Spatial Data Science and BIG DATA Analytics for Geographic Information Sciences

Sudipto Banerjee

Professor and Chair of Biostatistics
Professor of Statistics
Affiliate Member, Institute of the Environment & Sustainability
University of California Los Angeles (UCLA)
sudipto@ucla.edu

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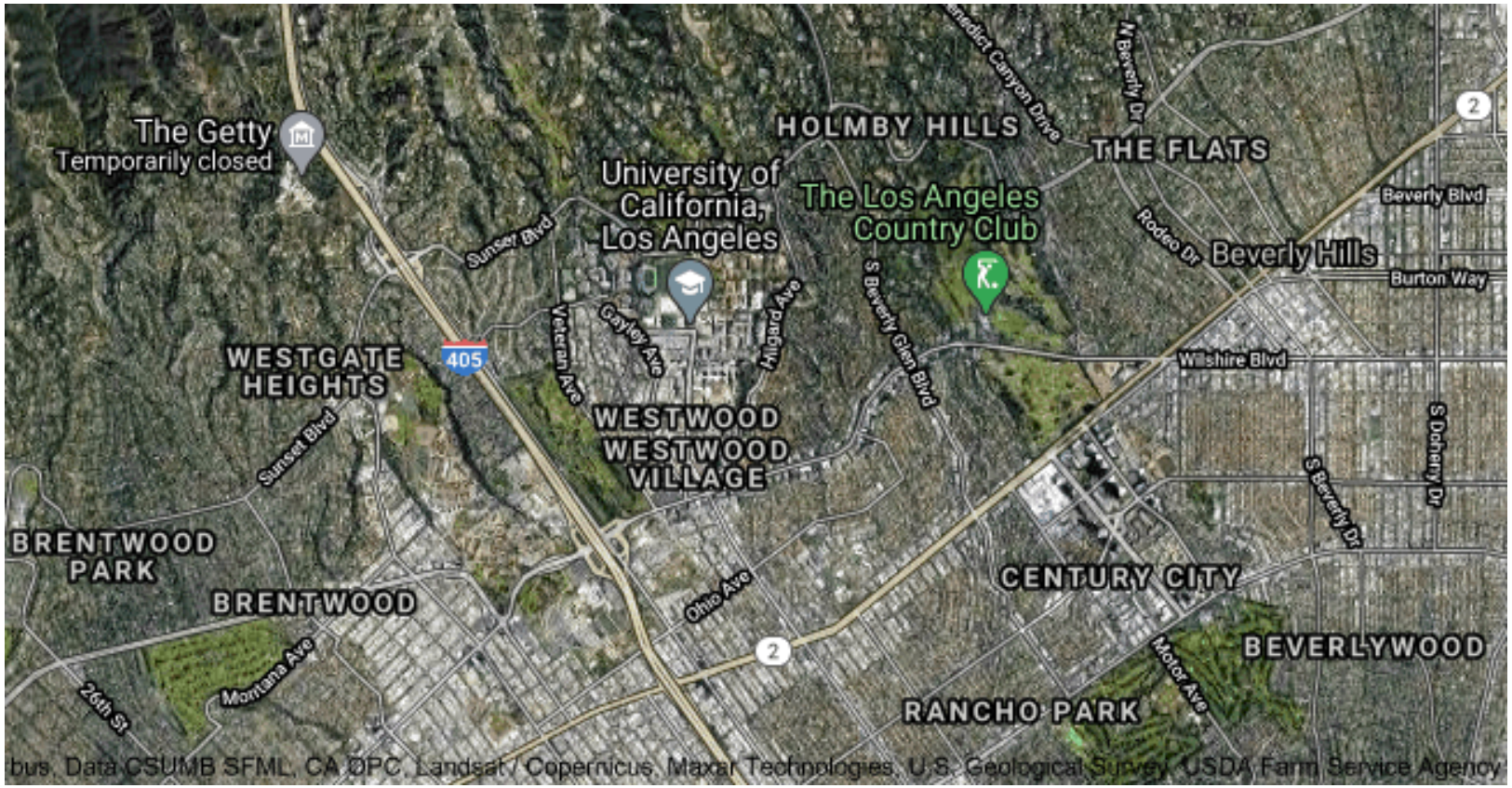
UCLA FIELDING SCHOOL OF PUBLIC HEALTH

SIT: Spatial Information Technologies

Some neighbourhoods in Kolkata



Creating Databases for Maps

Global Positioning Systems (GPS)

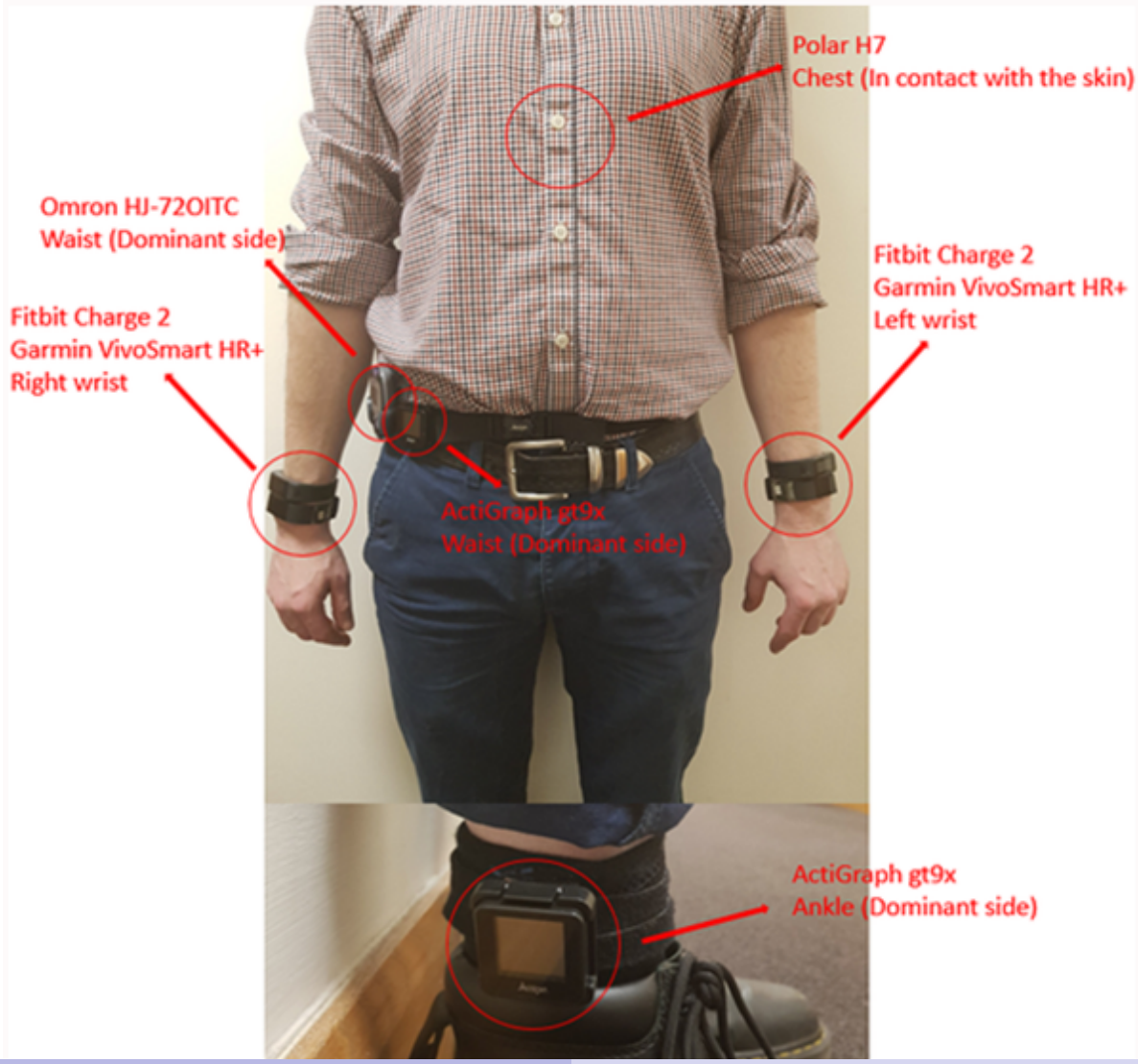
A wearable GPS device

Monitors for Physical Activity

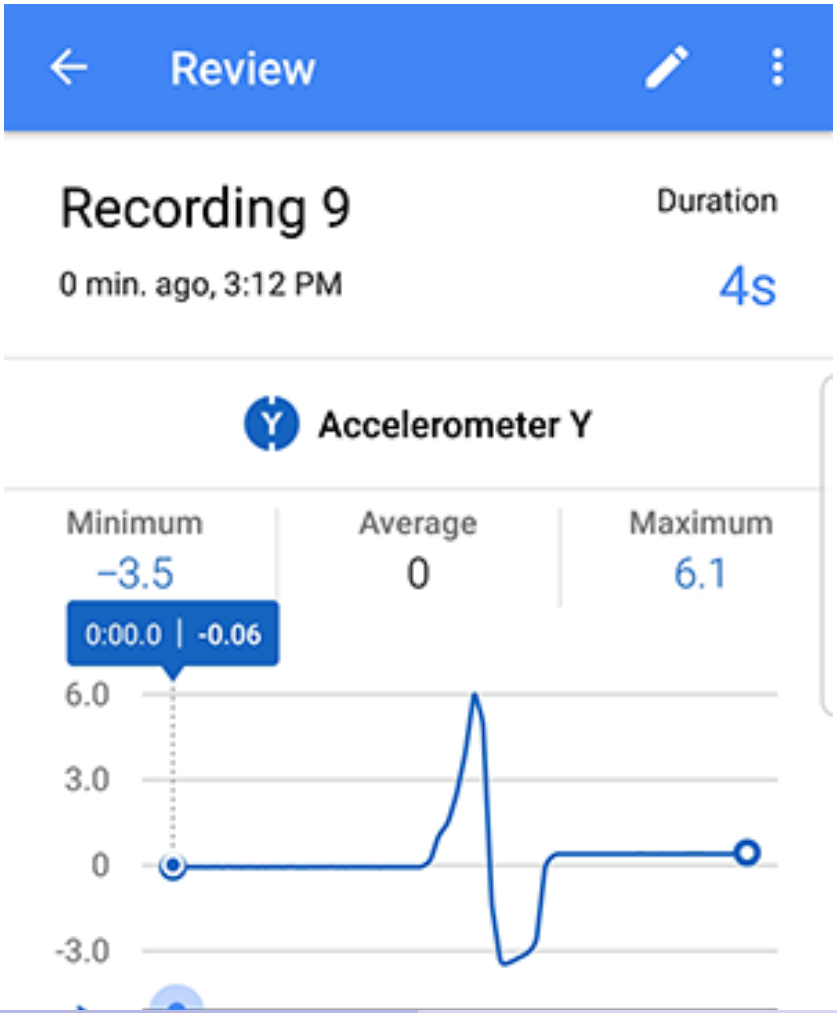
- Small motion sensor detectors (accelerometers) have generated substantial interest in monitoring human activity.
- Wearable devices, such as wrist-worn sensors that monitor gross motor activity (actigraph units) continuously record the activity levels of a subject, producing massive amounts of high-resolution measurements.

Actigraph units

Actigraph units (source: https://journals.plos.org/plosone/article/figures?id=10.1371/journal.pone.0216891)



Accelerometers: (source: https://www.sciencebuddies.org/science-fair-projects/references/accelerometer)



Accelerometers: From MAGs to METs

- Measure acceleration along multiple axes (2 or 3).

$$r(t) = \begin{pmatrix} x(t) \\ y(t) \\ z(t) \end{pmatrix}; \quad v(t) = \frac{d}{dt} r(t); \quad a(t) = \frac{d}{dt} v(t) = \begin{pmatrix} \ddot{x}(t) \\ \ddot{y}(t) \\ \ddot{z}(t) \end{pmatrix} .$$

- Accelerometers calculate $a(t)$ over small time-intervals
- Magnitude of acceleration:

$$MAG_{accel} = \sqrt{a_x^2 + a_y^2 + a_z^2},$$

where a_x, a_y and a_z are averaged accelerometer readings along the three axes over small (e.g., 10-sec) time windows (epochs).

- Metabolic Equivalent of Task (Sasaki, 2011):

$$\text{MET} = 0.000863 \cdot MAG + 0.668876$$

- With *MAG* readings from hip and ankle (Mortazavi et al., 2013):

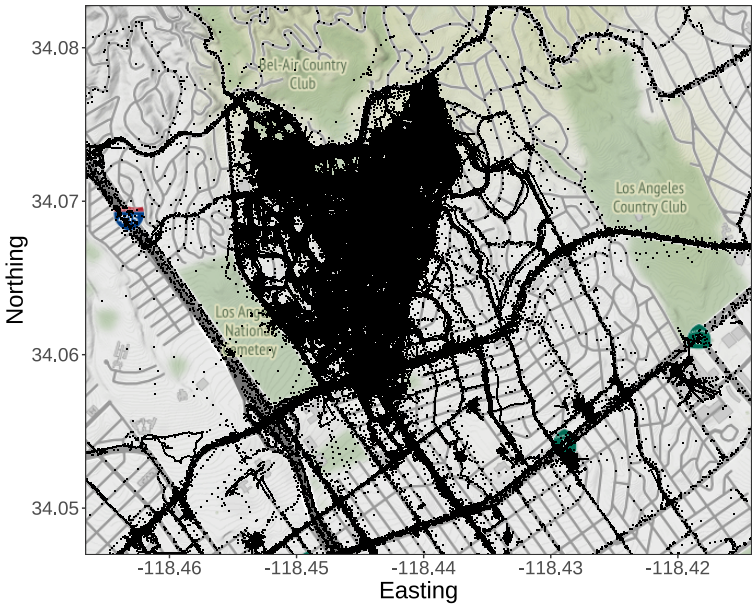
$$\text{MET} = 5.289 \cdot (MAG_{hip} + MAG_{ankle}) - 8.5548$$

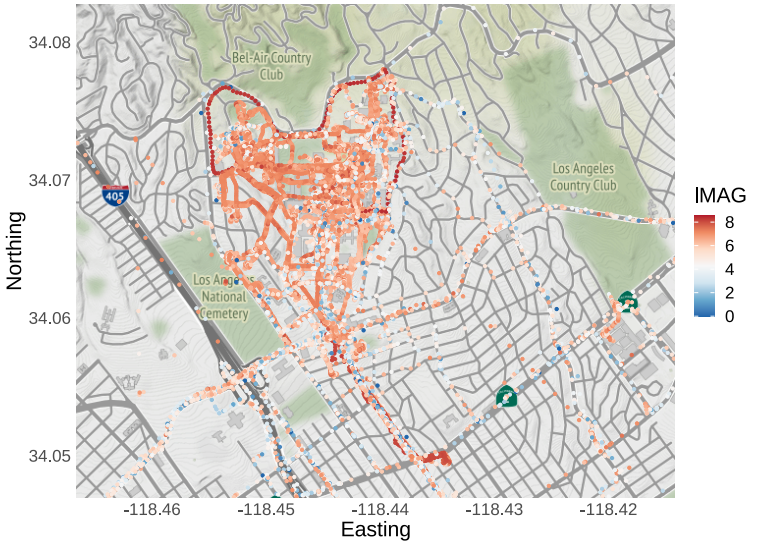
METs and MAGs by Activity Levels

Activity intensity	MET range	MAG
Sedentary or light	[0, 3)	[0, 493)
Moderate	[3, 6)	[493, 1029)
Hard	[6, 9)	[1029, 1608)
Very hard	[9, ∞)	[1608, ∞)

Table: MAG activity count cut-points for different PA intensity levels

Trajectories (from GPS) carved out by subjects



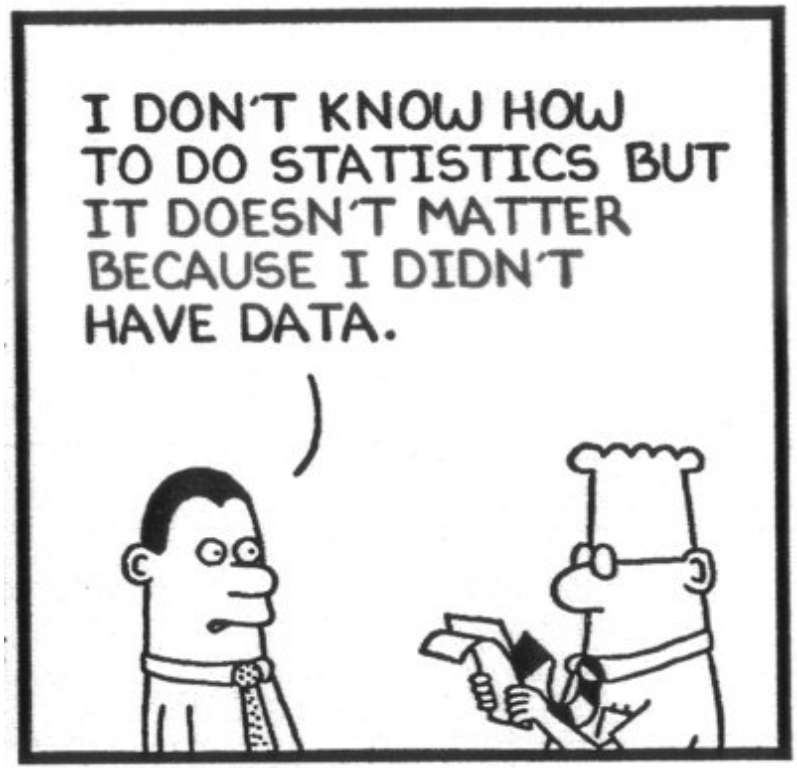


Statistics and Data Science...Is Happening

Hal Varian, Google's chief economist:

The ability to take data-to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it-that's going to be a hugely important skill in the next decades

Source: `http://www.mckinseyquarterly.com/Hal_Varian_on_how_the_Web_challenges_managers_2286`



The Information Revolution

- We live in an Information Age.
- Computers collect and store information in quantities that were earlier unimaginable.
- What is this information?
  - Measurements, counts, costs, sales revenue...
  - arising in sciences, public health, business...
- Raw, "undigested" data stored on computer disks is useless unless we make sense of it.
- Statistics: the art and science of extracting meaning from seemingly incomprehensible data.
- Make good use of information to make sound decisions.

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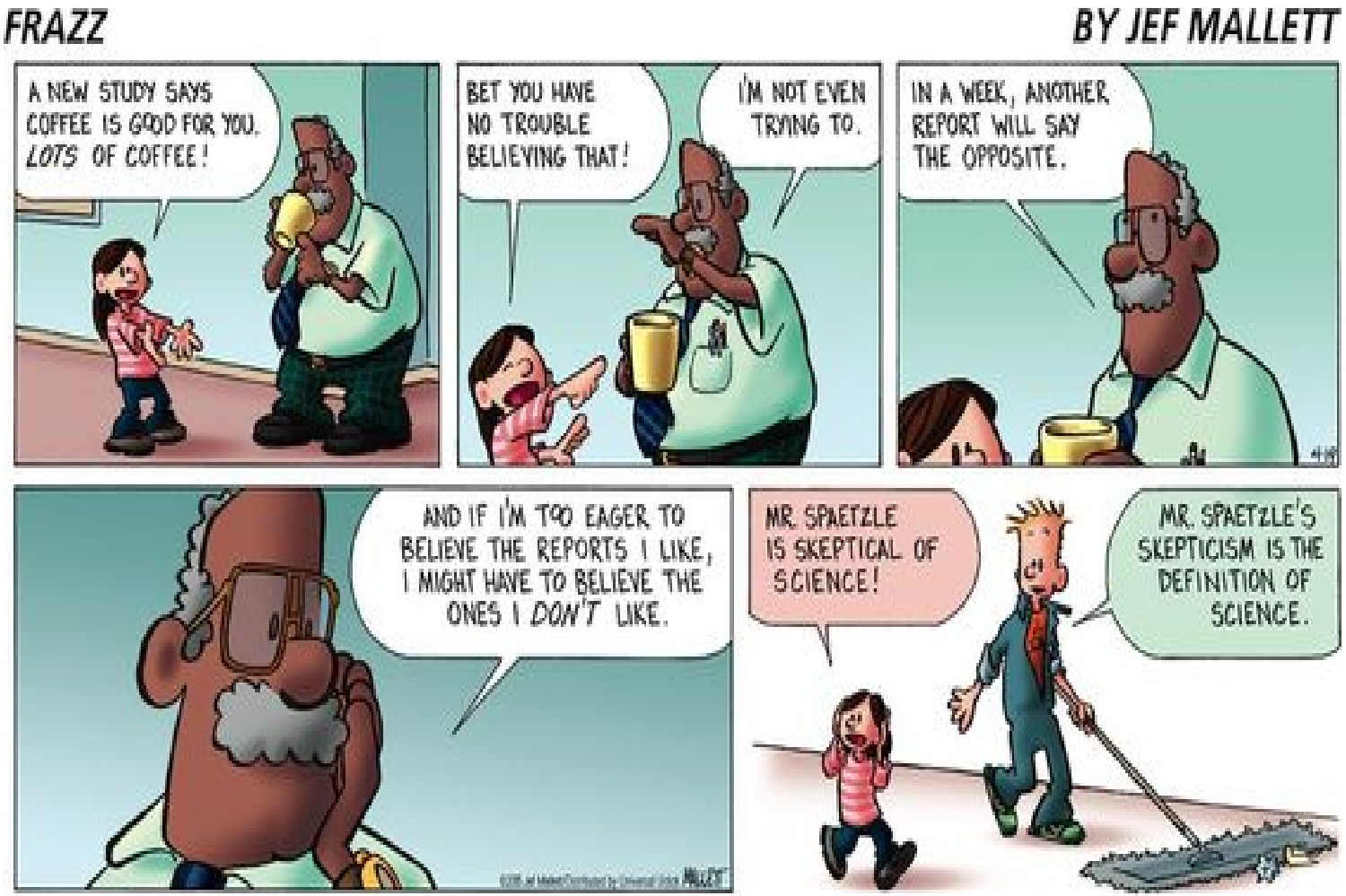
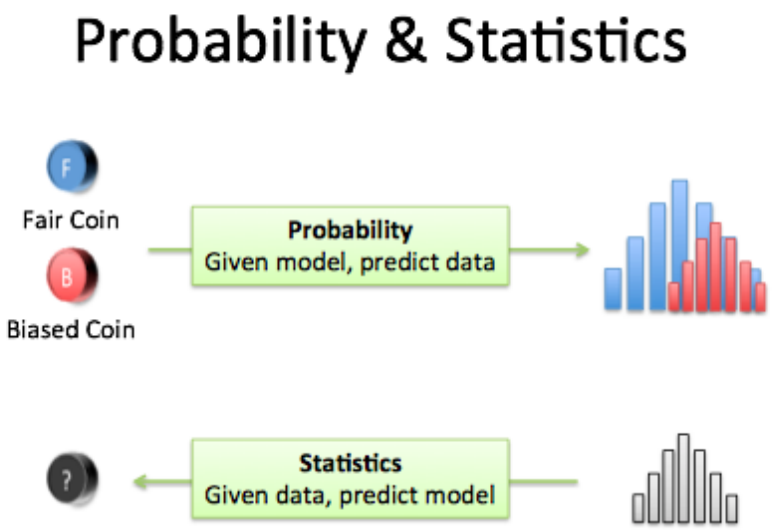
A favorite cartoon



What is Statistics?

Statistics uses math. Statistics is not math!

- Statistics: induction, inference, generalization.
- Statistics: From data, what can we conclude about the world?
- Mathematics: deduction.
- Math modeling: If this model is true, what data occurs?
- Problem: Data can occur under lots of models. Which model is right?
- Mathematics vital: Statistics uses math!



What is Statistics?

Statistics applies to almost any field of science

In one week a statistician may:

- help design an experiment to evaluate the effects of a new treatment for a disease,
- analyze data gathered in the Amazon rain forests by an ecologist,
- help predict how the California wild fires will spread,
- help Google design a better search engine,
- analyze data from researchers trying to find genes that cause breast cancer.

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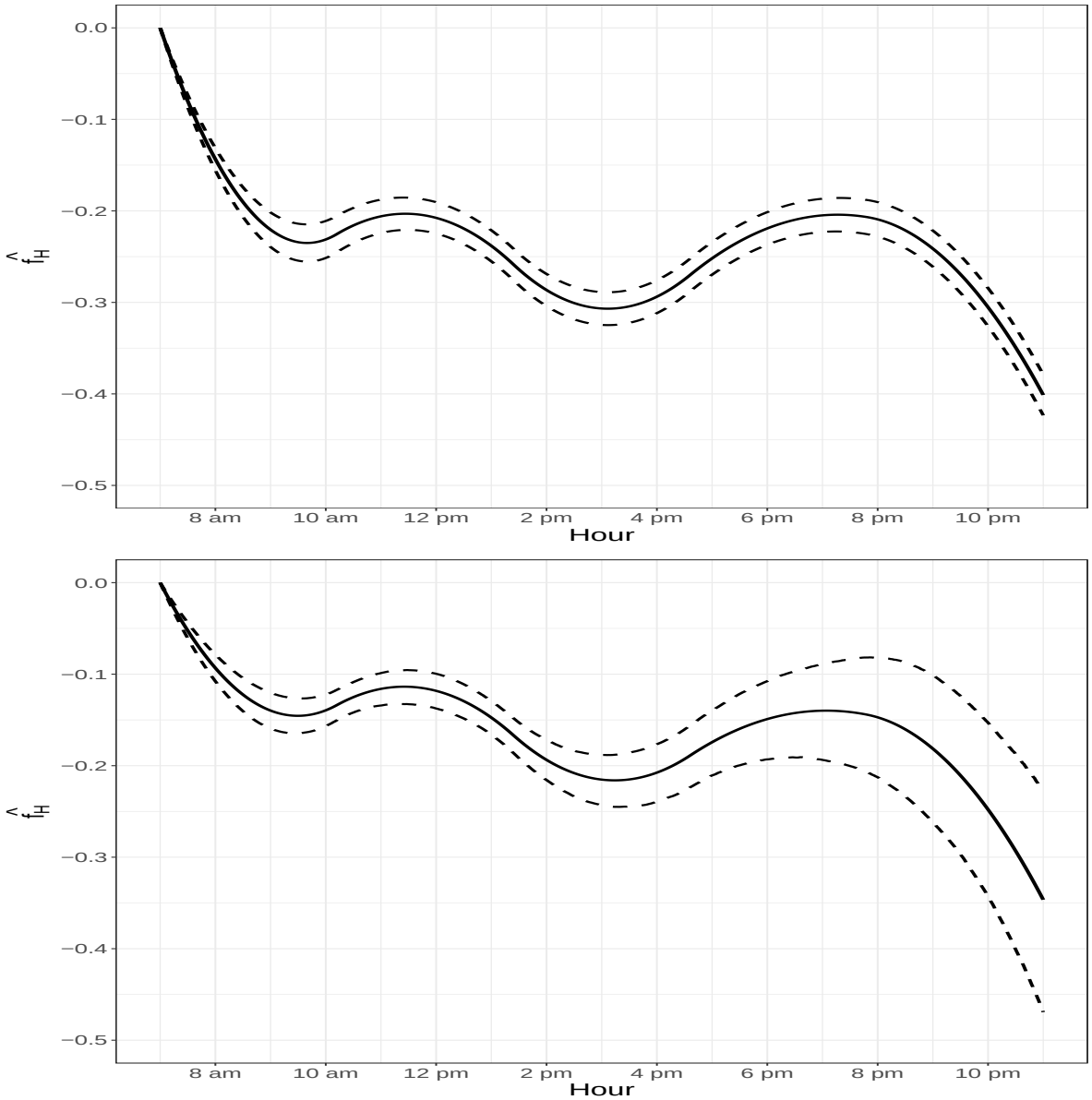
Bayesian Statistical Modeling and Inference

$$[\text{Unknown} \,|\, \text{Known}] = [\text{process}, \text{parameters} \,|\, \text{data}]$$

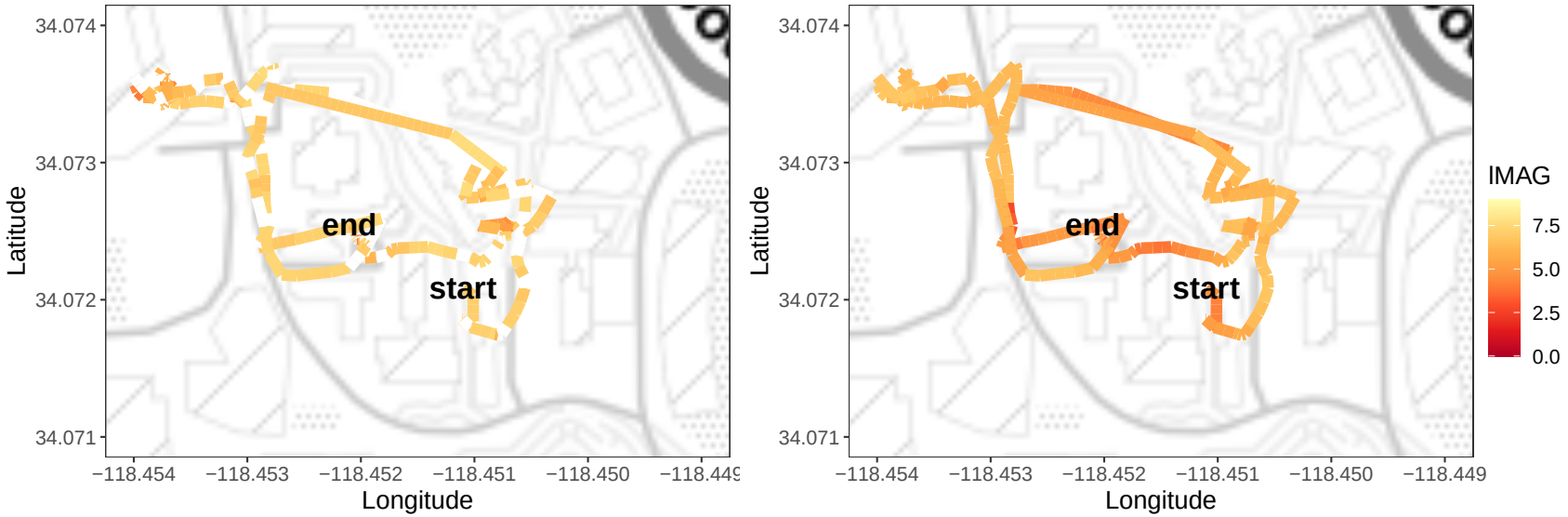
$$[\text{data} \,|\, \text{process}, \text{parameters}] \times [\text{process} \,|\, \text{parameters}] \times [\text{parameters}] \ .$$

- Process drives inference;
- Interpolate process at arbitrary locations;
- Predict scientific phenomenon (weather);
- Keep an eye on scalability (BIG DATA).

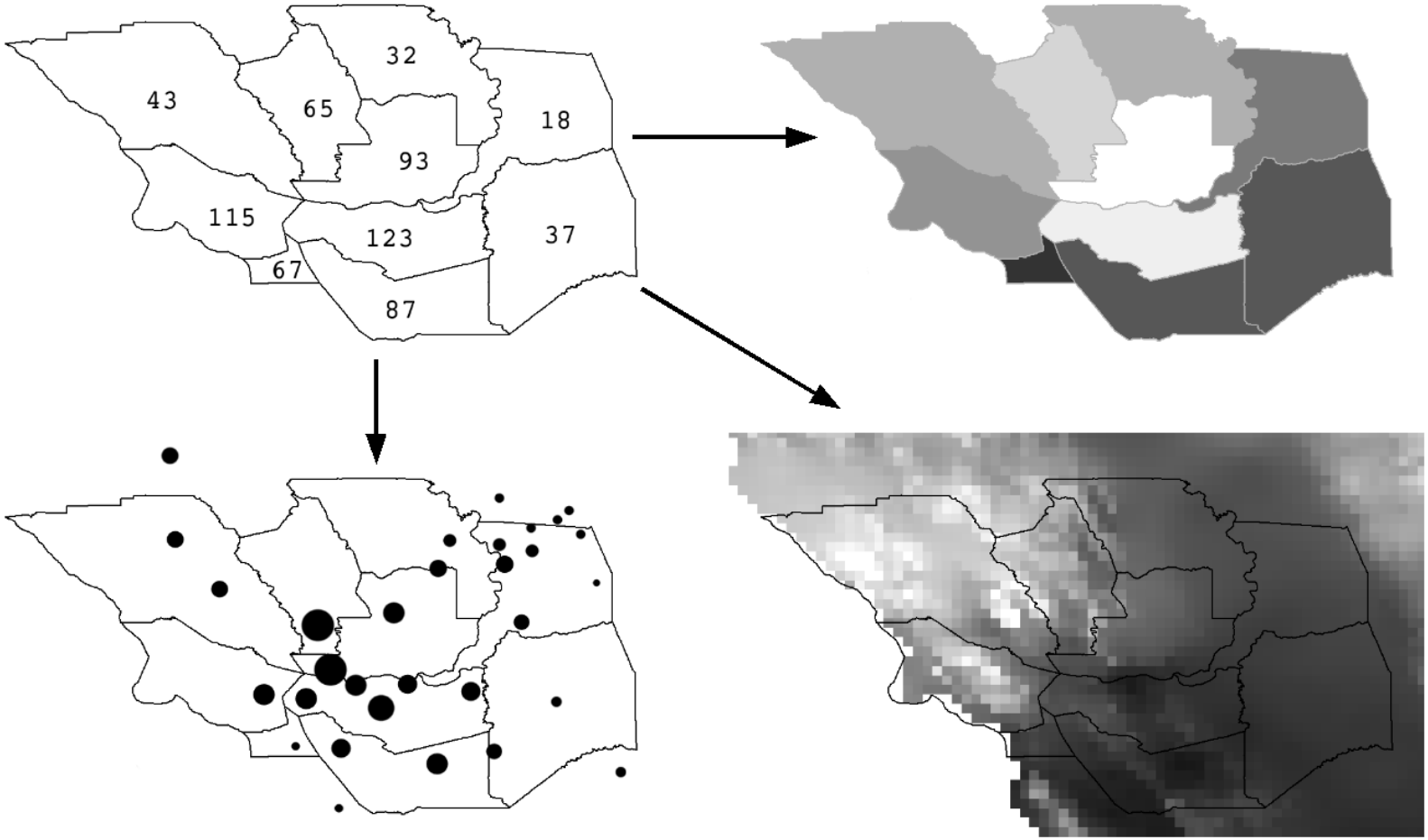
Estimating daily “periodic” behavior



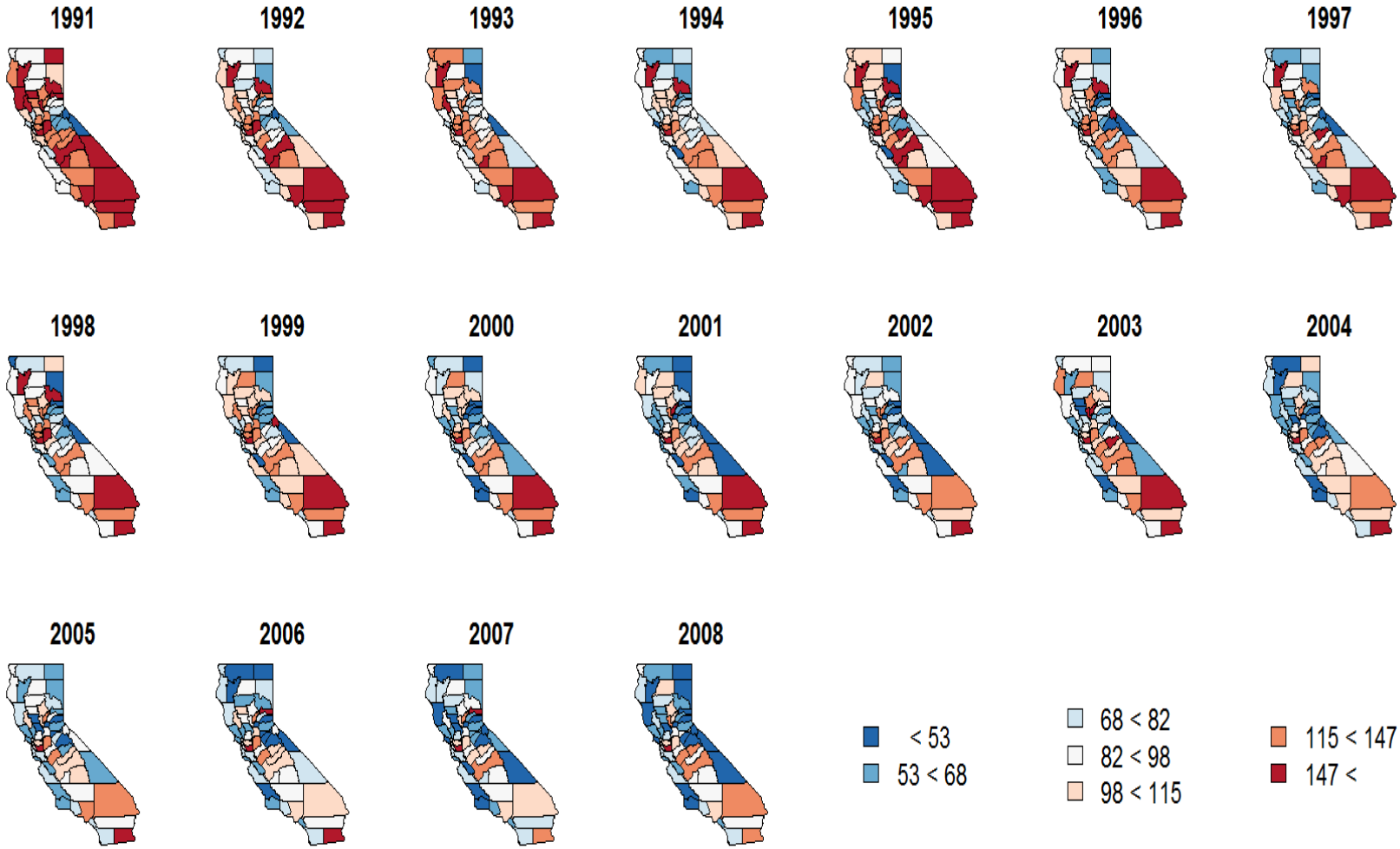
Predicted METs along trajectories



Spatially Misaligned Data



Mapping asthma hospitalizations in California



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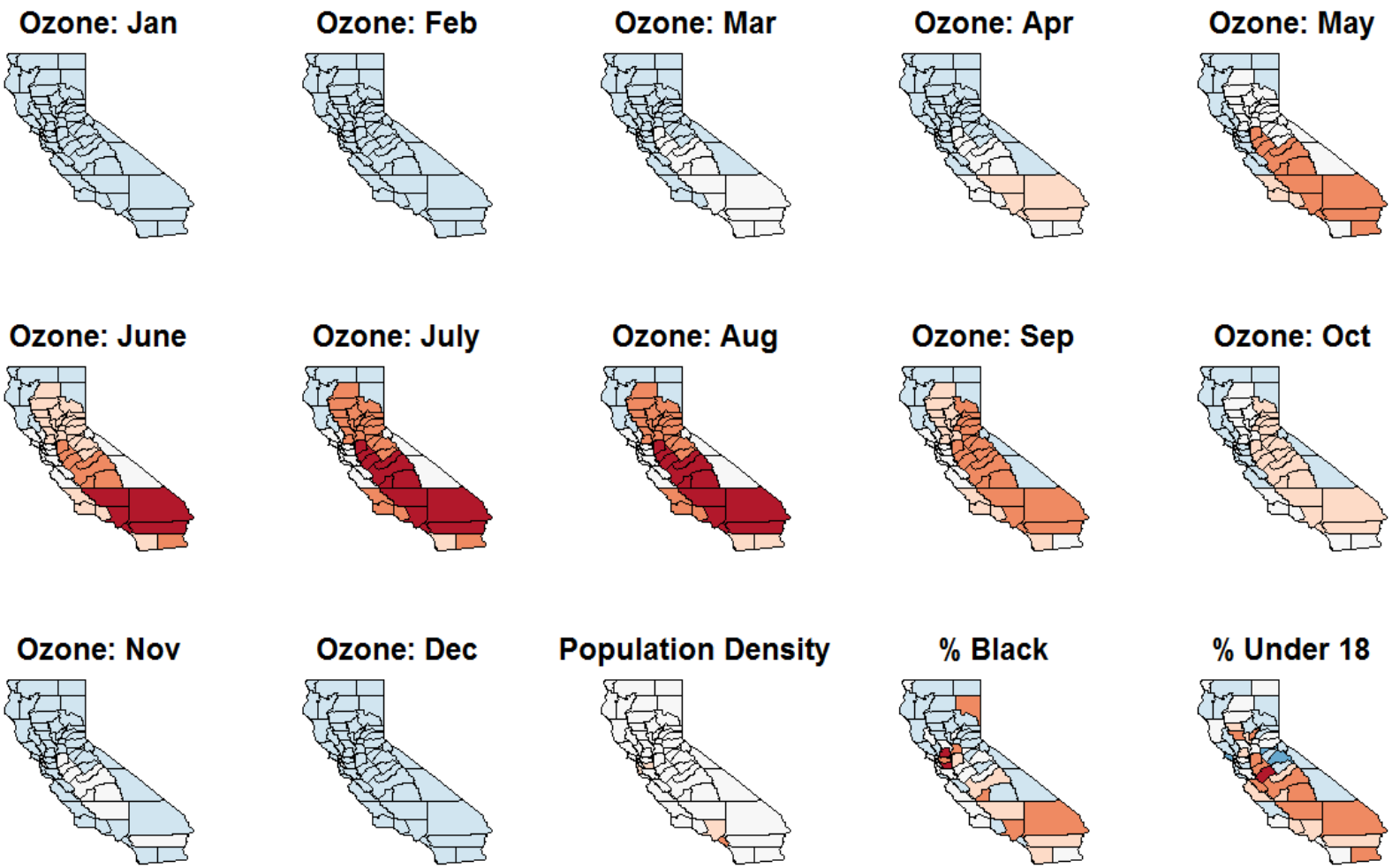
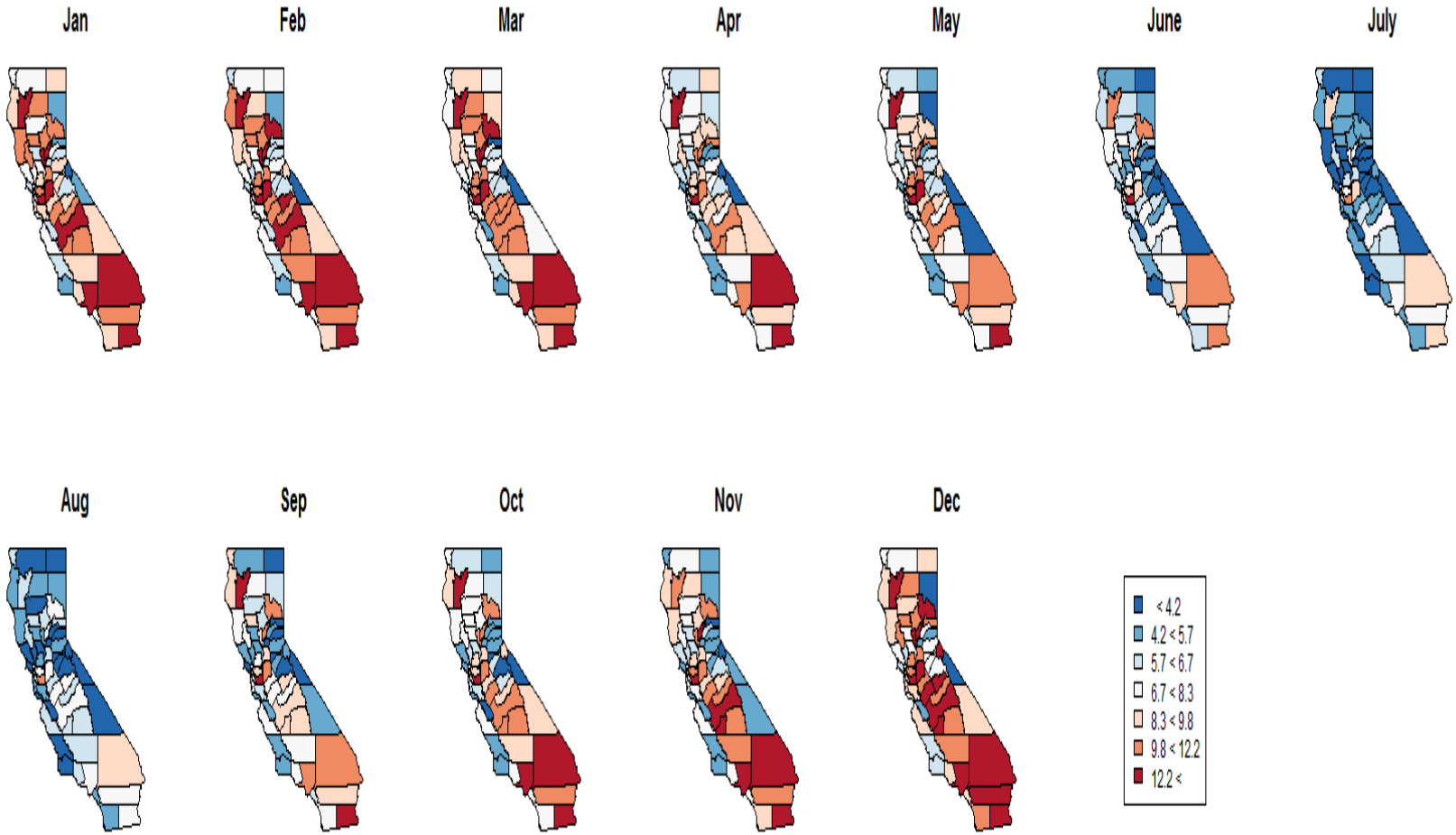


Mapping asthma hospitalizations in California

$$[\text{Asthma}]_t = [\text{Trends}]_t + [\text{Explanatory}]_t + [(\text{Space-time}) \text{ Interactions}]_t$$



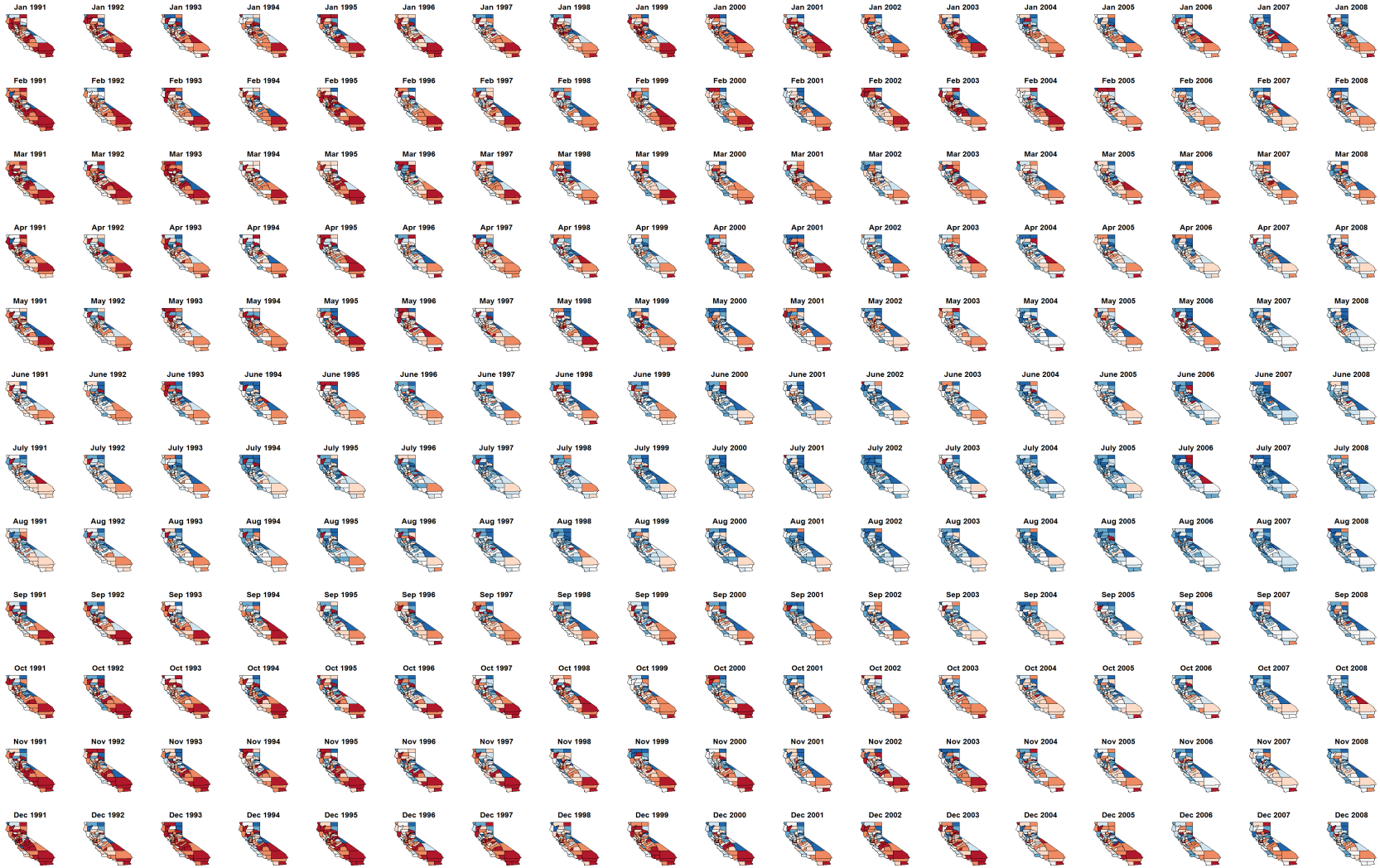
Data Analysis—Parameter Estimates

Parameter	Median (95% CI)	Parameter	Median (95% CI)
β_0 (Intercept)	9.51 (8.46, 10.51)	$\beta_{15} - \beta_{26}$ (Ozone)	
β_1 (Pop Den)	0.63 (0.55, 0.71)	— January	0.51 (-0.95, 1.94)
β_2 (% Black)	1.23 (1.13, 1.33)	— February	0.39 (-0.61, 1.53)
β_3 (% $<$ 18)	1.24 (1.13, 1.34)	— March	0.42 (-0.05, 0.89)
β_4 (Feb)	-0.36 (-1.49, 0.85)	— April	0.21 (-0.05, 0.49)
β_5 (Mar)	-0.24 (-1.32, 0.83)	— May	-0.17 (-0.33, 0.00)
β_6 (Apr)	-1.60 (-2.66, -0.51)	— June	-0.36 (-0.53, -0.20)
β_7 (May)	-1.39 (-2.46, -0.30)	— July	-0.22 (-0.35, -0.09)
β_8 (June)	-2.46 (-3.59, -1.37)	— August	-0.20 (-0.33, -0.07)
β_9 (July)	-3.29 (-4.47, -2.19)	— September	-0.28 (-0.42, -0.12)
β_{10} (Aug)	-3.16 (-4.33, -2.08)	— October	0.06 (-0.13, 0.25)
β_{11} (Sep)	-1.94 (-3.03, -0.88)	— November	0.52 (0.03, 1.05)
β_{12} (Oct)	-1.78 (-2.82, -0.70)	— December	3.15 (1.43, 5.08)
β_{13} (Nov)	-0.87 (-1.94, 0.24)	Spatial smoothing	0.88 (0.85, 0.90)
β_{14} (Dec)	2.42 (1.12, 3.64)	Temporal decay	1.24 (1.18, 1.30)

Table: Estimates and Credible Values of variables on asthma hospitalization rates.

Spatial-Temporal BIG DATA Analytics

$$[\text{Asthma}]_t = [\text{Intercept}]_t + [\text{Explanatory Variables}]_t + [\text{Space-time Interactions}]_t$$



Example 1: U.S. forest biomass data

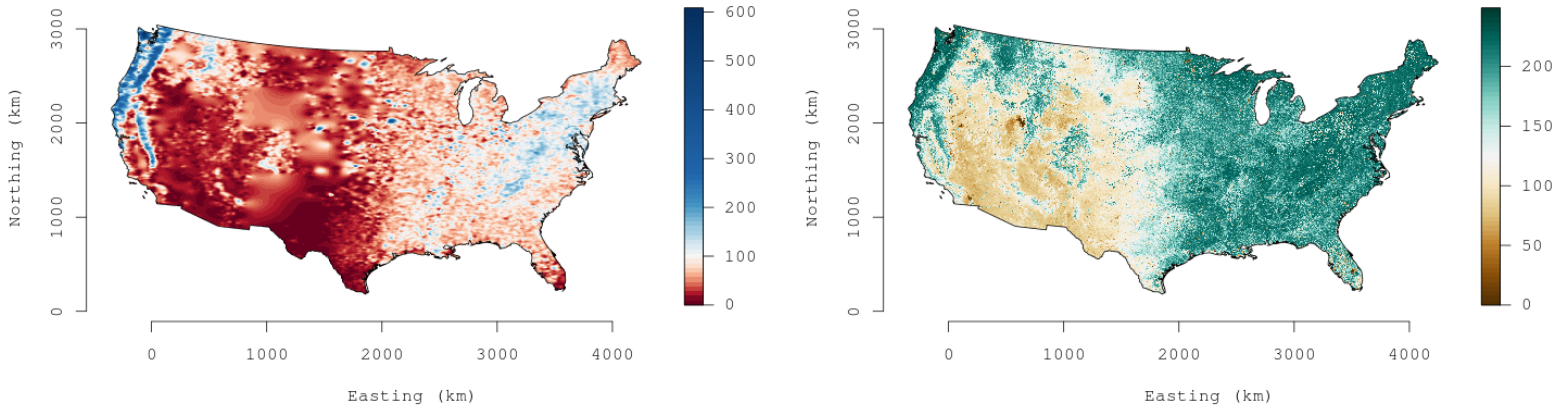
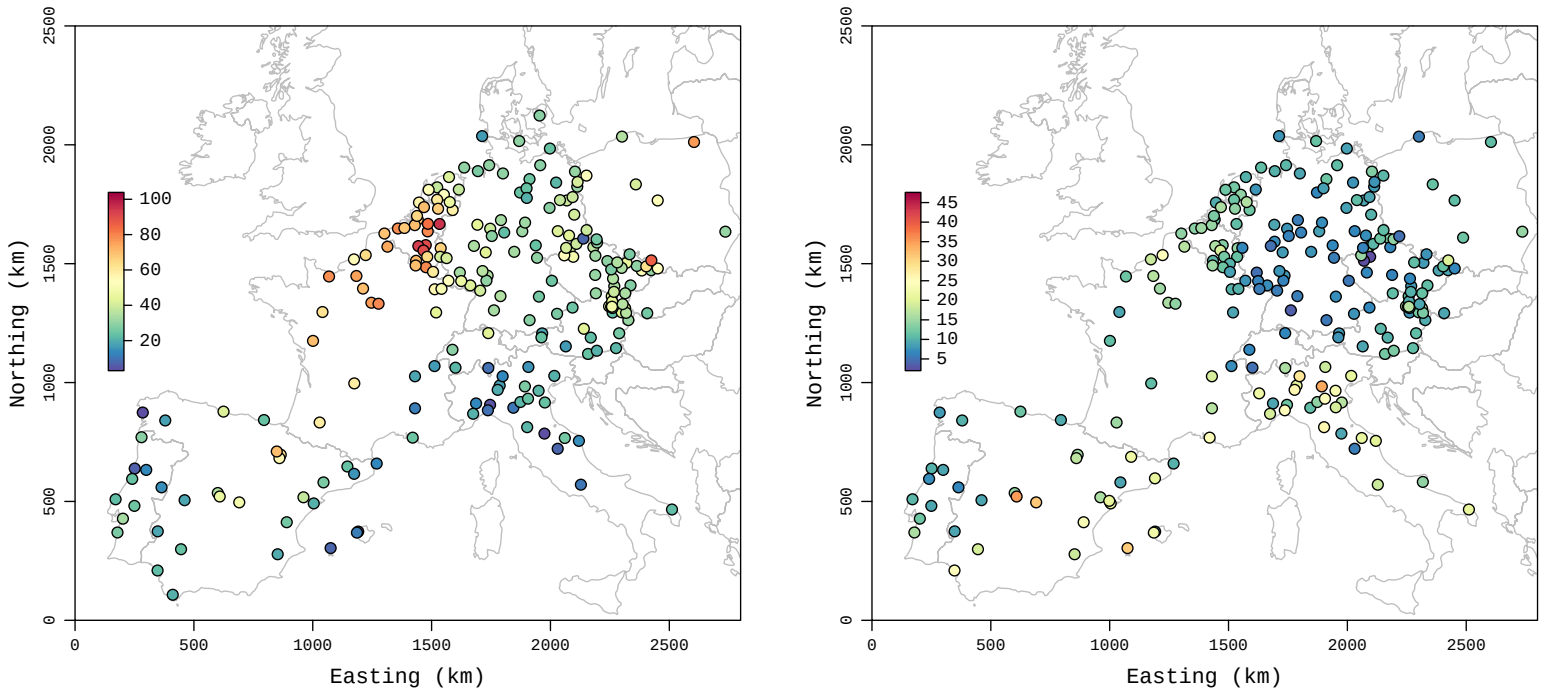


Figure: Observed biomass (left) and NDVI (right)

- Forest biomass data collected over 114,371 plots
- Normalized Difference Vegetation Index (NDVI) is a measure of greenness
- Forest Biomass Regression Model:
  $Biomass(\ell) = \beta_0(\ell) + \beta_1(\ell) NDVI(\ell) + error$

Spatial-Temporal BIG DATA Analytics

Example 2: European Particulate Matter (PM_{10}) data

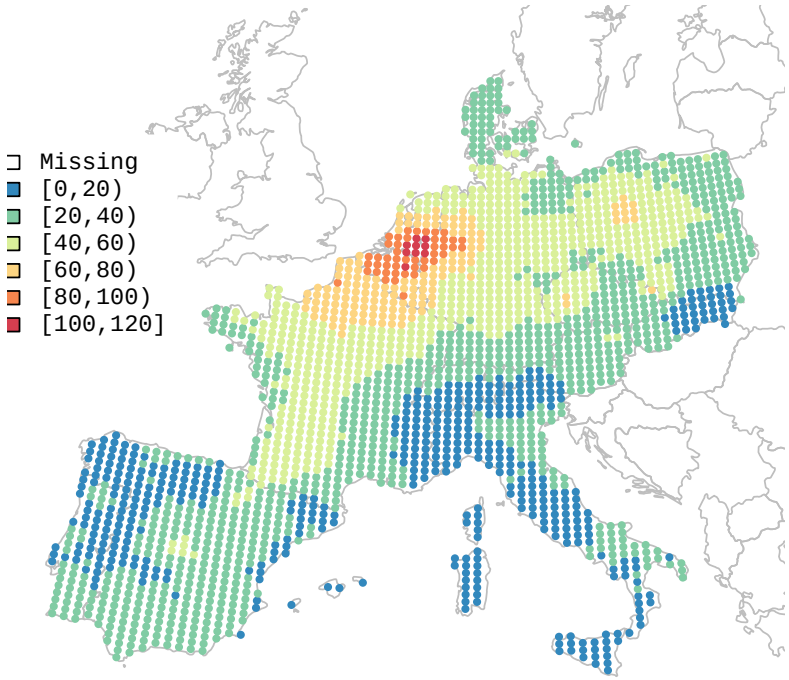


(a) PM_{10} levels in March, 2009 (b) PM_{10} levels in June, 2009

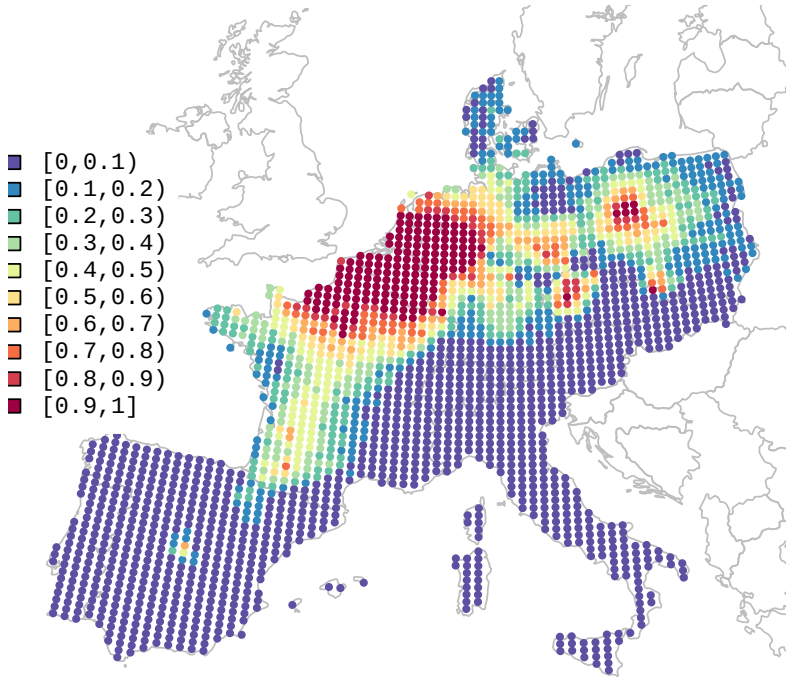
- Significant variation across space and time
- Daily observations at 308 stations for 2 years i.e., $n = 308 \times 730 = 224,840$

Statistical mapping with BIG DATA

European PM_{10} Dataset



(c) $\widehat{\text{PM}_{10}}$ for 04.03.2009



(d) $Pr(\widehat{\text{PM}_{10}} > 50\mu gm^{-3})$

Statistical mapping with BIG DATA

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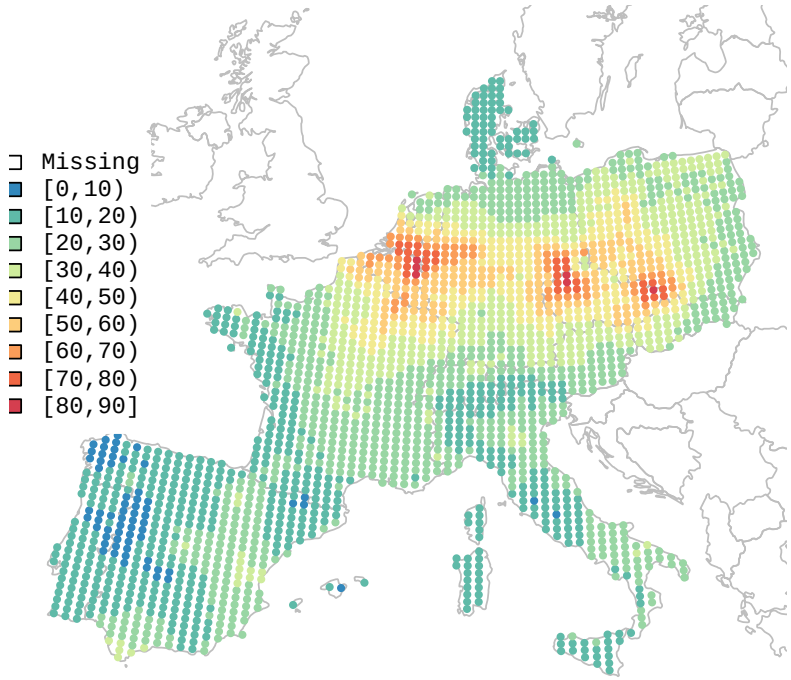
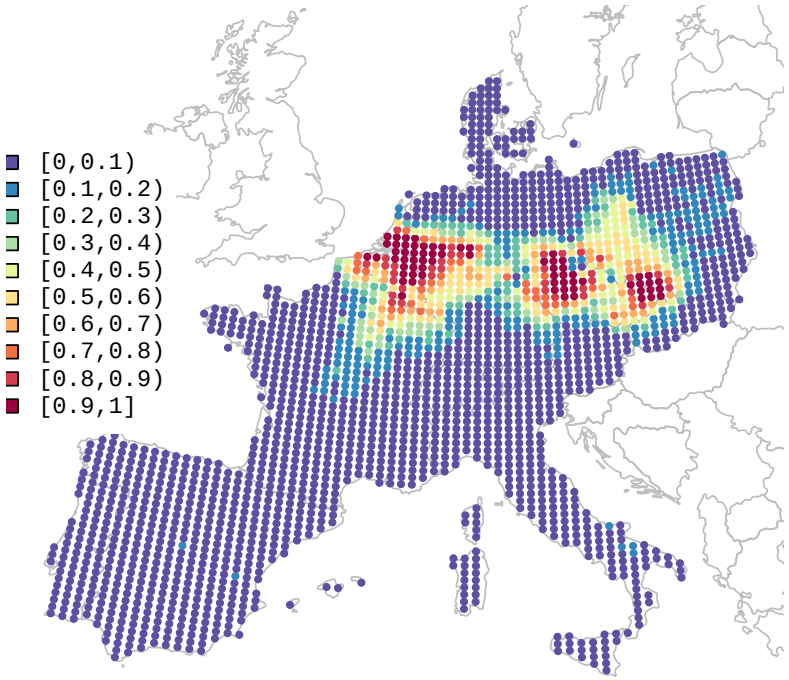


(a) $\widehat{\text{PM}_{10}}$ for 04.05.2009



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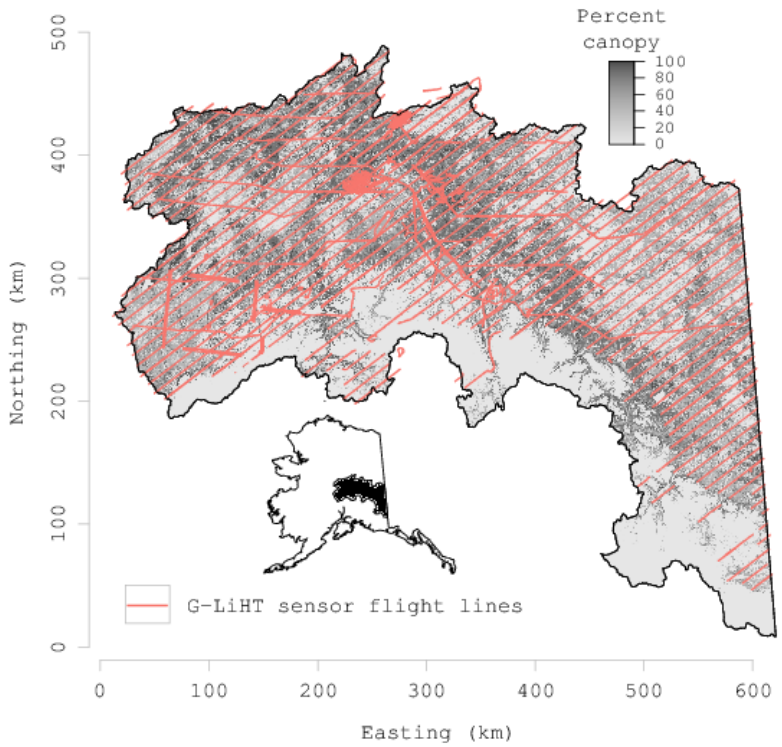
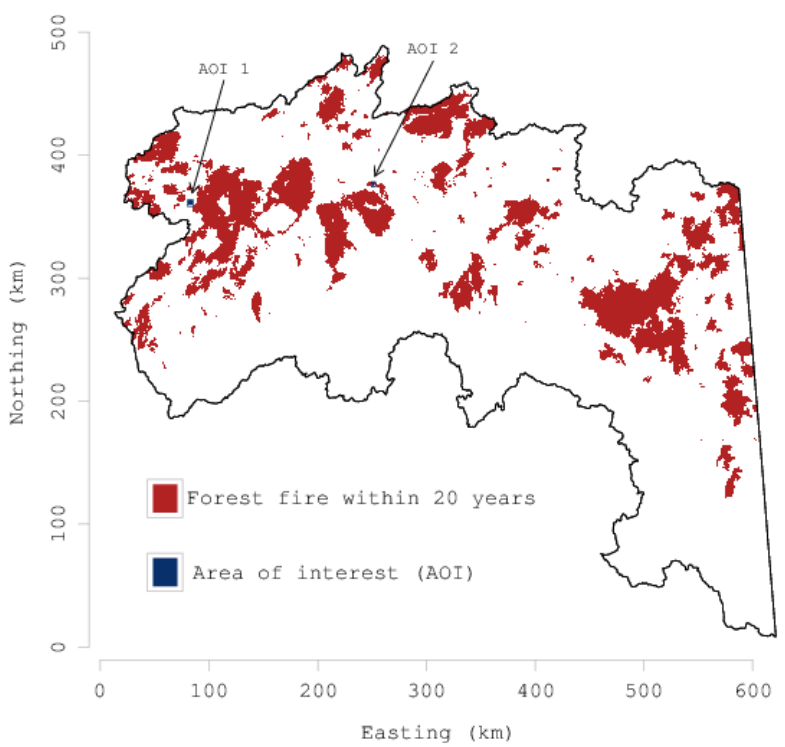
Case Study: Tanana Valley Forest Height Analysis



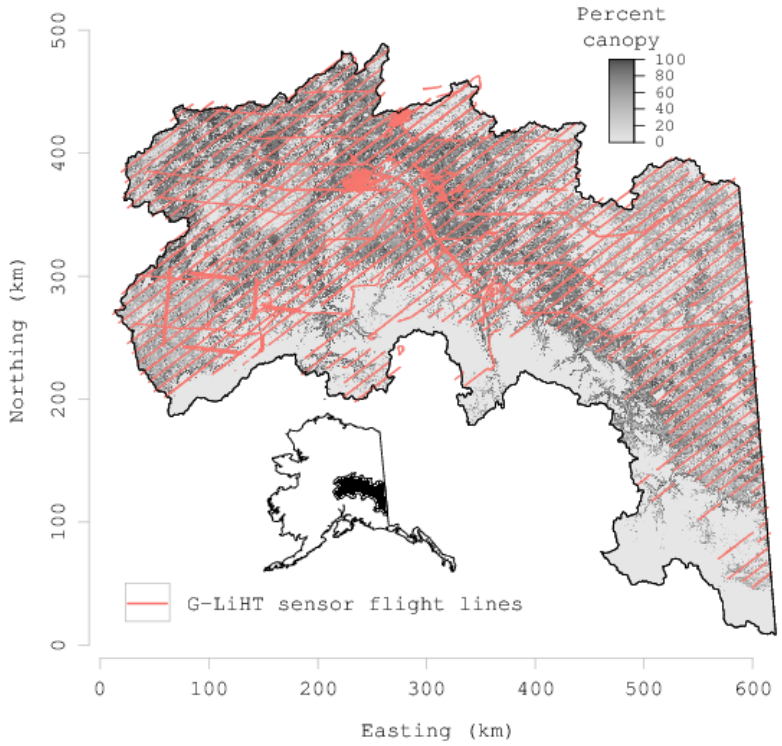
(c) Forest height and tree cover



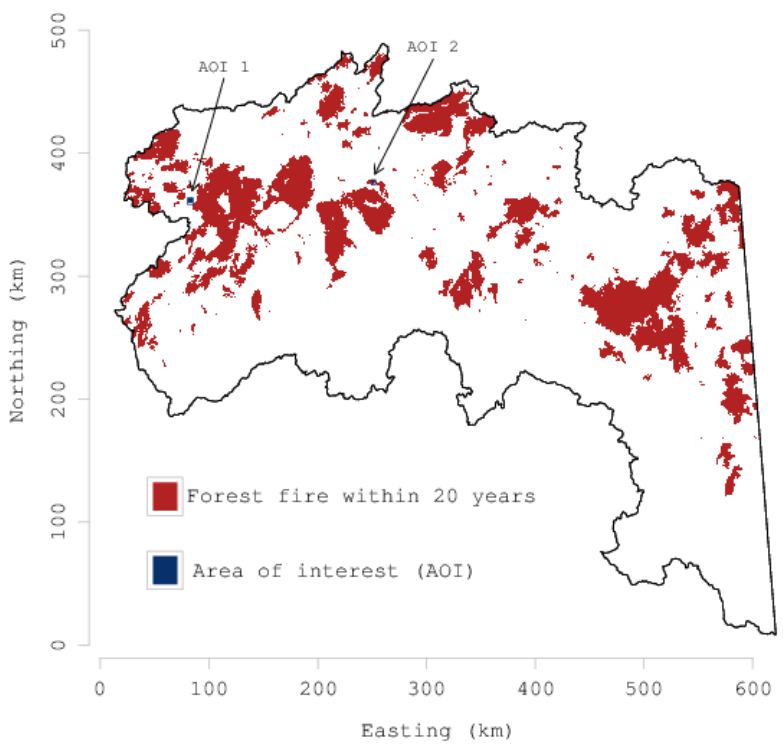
(d) Forest fire history

- Forest height (red lines) data from LiDAR at 40×10^6 locations
- Knowledge of forest height is important for biomass assessment, carbon management etc

Case Study: Tanana Valley Forest Height Analysis



(e) Forest height and tree cover



(f) Forest fire history

- Goal: High-resolution domainwide prediction maps of forest height
- Biomass $=$ [Mean] $+$ [Tree Cover] $+$ [Forest Fire] $+$ [Spatial Process]
- Methodology: Entire model-based spatial data analysis done is 2 minutes on a modest laptop.

Selected papers on Spatial BIG DATA analysis

- Banerjee, S. (2017). High-dimensional Bayesian geostatistics. Bayesian Analysis, 12, 583–614. DOI: http://dx.doi.org/10.1214/17-BA1056R
- Banerjee, S. (2020). Modeling massive spatial datasets using a conjugate Bayesian linear modeling framework. Spatial Statistics, 37, 10047. DOI: https://doi.org/10.1016/j.spasta.2020.100417
- Banerjee, S., Gelfand, A.E., Finley, A.O. and Sang, H. (2008). Gaussian predictive process models for large spatial datasets. Journal of the Royal Statistical Society Series B, 70, 825–848. DOI: http://dx.doi.org/10.1111/j.1467-9868.2008.00663.x
- Datta, A., Banerjee, S., Finley, A. O., and Gelfand, A. E. (2016). Hierarchical Nearest-Neighbor Gaussian Process models for large geostatistical datasets. Journal of the American Statistical Association, 111, 800–812. DOI: http://dx.doi.org/10.1080/01621459.2015.1044091
- Datta, A., Banerjee, S., Finley, A. O., Hamm, N. A. S., and Schaap, M. (2016). Non-separable dynamic Nearest-Neighbor Gaussian Process models for large spatio-temporal data with an application to particulate matter analysis. Annals of Applied Statistics, 10, 1286–1316. DOI: http://dx.doi.org/10.1214/16-AOAS931
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Thank You!