Asthma and Air Quality in the Presence of Fires: A Foundation for Public Health Policy in Florida

Collaborators

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Motivation

- Outdoor air quality and its associated impacts on respiratory problems in Florida are of public health significance.

- The outdoor air quality in Florida can be poor during periods of little rainfall or during the extended wildfire seasons, threatening persons with compromised respiratory systems each year.

- During periods of wildfires and for some prescribed burns, increased levels of PM cause respiratory problems in humans.

Motivation

- Increased levels of PM lead to increased ER visits and hospitalizations. The association between reduced air quality resulting from wildfires and/or prescribed burns and the incidence of asthma is unknown.

- The wildfire and prescribed burn data will be used to assess whether the presence of these natural environmental hazards are related to the health outcome of asthma as measured by hospitalizations and ER visits.

Objectives

The objectives of the research are to:

- Develop high-quality spatial data sets of environmental variables
- Link these environmental data sets with public health data consisting of hospitalization admissions and ER visits associated with asthma and socio-demographic variables
- Develop spatial-temporal models of the association between asthma and air quality
- Provide the linked data sets and associated analyses to local, state and federal end-user groups

Project Components

1) Link the MODIS derived $PM_{2.5}$ data with the Florida Division of Forestry's (DOF's) Surface Fuels database and the Live Fuels database to assess the effectiveness in determining the possibility of increased PM and decreased air quality in the presence of fires.

2) Link the asthma data with the predicted $PM_{2.5}$ data developed in task (1) and the socio-demographic data from the U.S. Census Bureau and CDC's Behavioral Risk Surveillance Survey (BRSS) and additional meteorological data.

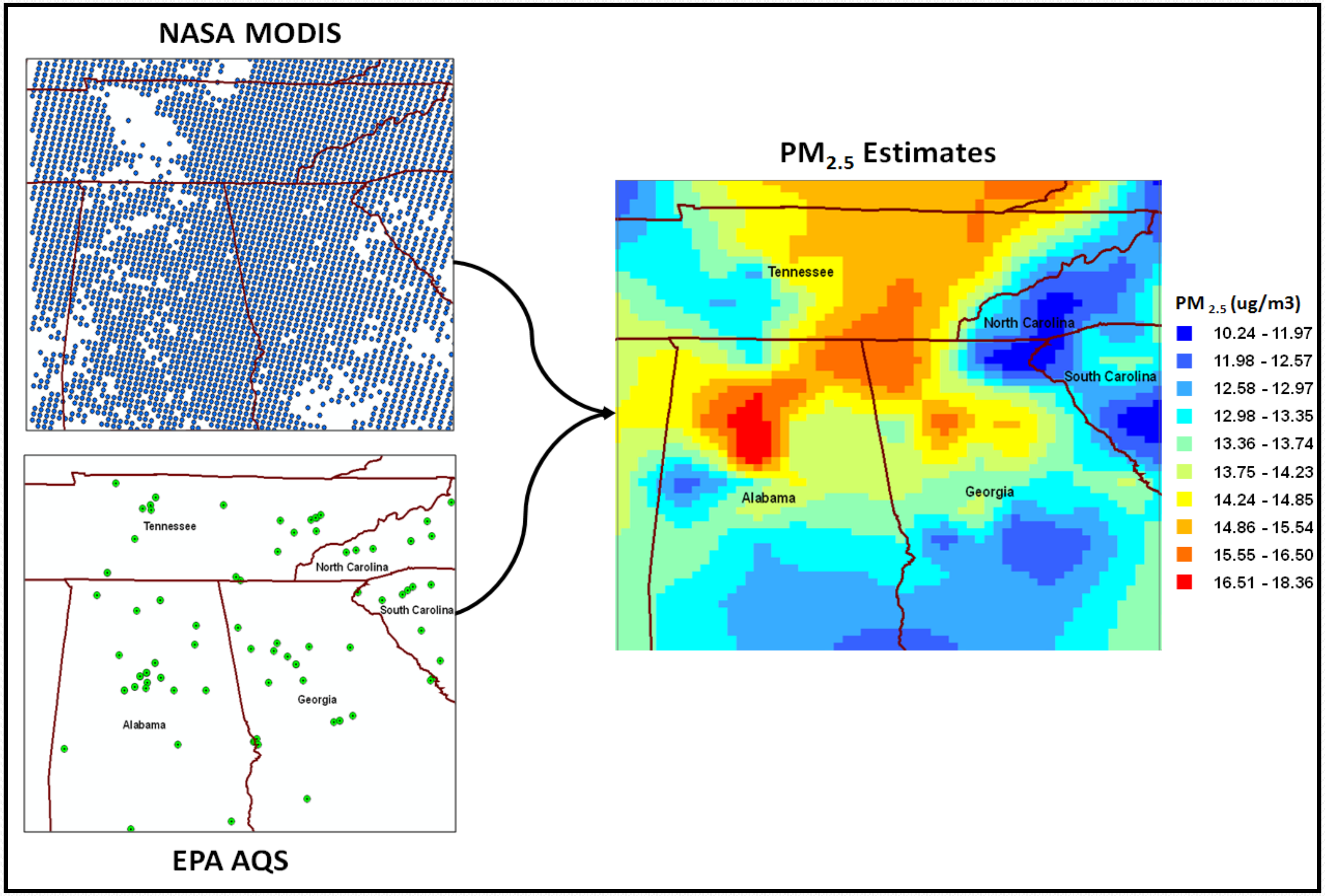
3) Investigate the use of hospital and ER cases with asthma as the primary or secondary cause of hospital visits as a health outcome indicator of human response to environmental air quality indicators.

Project Components

4) Assist the State of Florida (Florida Department of Health, emergency management) in establishing a public health policy for posting county-level advisories and alerts of poor air quality, with associated steps citizens should take to protect their health based on indicators developed in tasks 1, 2, and 3.

5) Improve the Florida Environmental Public Health Tracking (FEPHT) program's state portal in cooperation with CDC's national Environmental Public Health Tracking (EPHT) program.

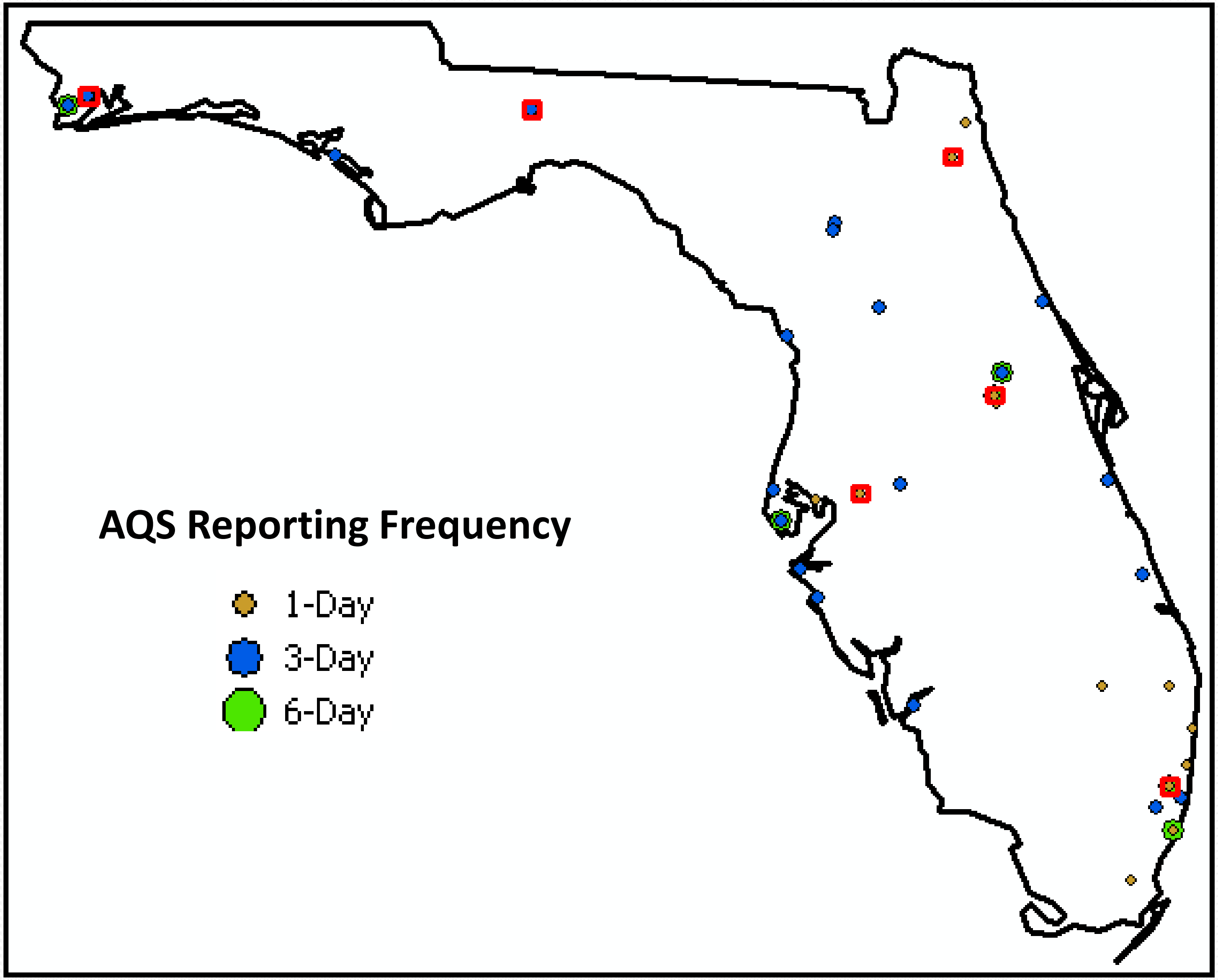
Fine Particulate Matter Exposure Assessment

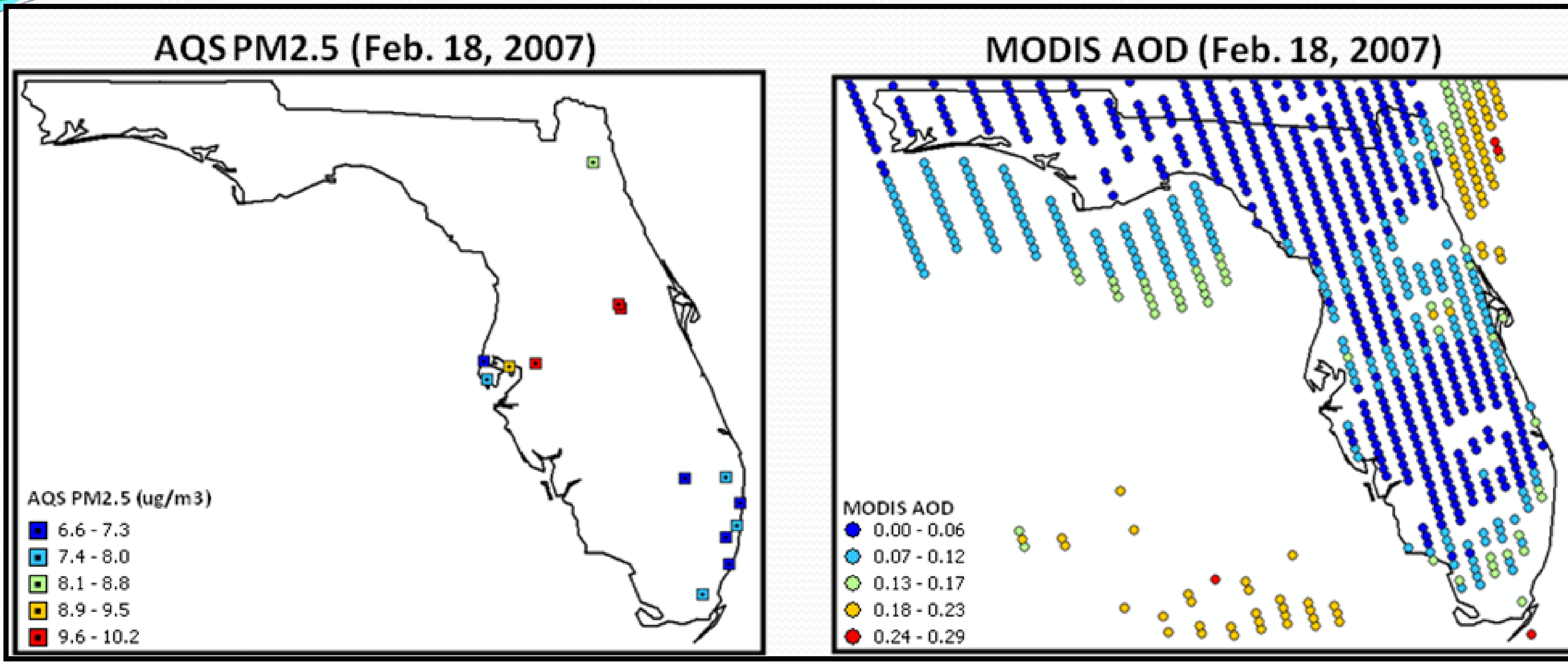


(Al-Hamdan et al., 2009)

Reference: Al-Hamdan, et al., 2009 M., Crosson, W., Limaye, A., Rickman, D., Quattrochi, D., Estes, M., Qualters, J., Sinclair, A., Tolsma, D, Adeniyi, K., Niskar, A. 2009. Methods for characterizing fine particulate matter using ground observations and remotely sensed data: potential use for environmental public health surveillance. *Journal of the Air and Waste Management Association*, 59, 865–881.

AQS PM2.5 Reporting Frequency





AQS PM2.5 monitors: (1) concentrated in urban areas
(2) observed every one to six days

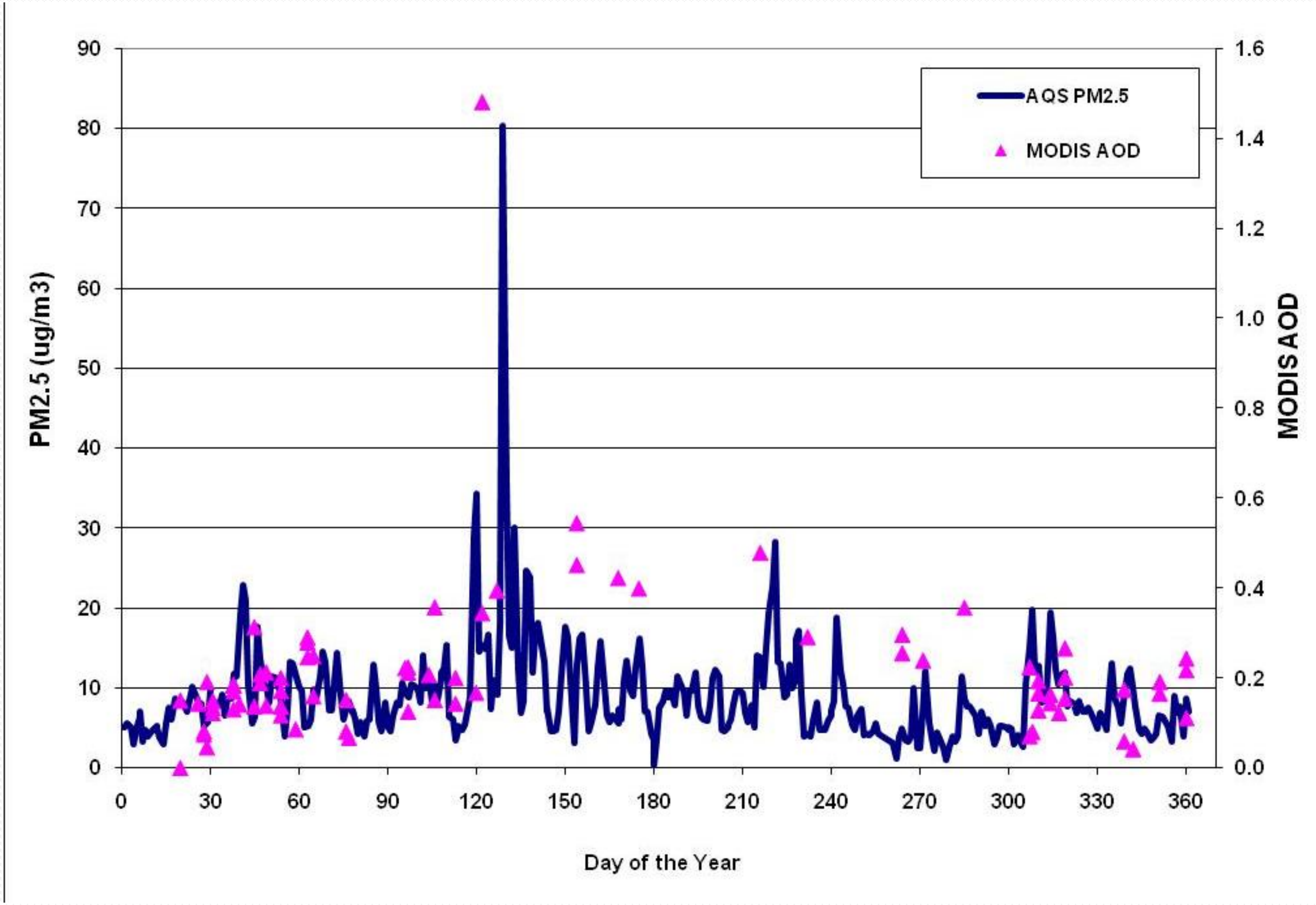
NASA MODIS satellite sensor: (1) provides good spatial coverage
(2) available only for clear-sky coverage

Combining AQS and MODIS Data

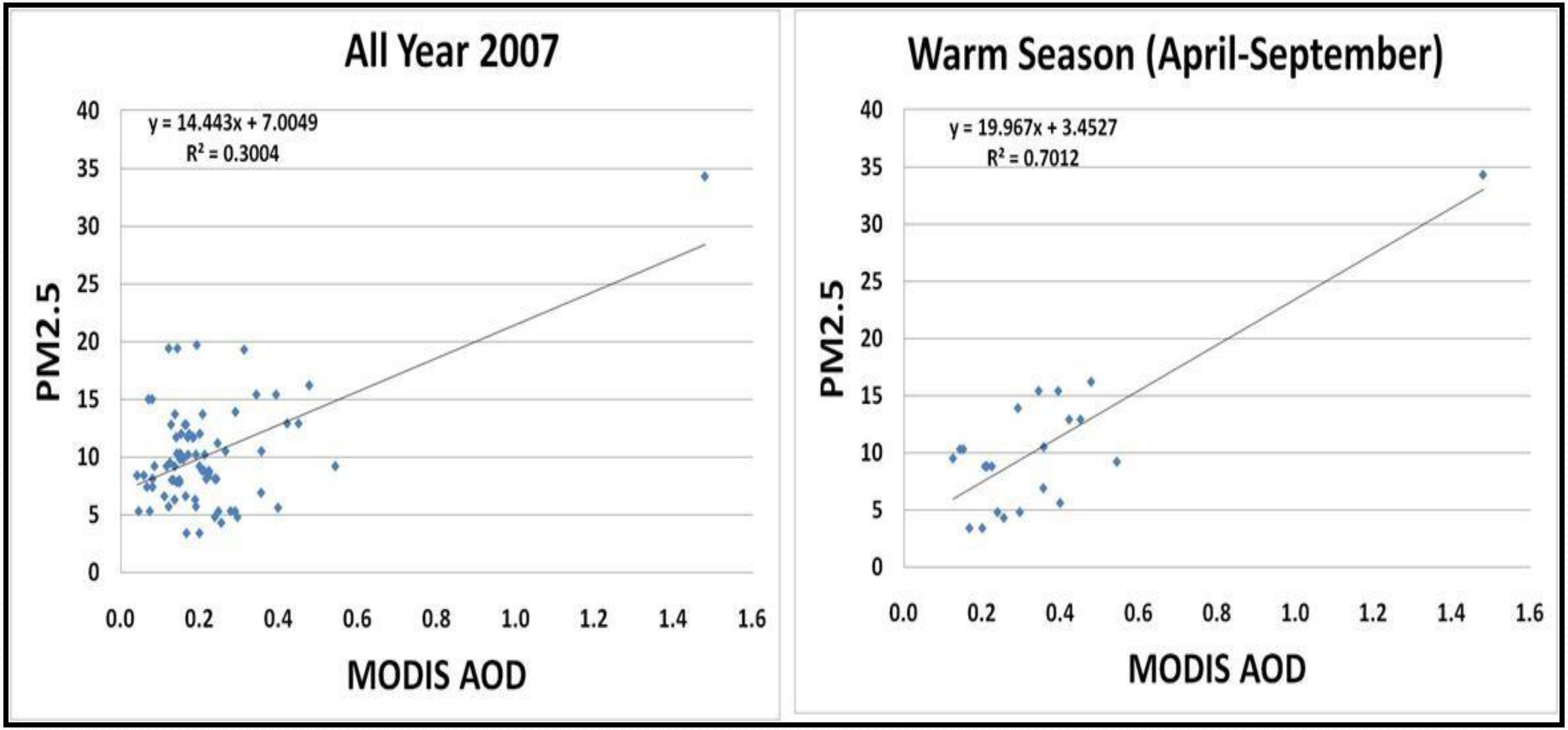
MODIS AOD data extracted for six AQS sites in diverse locations and settings

- Jacksonville
- Orlando
- Miami
- Tampa
- Tallahassee
- Pensacola

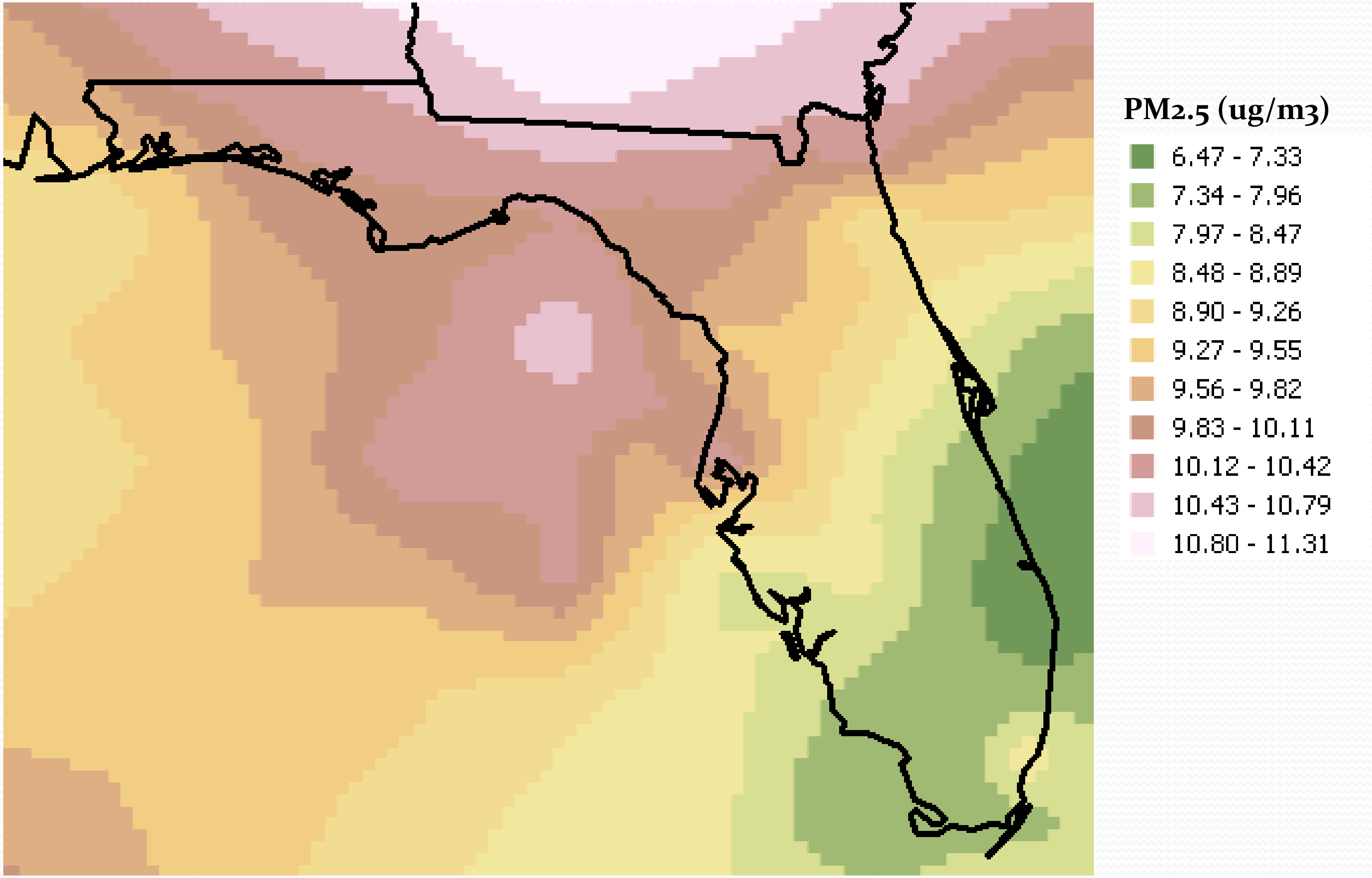
2007 AQS PM2.5 and MODIS AOD for Miami, FL



AQS PM2.5 and MODIS AOD for Miami Site



PM2.5 B-spline Surfaces Year 2007 Composite



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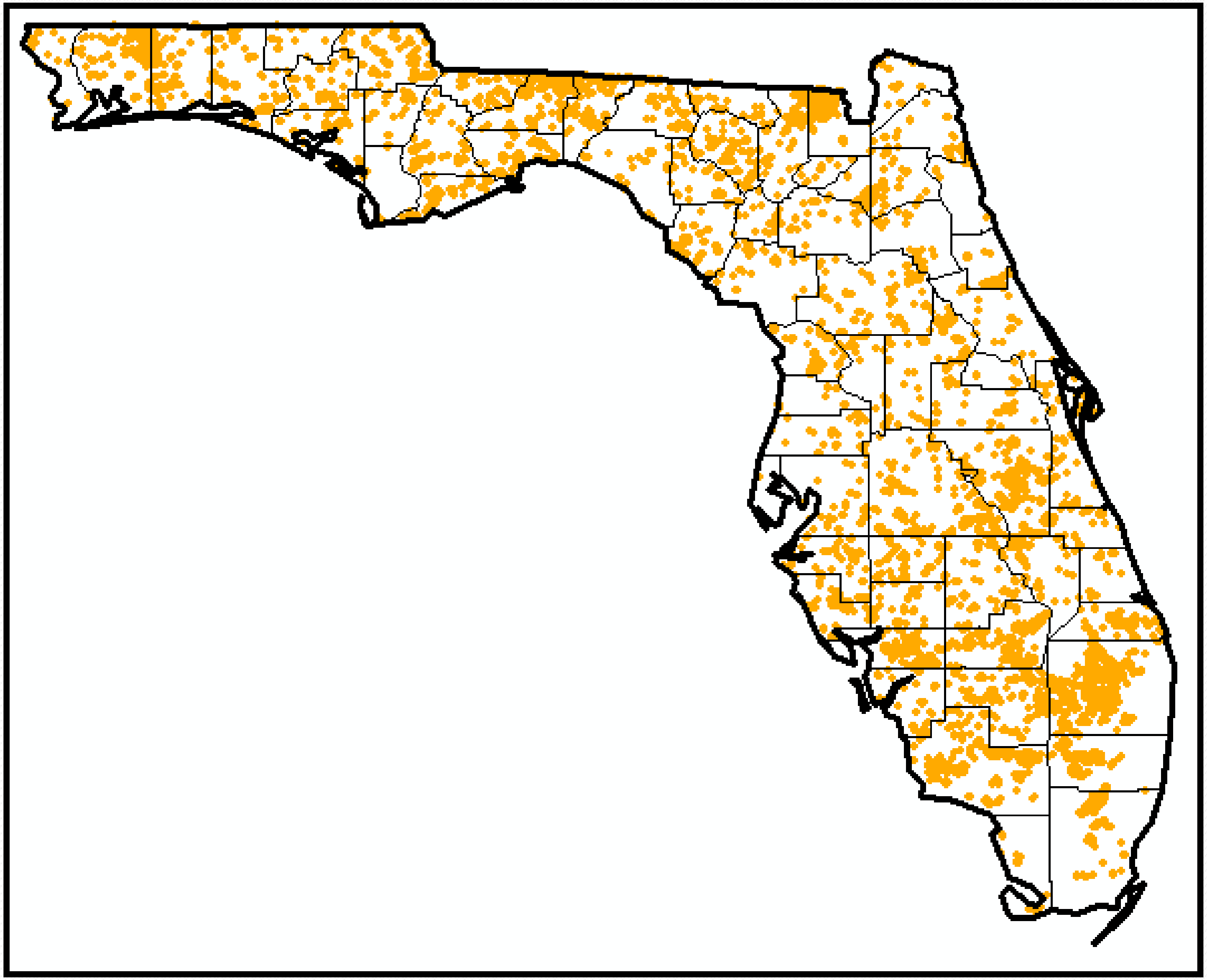
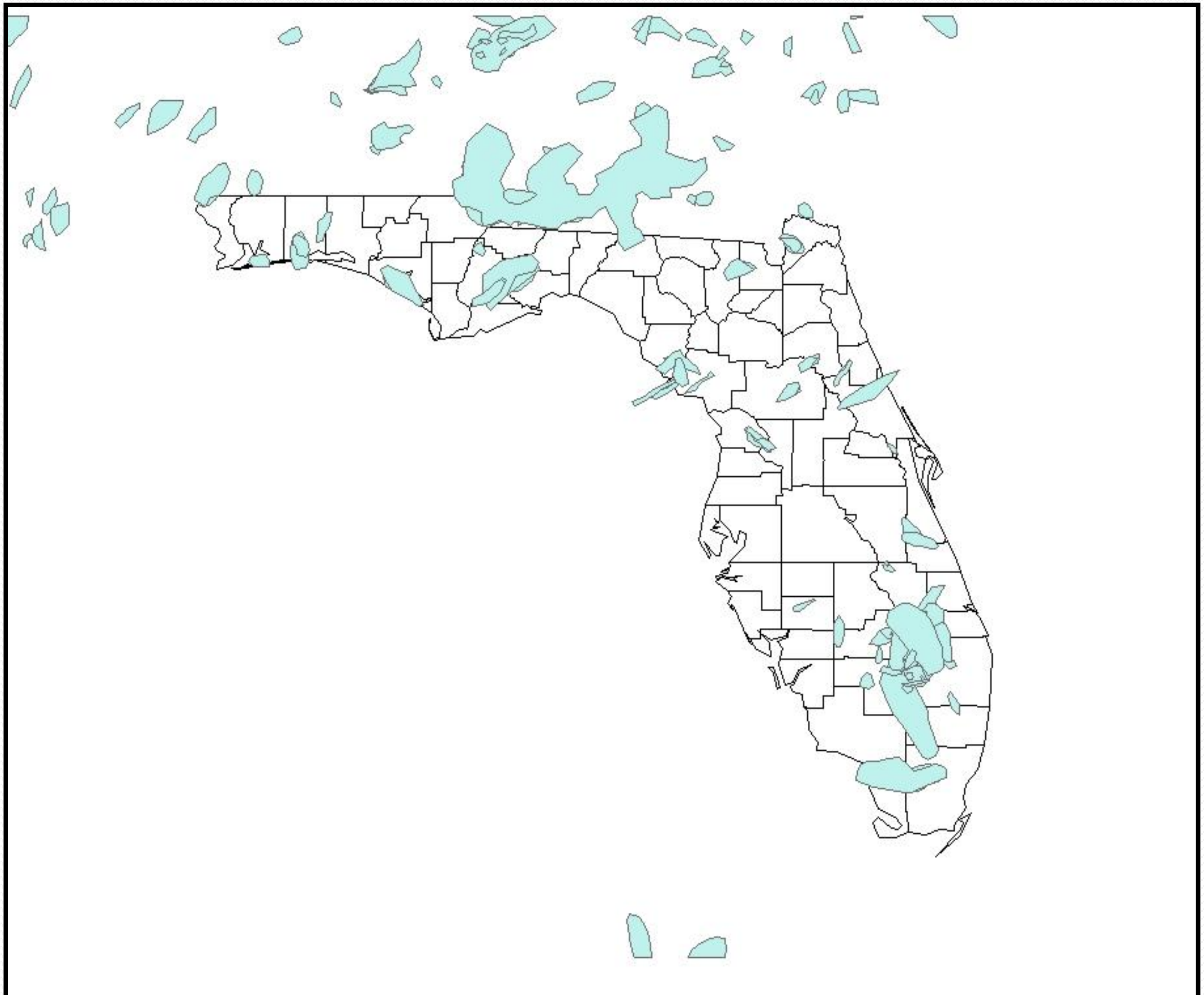
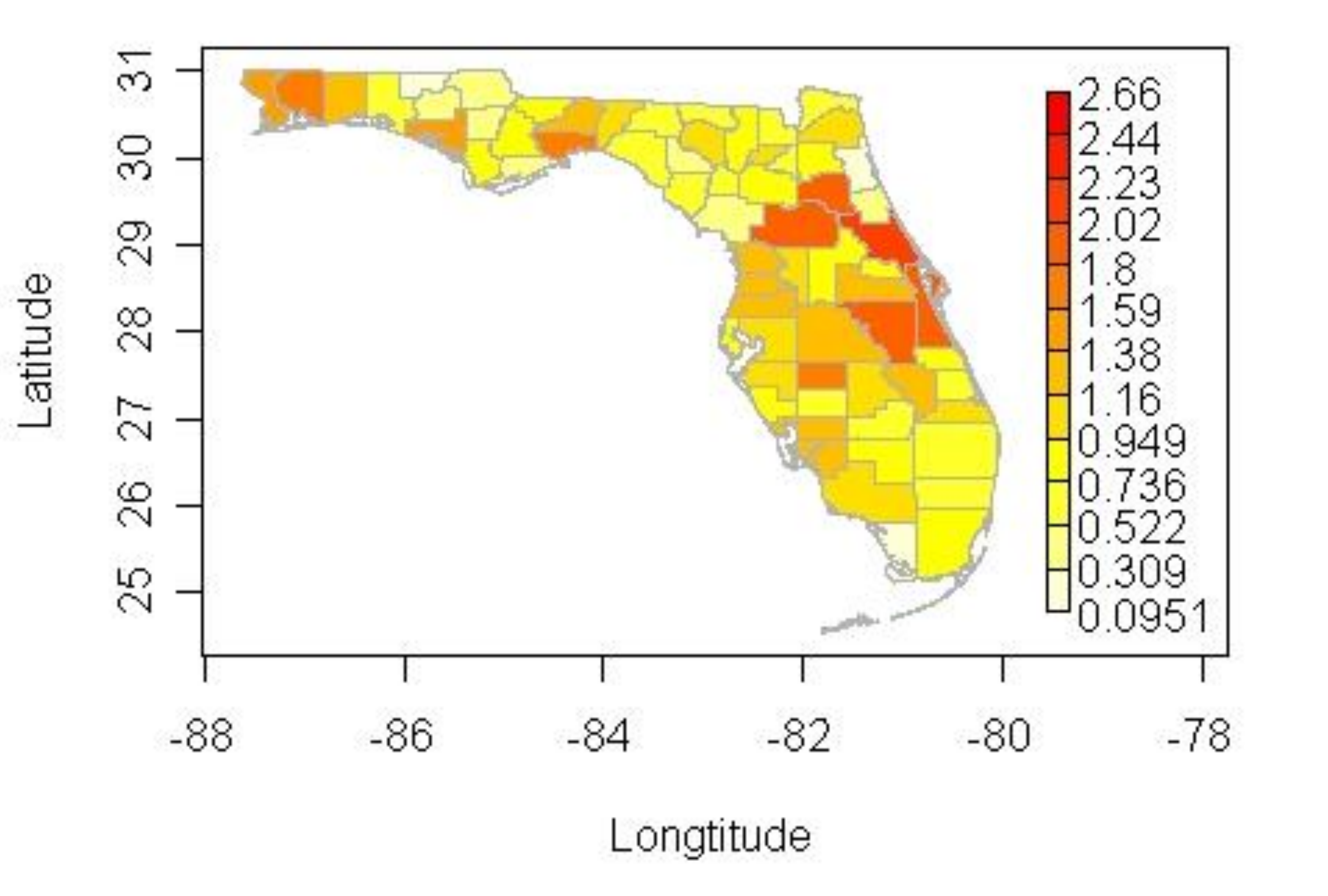
2007 MODIS Fire Detections



January, 2007 Smoke Plume Data

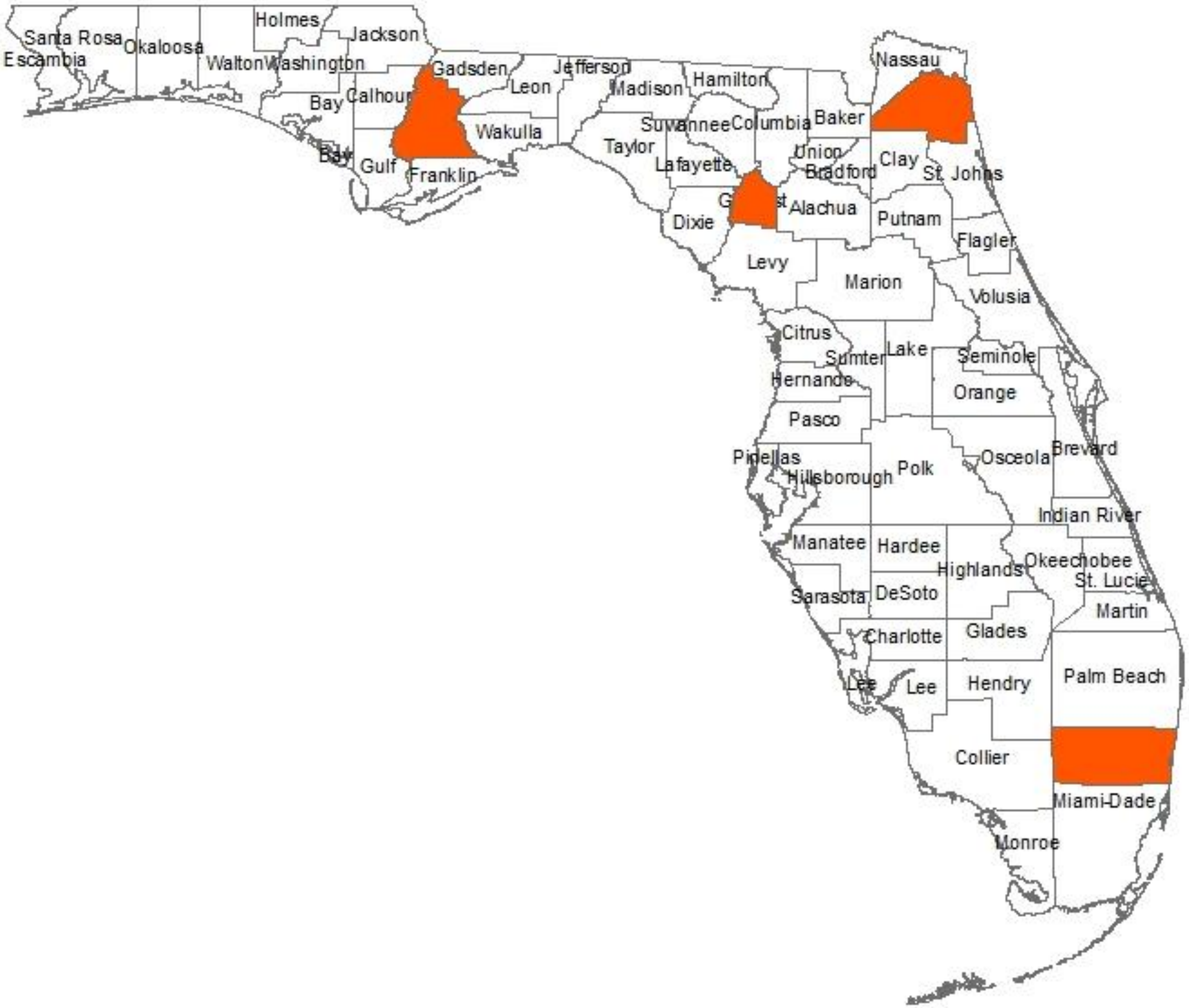


Public Health Data



Florida County Map of Relative Asthma SER for July 2007, Adjusted for Age, Ethnicity, Sex

Four Florida Counties Used for Exploration



Number of Days in 2007 Having Stated Number of Asthma Cases

County	0 Cases	1 Case	2-5 Cases	6-10 Cases	11-20 Cases	21-40 Cases	>40 Cases
Broward	0	0	0	1	55	257	52
Duval	0	0	2	51	187	125	0
Gilchrist	328	33	4	0	0	0	0
Liberty	340	25	0	0	0	0	0

Number of Weeks in 2007 Having Stated Number of Asthma Cases

County	0 Cases	1 Case	2-10 Cases	11-60 Cases	61-100 Cases	101-200 Cases	>200 Cases
Broward	0	0	0	0	1	20	32
Duval	0	0	0	1	13	39	0
Gilchrist	28	15	10	0	0	0	0
Liberty	33	15	5	0	0	0	0

Regression Relating Health Outcome to Environmental Exposure

Consider the simple linear regression

$$\mathbf{y}(\mathbf{s}_u) = \beta_0 + \beta_1 \mathbf{x}(\mathbf{s}_u) + \mathbf{e}(\mathbf{s}_u)$$

where $\mathbf{e} \sim \mathrm{N}(\mathbf{0}, \mathbf{\Sigma}_e)$ and

$$\mathbf{x}(\mathbf{s}) \sim \mathrm{N}(C(\mathbf{s})\xi, \mathbf{\Sigma}_{\mathbf{x}}) \quad \forall \mathbf{s} \in \mathrm{D} \subset \Re^2$$

Note:

$\mathbf{y}(\mathbf{s}_u)$ is observed health outcome
$\mathbf{x}(\mathbf{s}_u)$ is unobserved exposure
$\mathbf{x}(\mathbf{s}_o)$ is observed exposure

Classical Measurement Error

Suppose that a model is used to predict exposure at the points of observed health outcomes. Further assume that the model provides unbiased predictions with normally distributed measurement error; that is,

$$\tilde{\mathbf{x}}(\mathbf{s}_u) = \mathbf{x}(\mathbf{s}_u) + \mathbf{w}$$

where $\mathbf{w} \sim \mathrm{N}(\mathbf{0}, \sigma_w^2 \mathbf{I})$. This is **classical measurement error**. The predicted exposure is more variable than the true exposure.

Ignoring Prediction Error Model and Regress

Ordinary Least Squares:

$$\hat{\boldsymbol{\beta}}_{\mathrm{M}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

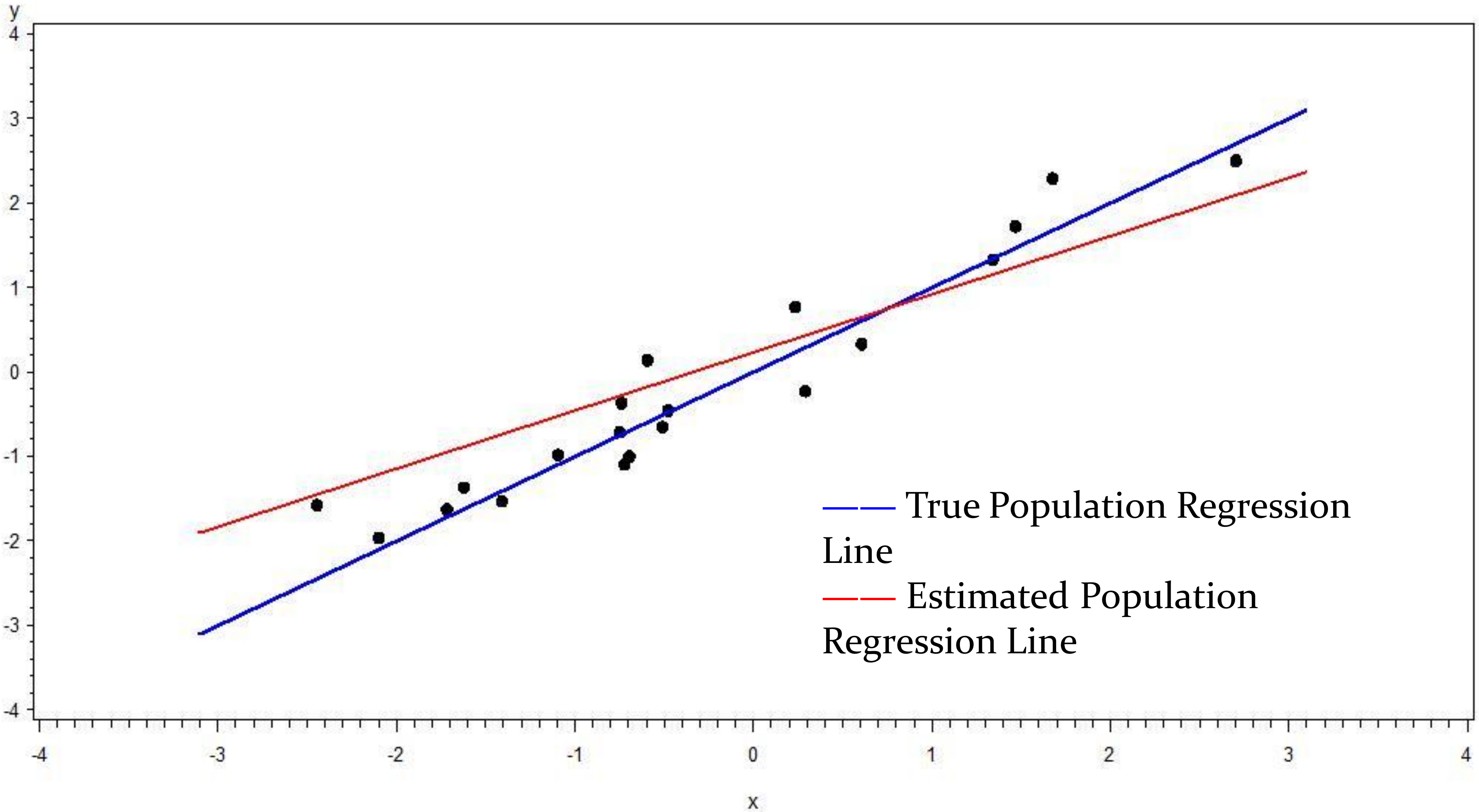
where

$$\mathbf{X} = (\mathbf{1}_{n\times 1} \quad \tilde{\mathbf{x}}(\mathbf{s}))$$

$\hat{\boldsymbol{\beta}}_{\mathrm{M}}$ is

- Biased estimator of $\boldsymbol{\beta}$
- Uncertainty associated with predicting exposure results in standard errors being under-estimated

Classical Measurement Error



Berkson Error

Suppose kriging or some other smoothing method is used to predict exposure at the points of observed health outcomes.

Then

$$\mathbf{x}(\mathbf{s}_u) \,|\, \mathbf{x}(\mathbf{s}_0) = \boldsymbol{\mu}_k(\mathbf{s}_u) + \mathbf{v}, \quad \mathbf{v} \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma}_k)$$

Unlike classical measurement error, here the true values are more variable than the predicted one. This type of error is known as **Berkson error.**

Berkson Error

Using the predicted exposure, $\hat{\mathbf{x}}(\mathbf{s}_u) = \boldsymbol{\mu}_k(\mathbf{s}_u)$, results in a smoother surface than the true exposure $\mathbf{x}(\mathbf{s}_u)$; that is,

$$\mathbf{x}(\mathbf{s}_u) = \boldsymbol{\mu}_k(\mathbf{s}_u) + \mathbf{v} = \hat{\mathbf{x}}(\mathbf{s}_u) + \mathbf{v}$$

Thus,

$$\begin{aligned}
\mathbf{y}(\mathbf{s}_u) \mid \mathbf{x}(\mathbf{s}_o) &= \beta_0 \mathbf{1}_{n\times 1} + \beta_1(\boldsymbol{\mu}_k(\mathbf{s}_u) + \mathbf{v}) + \mathbf{e} \\
&= \beta_0 \mathbf{1}_{n\times 1} + \beta_1 \boldsymbol{\mu}_k(\mathbf{s}_u) + (\beta_1 \mathbf{v} + \mathbf{e}) \\
&= \beta_0 \mathbf{1}_{n\times 1} + \beta_1 \boldsymbol{\mu}_k(\mathbf{s}_u) + \boldsymbol{\eta}
\end{aligned}$$

where $\boldsymbol{\eta} = \beta_1 \mathbf{v} + \mathbf{e}$.

Ignoring Prediction Error: Krige and Regress

Ordinary Least Squares:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

where

$$\mathbf{X} = (\mathbf{1}_{n\times 1} \quad \boldsymbol{\mu}_k(\mathbf{s}))$$

$\hat{\boldsymbol{\beta}}$ is

- Unbiased estimator of $\boldsymbol{\beta}$
- Uncertainty associated with predicting exposure results in standard errors being under-estimated

How does one account for the additional uncertainty induced by using kriging predictions in linear regression models?

Models Relating Asthma Cases to Exposure

Regression models

- Account for Berkson error from predicting PM2.5
- Account for classical measurement error from estimating the parameters associated with exposure
- Adjust for socio-demographic variables

Progress to Date

1) The association between MODIS and AQS data at 6 Florida sites has been explored.
2) This association has been used to combine MODIS and AQS data to establish 2007 daily predictions of PM2.5 using B-splines
3) The Kalman filter has been explored as an alternate method for combining the MODIS and AQS data
4) Kriging to obtain the daily PM2.5 predictions is currently being conducted so that prediction errors are also available.
5) 2007 and 2008 daily meteorological data have been obtained.

Progress to Date

6) 2007 and 2008 daily fire detections (from MODIS) as a percentage of the county area have been developed.
7) 2007 and 2008 daily smoke plume (from MODIS) as a percentage of the county area has been developed.
8) 2007 and 2008 daily asthma and yearly socio-demographic data have been obtained
9) The asthma data has been explored for 4 Florida counties to assess the best temporal scale for analysis.
10) Methods for modeling the association between asthma cases and PM2.5 that appropriately account from the prediction error for one point in time have been developed

Project Timeline

Study Task Numbers and Description		First Year				Second Year			
		1st Q	2nd Q	3rd Q	4th Q	1st Q	2nd Q	3rd Q	4th Q
1	Production of Environmental Data Sets								
2	Linkage of Health, Socio-demographic and Environmental Data								
3	Investigate Use of Hospital and ER cases of Asthma as Health Outcome Indicator								
4	Assist in the development of Public Health Policy Based on the Health Outcome Indicator								
5	Integrate with the FEPHT Program’s State Portal								

Going Forward

1) 2007 kriged air quality data with prediction errors
2) Determine whether additional useful information is available from burns database
3) Link the PM2.5, fire, meteorological, asthma, and socio-demographic data at the county level
4) Attempt to form models at the daily level
5) Develop models relating asthma to air quality and socio-demographic variables over space and time
6) Validate the models using 2008 data
7) Develop an advisory alert system
8) Place results on Florida's Environmental Public Health Tracking portal