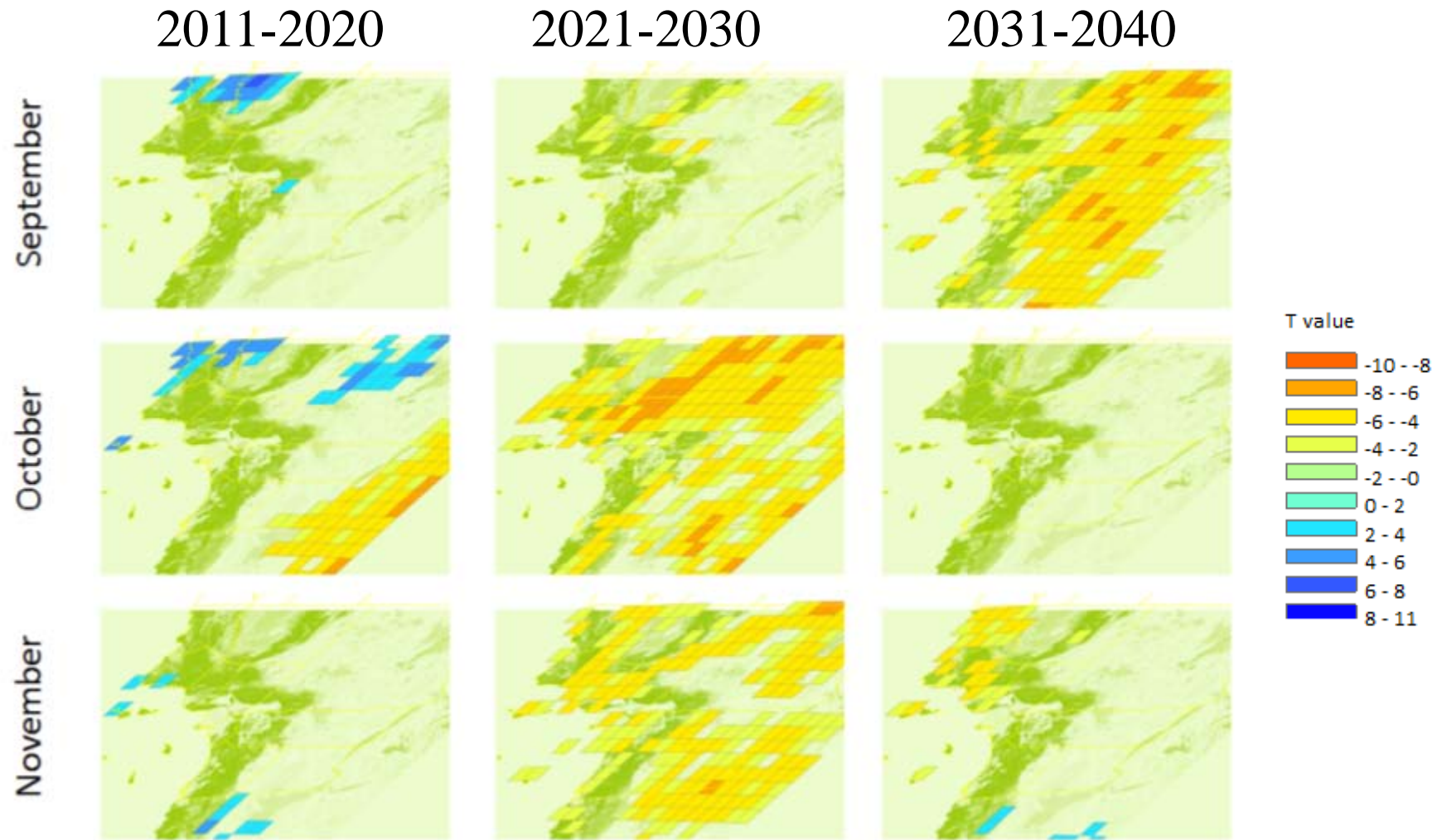




# Spatial and temporal patterns of climate-driven changes in fire weather: summer



# Spatial and temporal patterns of climate-driven changes in fire weather: fall



# Spatial patterns of future changes in fire weather

- The overwhelming majority of statistically significant ( $p < 0.001$ ) changes show low-level increases or decreases in mean monthly values.
- Most of the changes occur in the areas outside those with high potential for burning (as defined in FOM).
- Most notable increases in fire danger conditions in areas of high potential for burning are likely to occur in June
  - These increases are linked to an increased number of moderate fire danger days rather than necessarily high and extreme fire danger conditions.

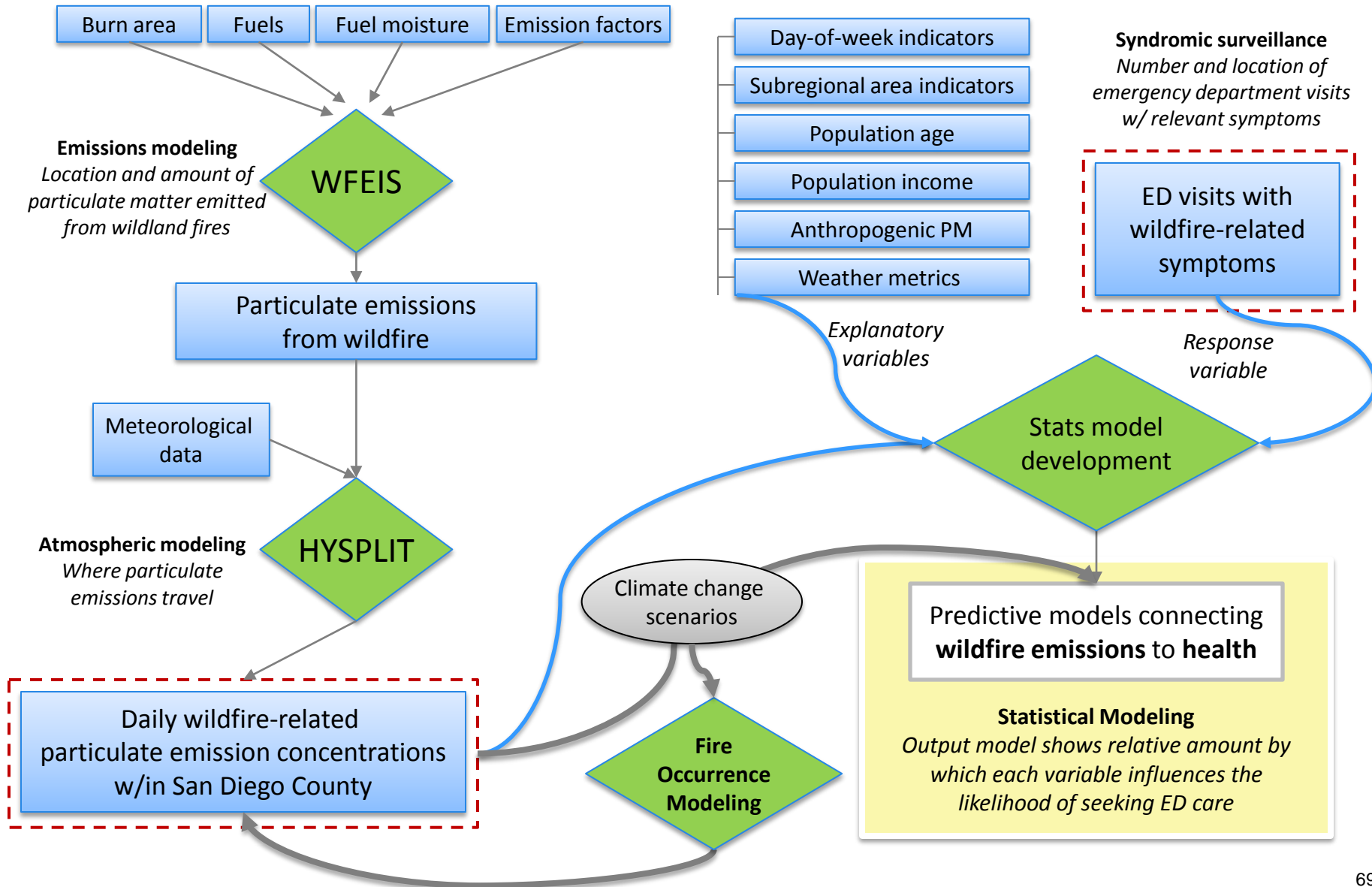
NOTE: GCM modeling by others for further in the future show a likely increase in fire across California (Westerling et al. 2011)



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# Summary: Methodology overview



# Additional Studies

- Effect of Santa Ana winds on wildland fire progression
  - These strong, hot, and dry winds have long been implicated as drivers of catastrophic wildfire events, but quantitative studies are scarce
  - We showed that daily wildland fire burn area under Santa Ana conditions is 2-3 times greater than that under non-Santa Ana conditions
- Sensitivity of Atmospheric Transport of Carbonaceous Aerosols to Aging Mechanism
  - We have implemented a new aging mechanism for carbonaceous aerosols in the GEOS-Chem model where the hydrophobic to hydrophilic conversion is affected by local conditions such as O<sub>3</sub> concentration and humidity.
  - The simulated hydrophobic to hydrophilic conversion of carbonaceous aerosols exhibit large spatial and temporal variation, which has **important implications for long-range transport of carbonaceous aerosols**
  - The updated aging mechanism has significant impacts on the model simulations of carbonaceous aerosols, with the largest effects found for the tropical regions and upper troposphere.

# Outputs

Papers in preparation or review:

- “Santa Ana winds and predictors of wildfire progression in southern California”,  
Billmire, M., et al. Submitted to *Fire Ecology*
- “Modeling acute respiratory illness during the 2007 San Diego wildland fires using a coupled emissions-transport system and generalized additive modeling”,  
Koziol, B., et al. In prep.
- An additional journal article on climate change scenarios & respiratory health



# Summary: Main Outcomes

- Developed a coupled statistical and process-based model system that:
  - Demonstrates an end-to-end methodology for generating reasonable estimates of wildland fire particulate matter concentrations and effects on respiratory health,
  - Applicable at resolutions compatible with syndromic surveillance health information,
  - Model coefficients and functional estimates are specific to San Diego County, but the method has applicability to other regions and syndromic responses.
  - Model results show that at peak fire particulate concentrations the odds of a person seeking emergency care is increased by approximately 50% compared to non-fire conditions.
- Future fire model shows San Diego County will experience approximately two extreme fire seasons each decade by 2040, similar to the present.
- Demonstrated the value of syndromic surveillance data collection and analysis capabilities that are rapidly being developed across the US.
- Promoted collaboration between public health and environmental modeling communities to better understand determinants of health during a disaster.

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# Questions & Discussion

1. The value of geospatial process modeling for linking to issues within the human dimension: *e.g. health impacts from disasters, application of process modeling for resource management or policy making*
2. The value of electronic health data resources such as syndromic surveillance
3. The challenge of conducting interdisciplinary science for societal benefit

