Human Exposure Assessment

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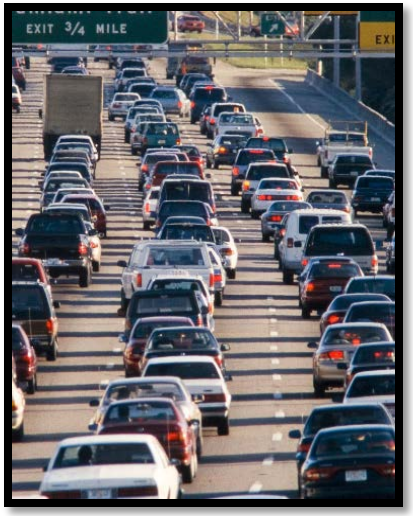
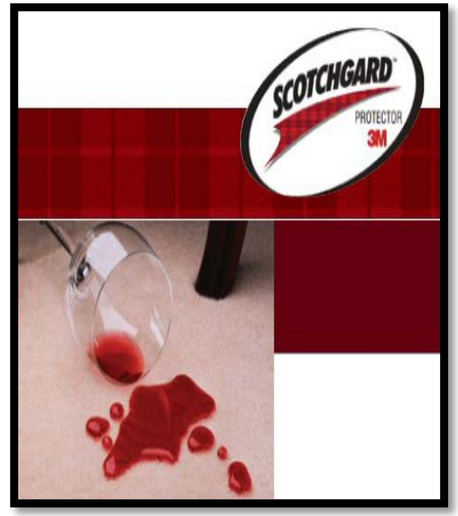
Common exposures of interest





Exposure data for environmental cancer epidemiology studies

De novo exposure data collections

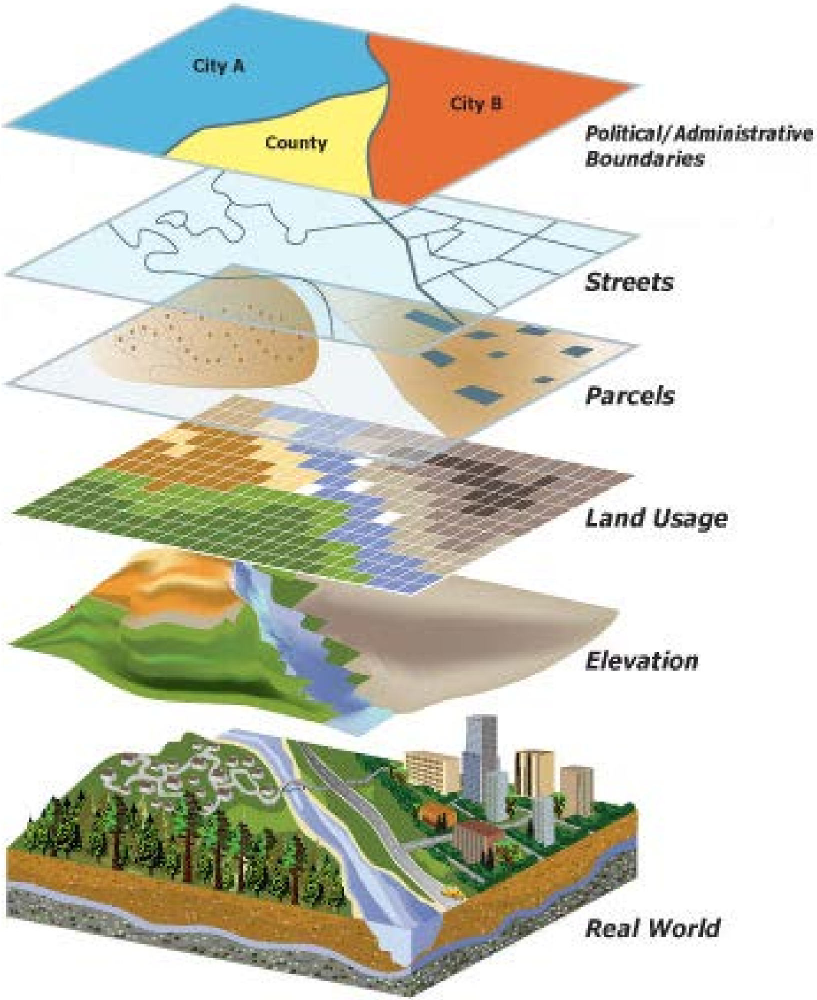
- Environmental monitoring – e.g., in air, water, soil
- Biologic media – e.g., blood, saliva, toenails, teeth, etc.
- Surveys

Secondary data

- Measurements collected for regulatory monitoring
- Area-based surveillance/census data
- Satellite imagery

- Typically, geographic location is the way we link these data to individuals

Geographic Information Systems

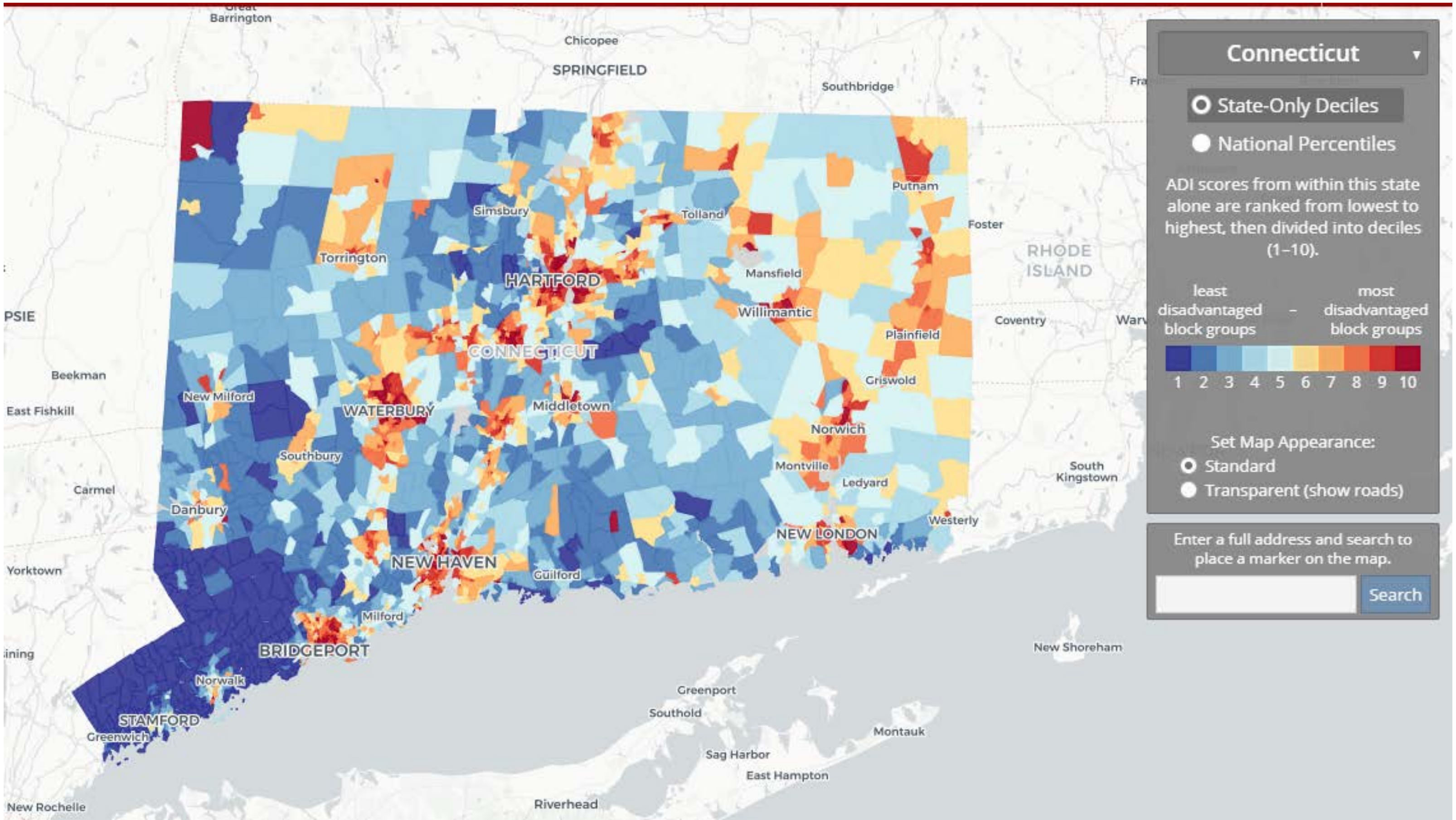


Software for geospatial data

i.e., a series of ‘stacked’ maps

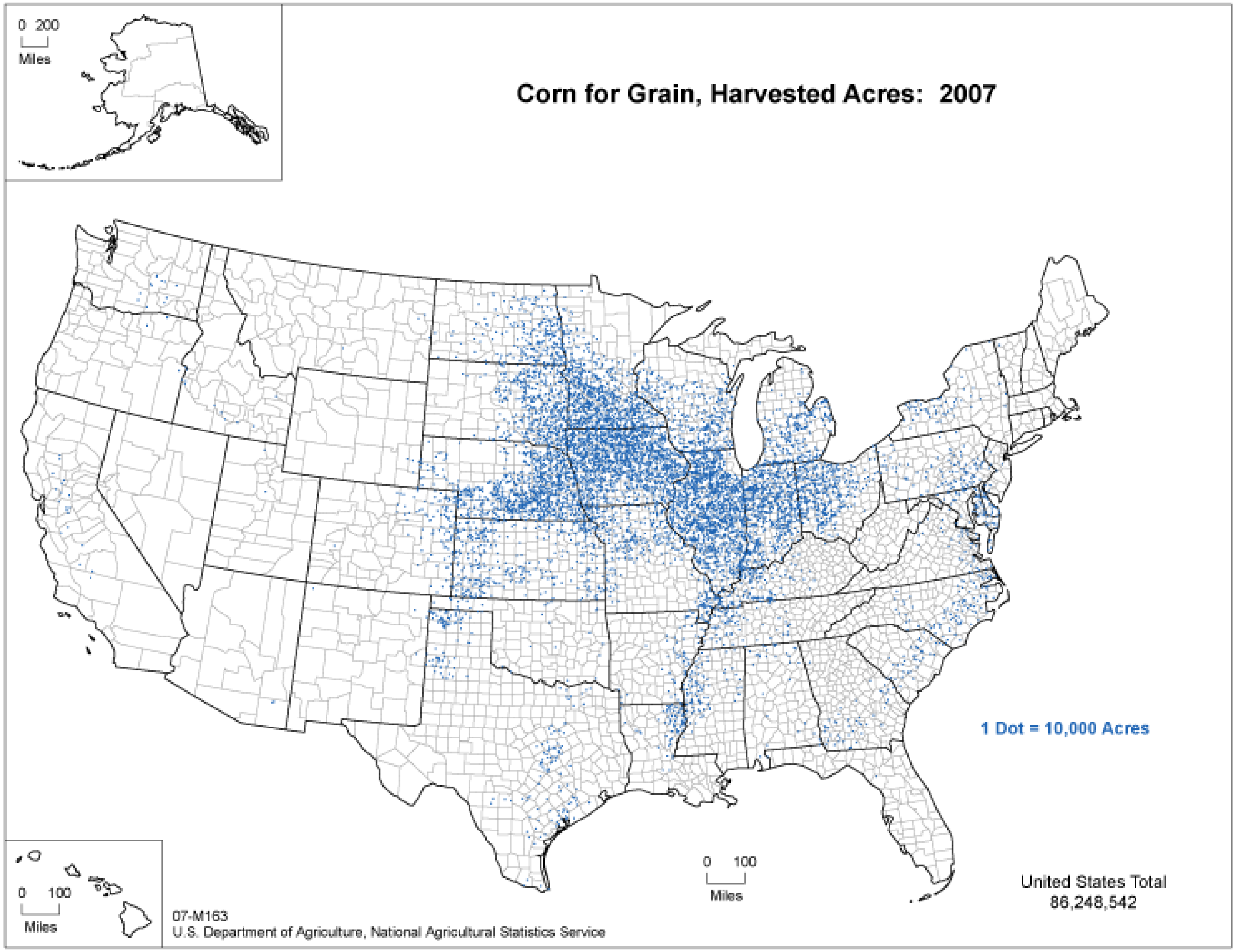
- Allows combination of spatially referenced datasets
- Create new exposure surrogate variables
- Create predictive models using GIS-derived variables

Linkages to environmental data - Census



U.S. Census data Used to create deprivation indices:
https://www.neighborhoodatlas.medicine.wisc.edu/

Linkages – land use



Exposure assessment vignettes

Predicting exposures without routinely collected monitoring data

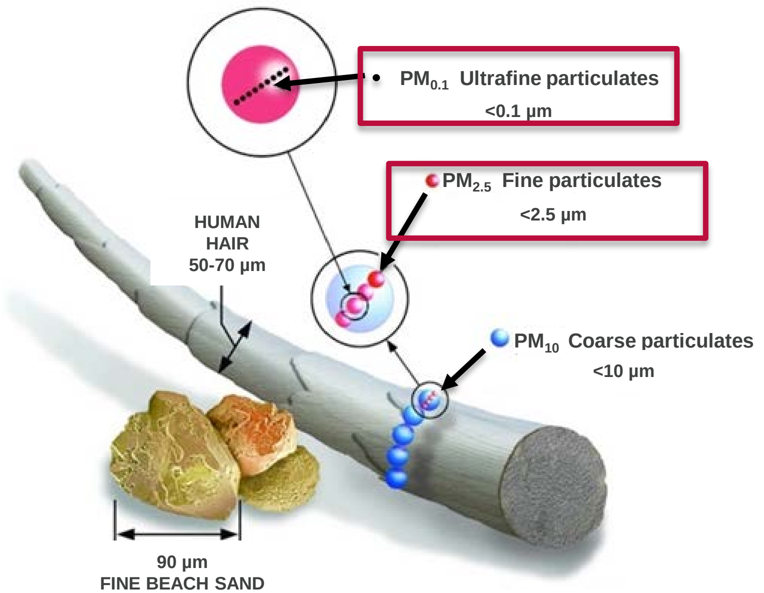
1. Traffic-related air pollutant

2. Drinking water contaminant

Leveraging regulatory data

3. Point source carcinogenic emissions

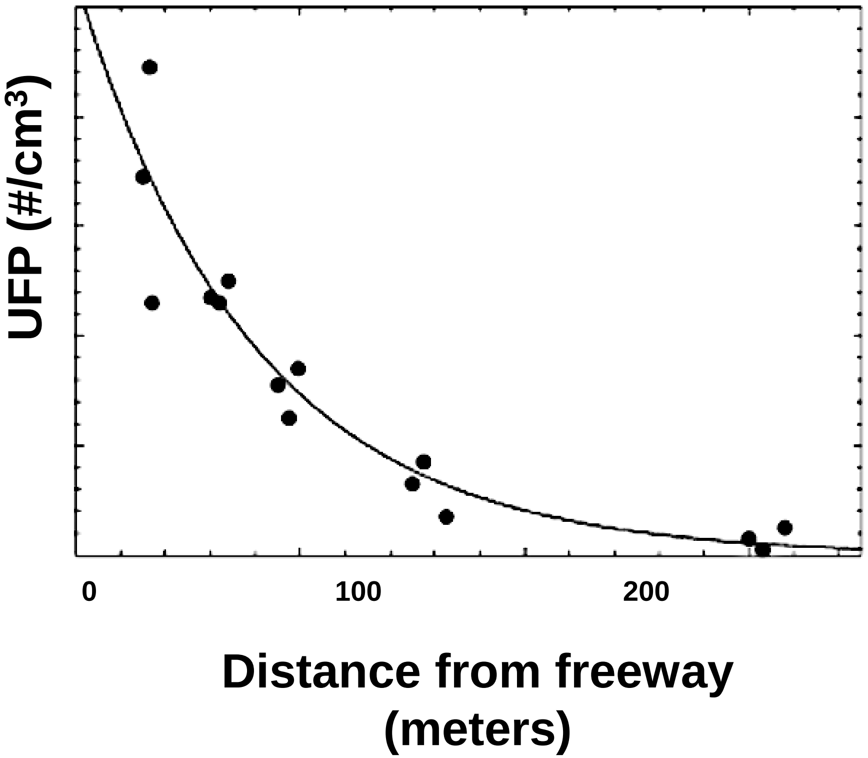
Outdoor air pollution is a carcinogenic mixture – Are associations with lung cancer driven by ultrafine particles (UFP)?



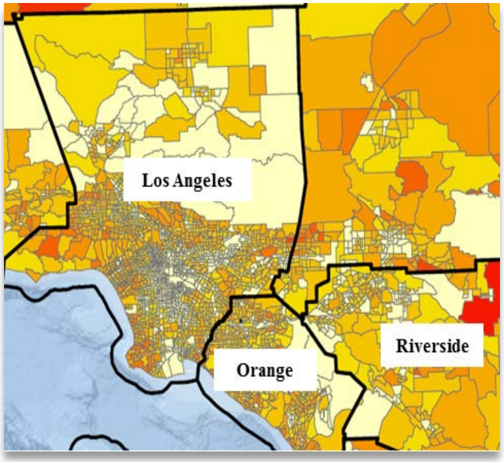
- Large surface area-to-mass ratio
- Carriers of toxic chemicals
  - Polycyclic aromatic hydrocarbons (PAHs)
  - Metals
- Behave as a gas
  - Diffuse across membranes
  - Travel through walls
- Few studies of UFP and lung cancer

UFP exposure assessment challenges

- Not regulated or routinely measured
- Highest exposures are close to the source



Los Angeles Ultrafines Study



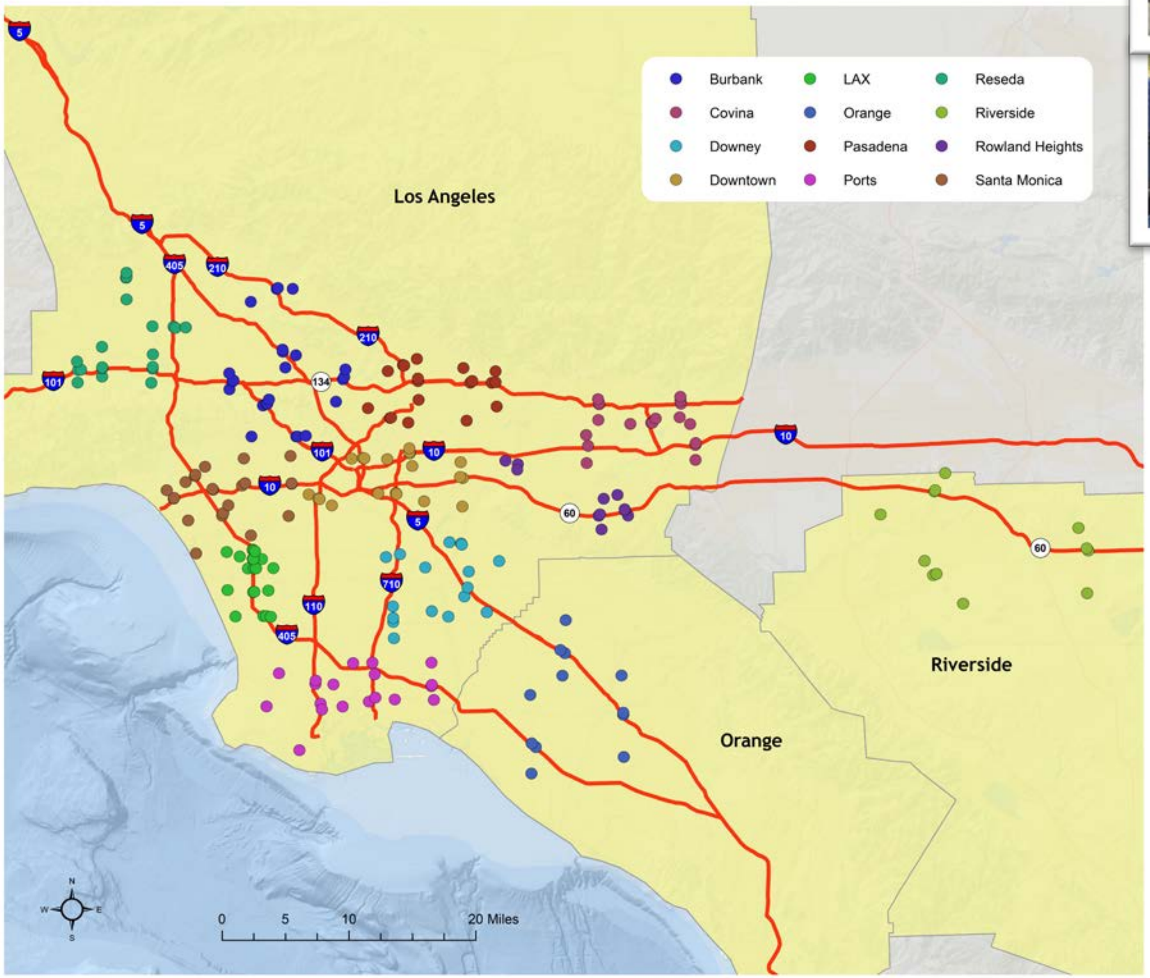
~52,000 participants

- NIH AARP Diet and Health Study
  - Enrolled in 1995
  - Aged 50+ years

Objective: To evaluate association between long-term exposure to outdoor UFP and lung cancer risk

Challenge: How to estimate exposure to UFP for participants without measurements?

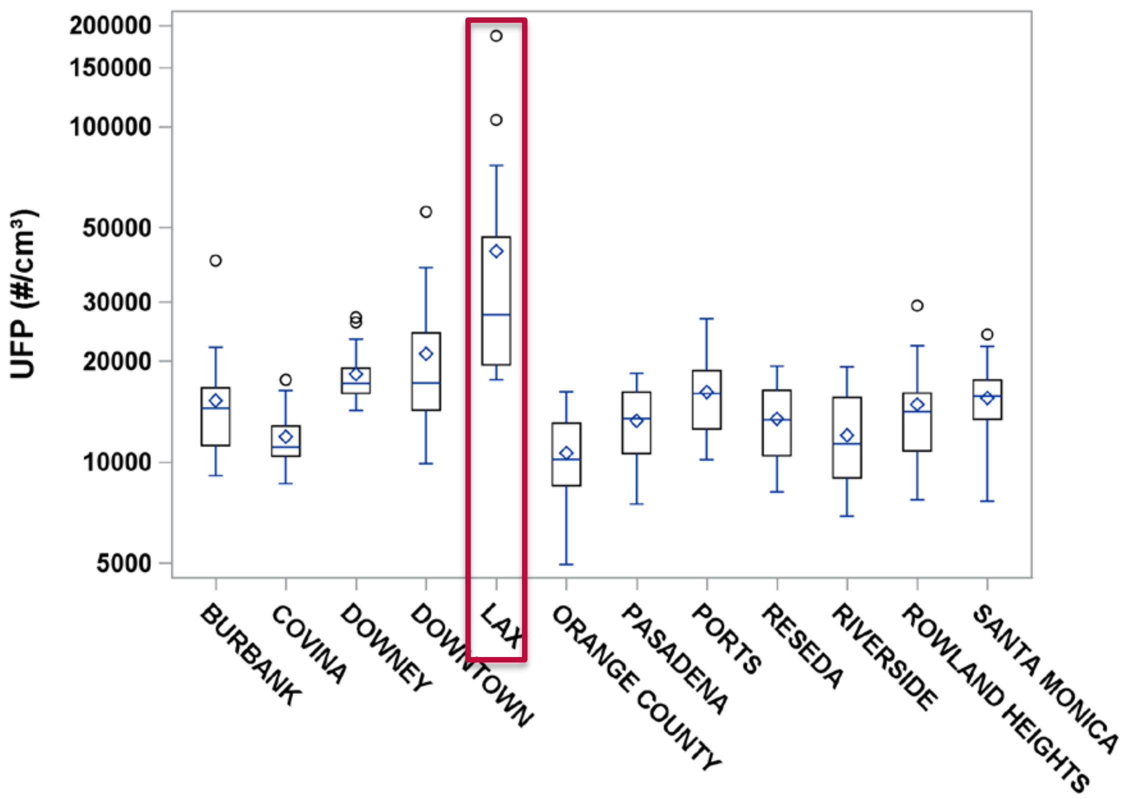
UFP mobile monitoring campaign



UFP
$PM_{2.5}$
Black carbon (BC)

Jones RR et al., *Sci Tot Env* 2020

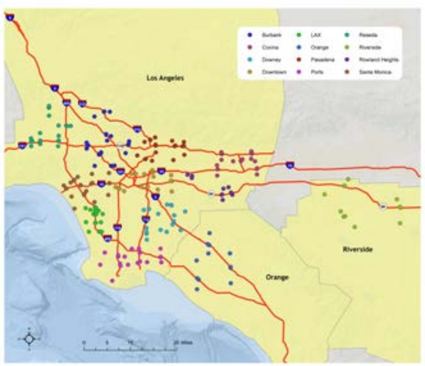
UFP monitoring results



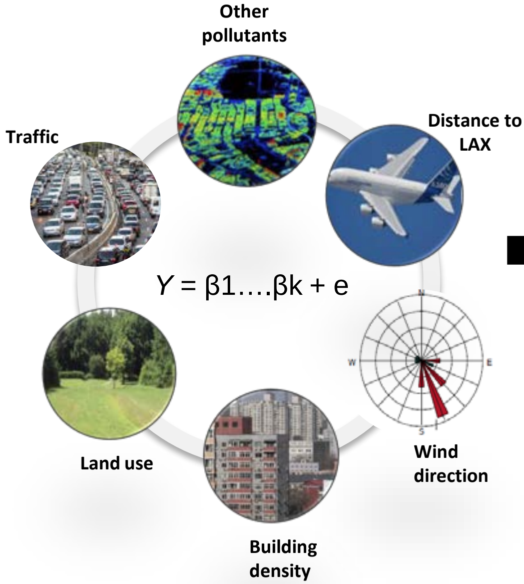
Jones, RR et al., *Sci Tot Env* 2020

Land Use Regression

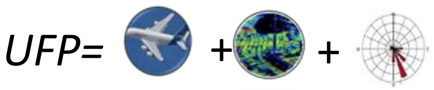
Newly collected measurements



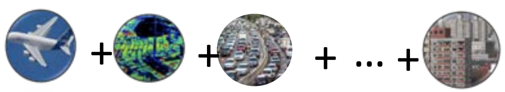
Characteristics of local environment



Use model to estimate exposure

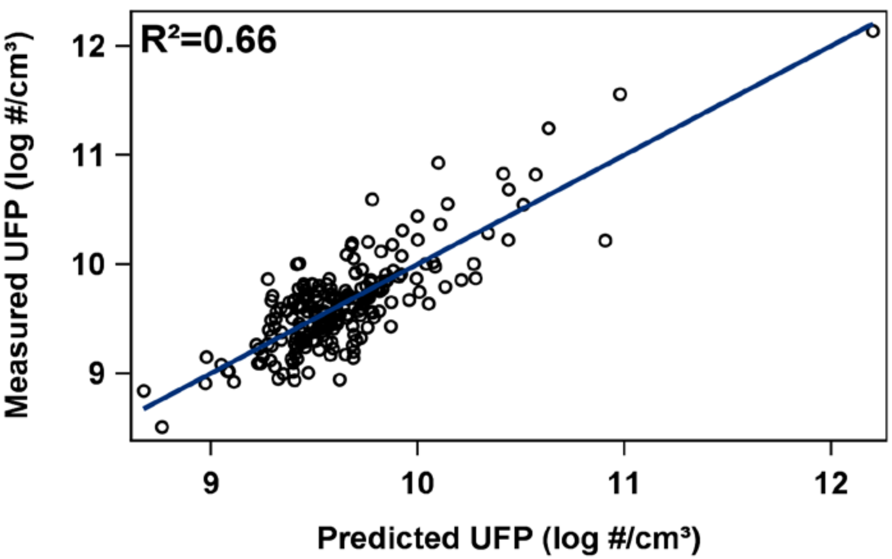


UFP modeling results

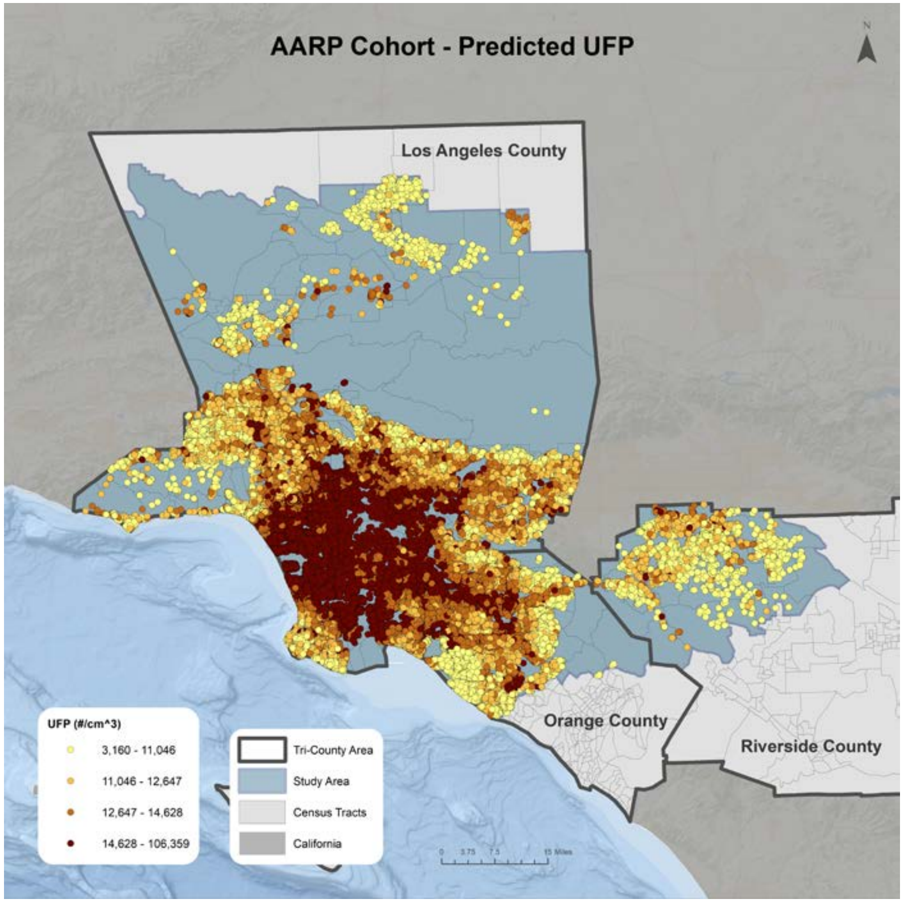
UFP= 

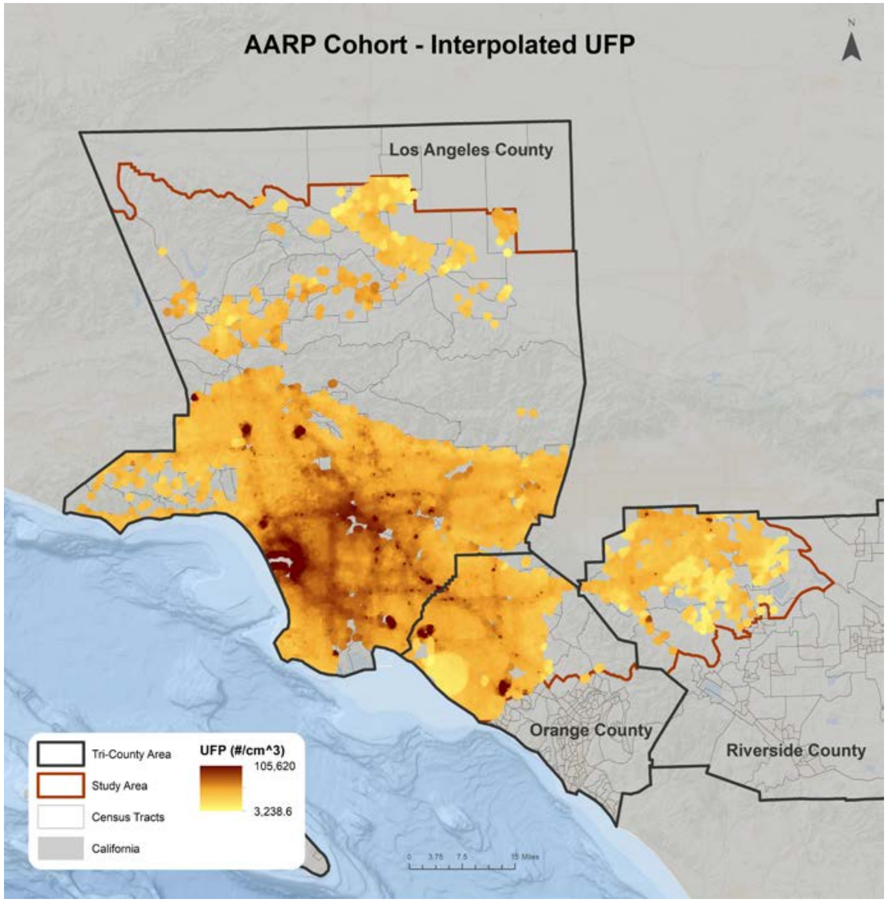
- Proximity to LAX
- Density of major highways
- Traffic load
- Developed land use

Cross-validation R^2=0.62



Use model to estimate UFP exposure at cohort residences





Drinking water contaminants

Regulated contaminants

Nitrate

Disinfection By-products

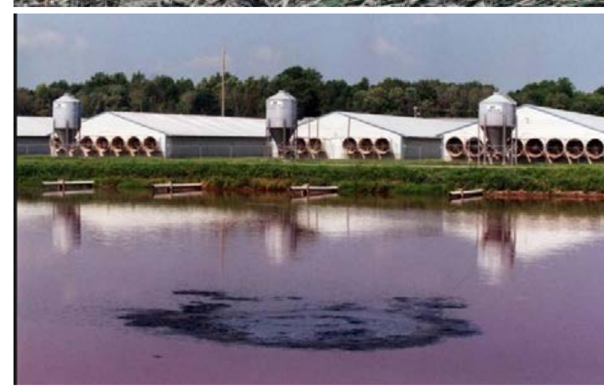
Emerging (and re-emerging) contaminants of concern

Per- and polyfluoroalkyl substances (PFAS)

Endocrine disrupting compounds

Nitrate in drinking water: sources and exposures

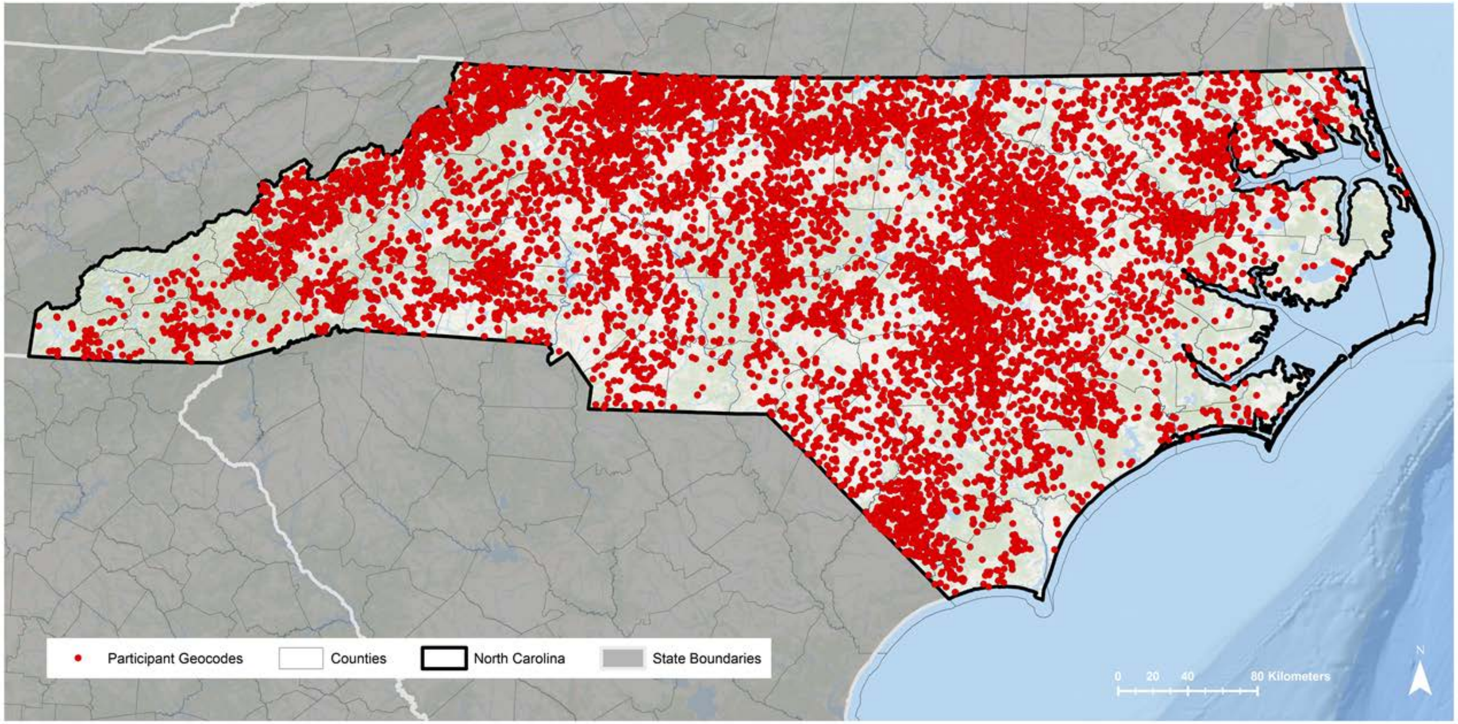
- Nitrogen fertilizers, animal and human waste
- Maximum contaminant level:
  10 mg/L as NO_3-N
- Highest exposures: private well users
- Measurements are sparse because private wells are not regulated



Estimating nitrate in private wells in North Carolina in the Agricultural Health Study cohort

- Private wells are not regulated
- Most water sources in AHS study are private wells

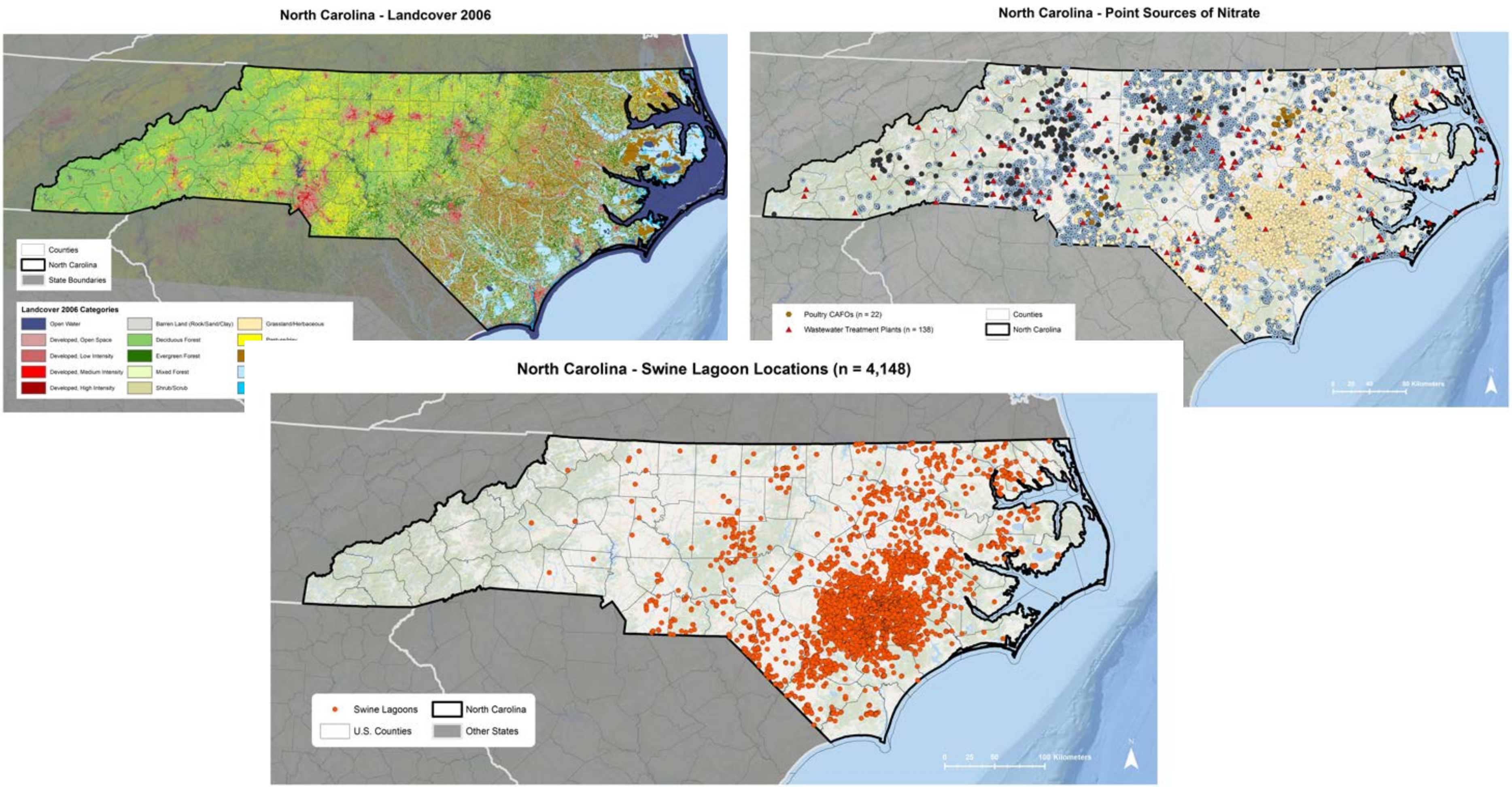
Agricultural Health Study - North Carolina Participants
Enrollment Addresses with a Good Geocode on a Private Well



Messier...Ward, STOTEN, 2019

GIS-based model of nitrate in private wells in NC

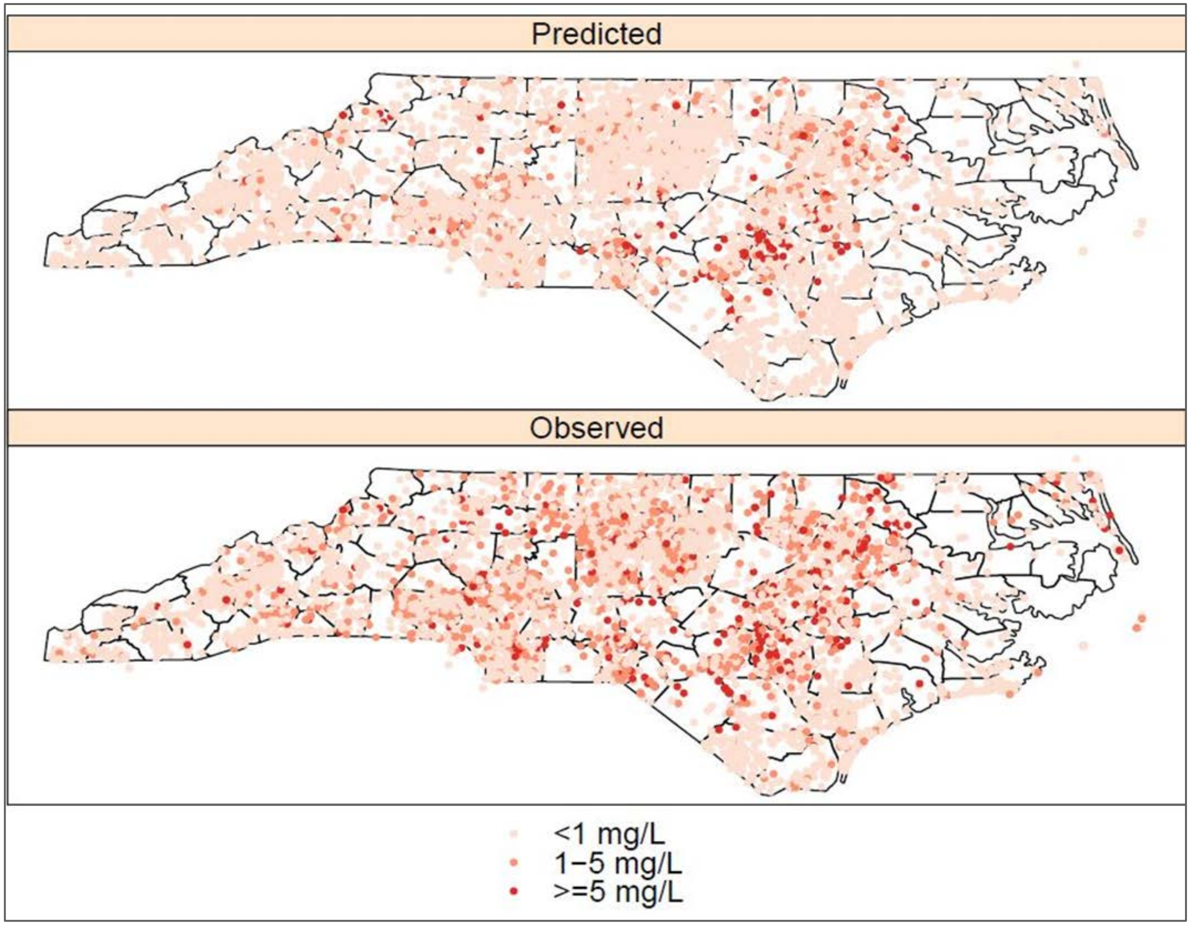
- ~22,000 nitrate measurements, training and testing dataset
- Evaluated 120 variables (e.g., land use, manure lagoons, geology, soils)



Messier...Ward, STOTEN, 2019

GIS-based model of nitrate in private wells in NC: results

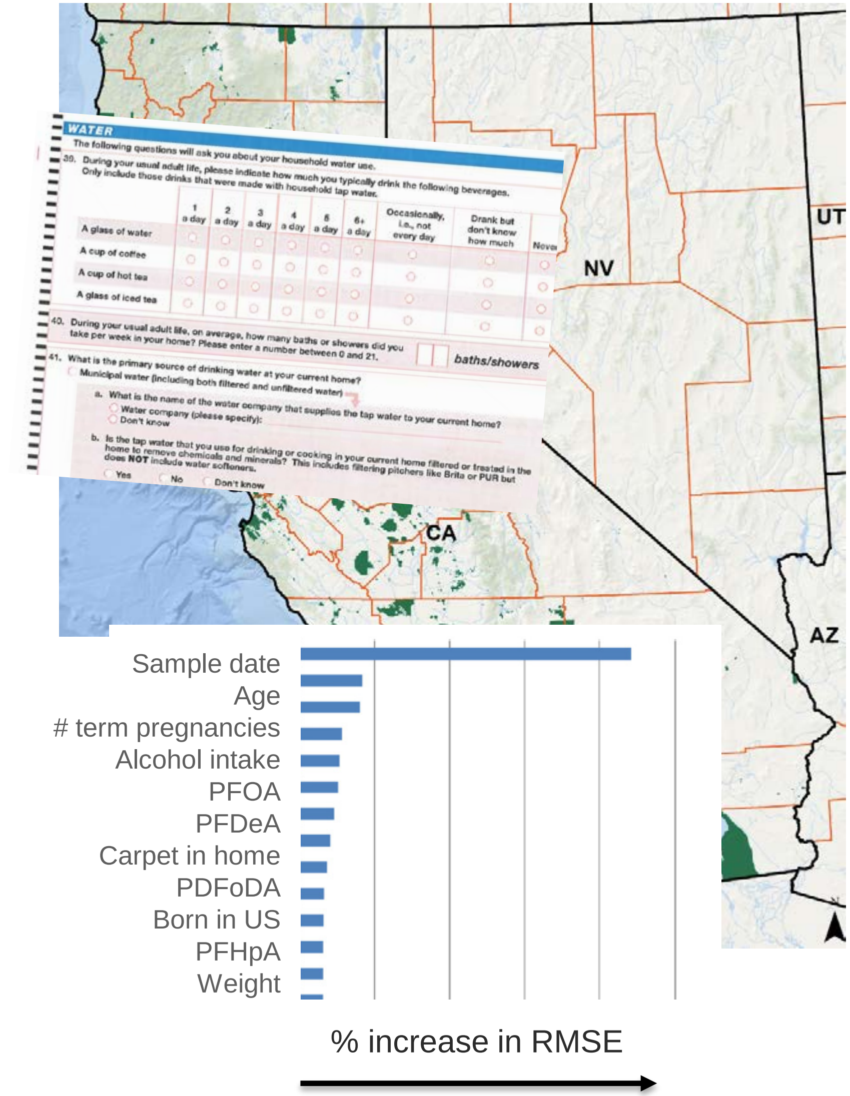
- Random forest model: 58 variables
- Top variables:
  - Swine lagoons
  - Well depth
  - Agricultural land 1992, 2000
  - Soil characteristics
- Overall accuracy: 75%
- High sensitivity <1 mg/L
- High specificity $\geq$5 mg/L



Messier...Ward, STOTEN, 2019

Ongoing work in PFAS in California

- California Teachers Study (CTS)
  - ~135k women, enrolled in 1995
- Evaluating feasibility of drinking water exposure assessment for PFAS
  - Developed drinking water questions for follow-up survey (2018-2019)
  - Assess PFAS measured in participants' water supplies from limited EPA data (UCMR 3)
  - Analysis of determinants of serum PFAS in ~1200 women via random forest modeling



Jones et al., unpublished

Carcinogenic exposures from point sources

Chicago Center for Health and Environment

Toxics Release Inventory

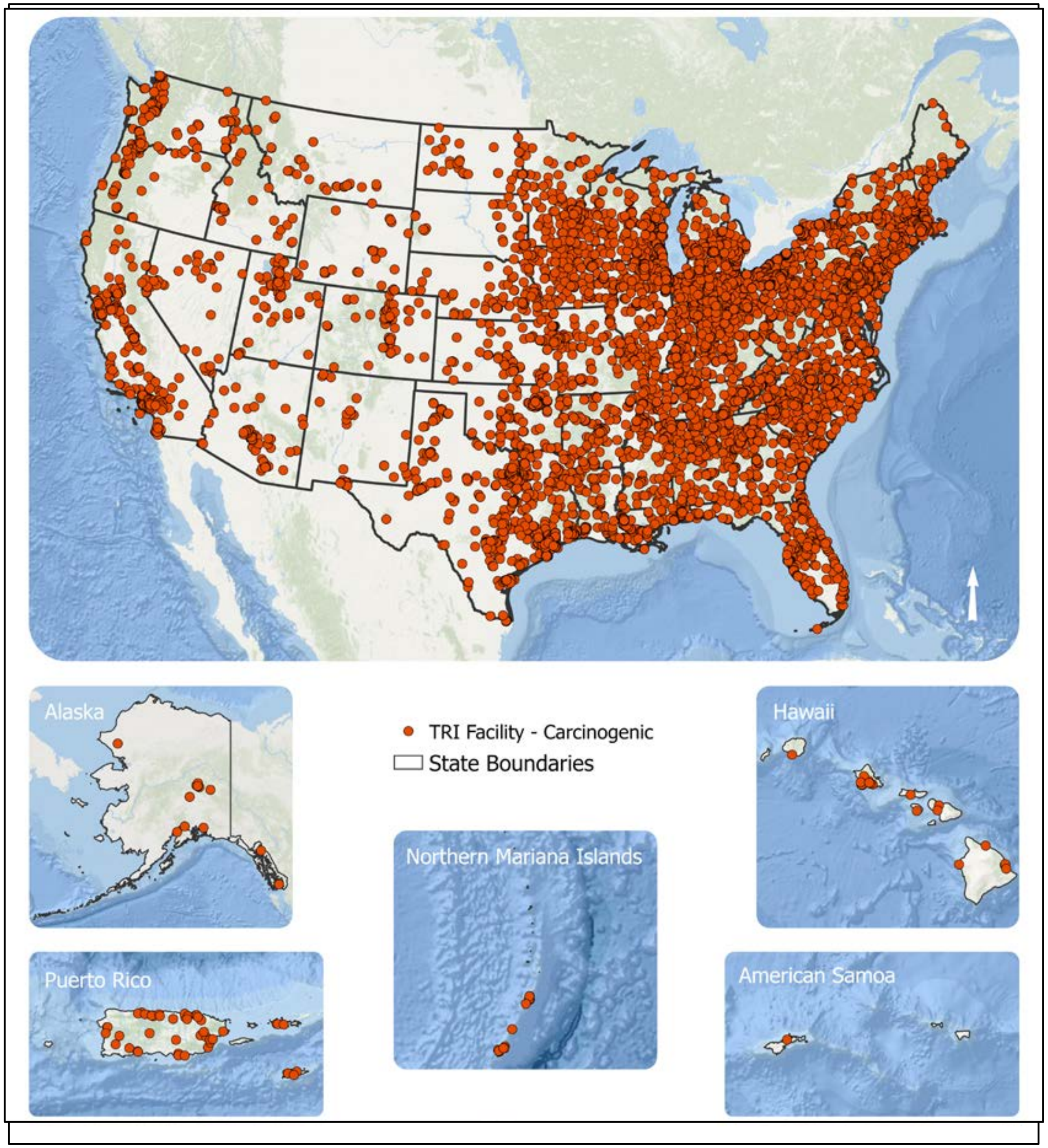
- Tracks the management of certain toxic chemicals that may pose a threat to human health and the environment

- Since 1987, facilities in different industry sectors must report <u>annually</u> how much of each chemical is released to the environment and/or managed through recycling, energy recovery and treatment

- 770 individual chemicals require reporting as of 2020

Industrial air emissions

- In 2018, 15,519 industrial facilities reported annual releases of 600 million pounds of toxic chemicals in the air across the U.S., DC, and 5 territories
- In 2018, 50% of facilities (n=7,852) reported air releases of IARC Group 1 and 2A compounds (known and probable carcinogens)

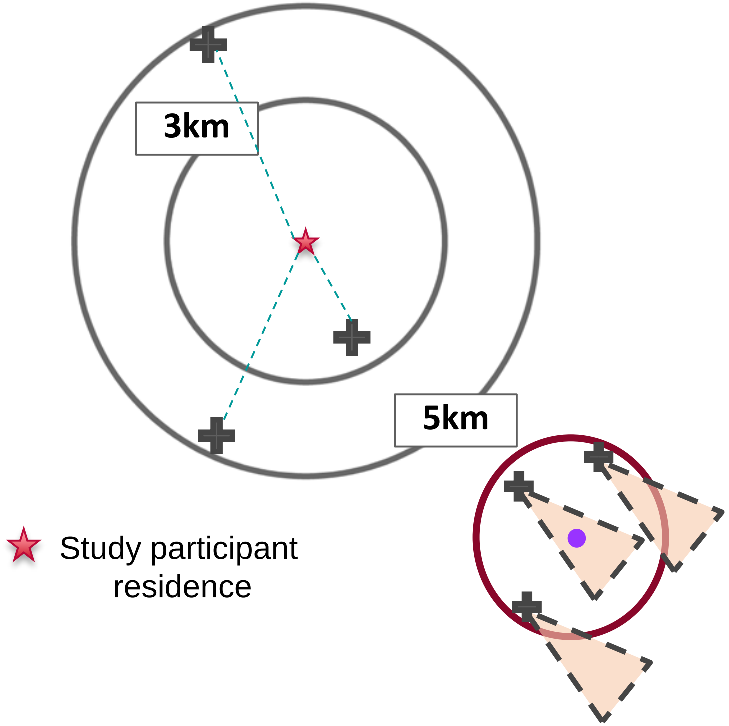


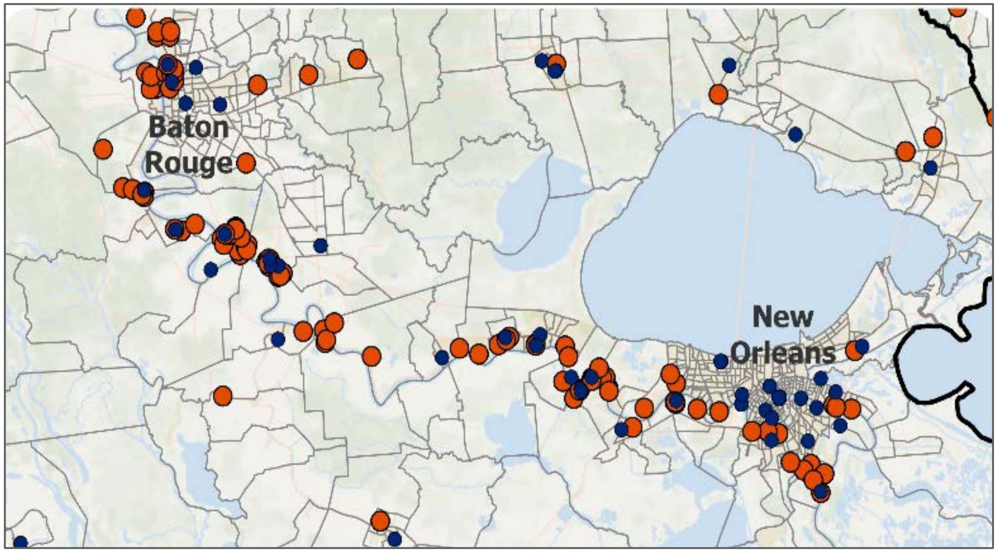
(Not pictured: Guam & US Virgin Islands)

Translating point source regulatory data into estimate of exposure

Annual emissions (in pounds) released from each facility, per year

Inverse distance-weighted average emissions index (AEI)

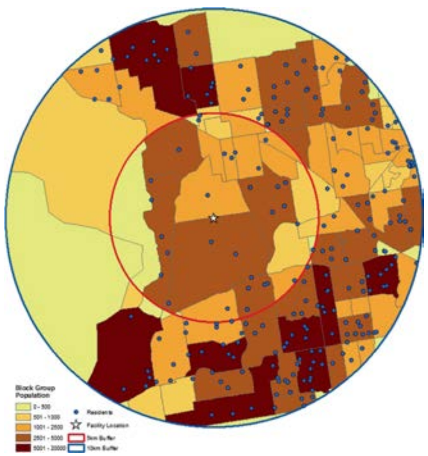




AEI= [(200 lbs EtO/5km) + (30 lbs benzene/2.9km) + (3000lbs TCE/4.9km)]

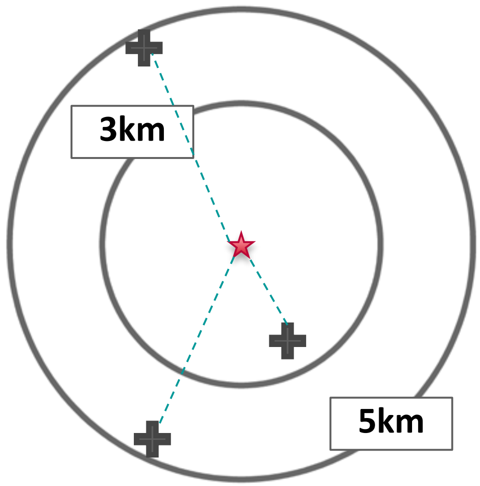
Enhancing point source exposure estimation

Improve source stack locations & characterize bias from location errors



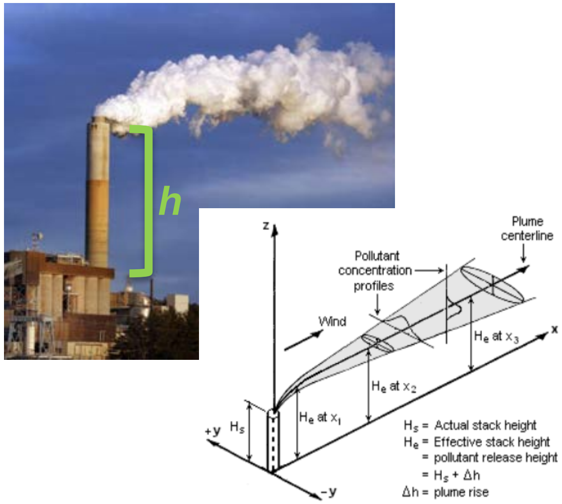
Jones RR et al, *J Exp Sci Env Epi,* 2018

Validate GIS-based exposure metrics using serum measures in NHANES

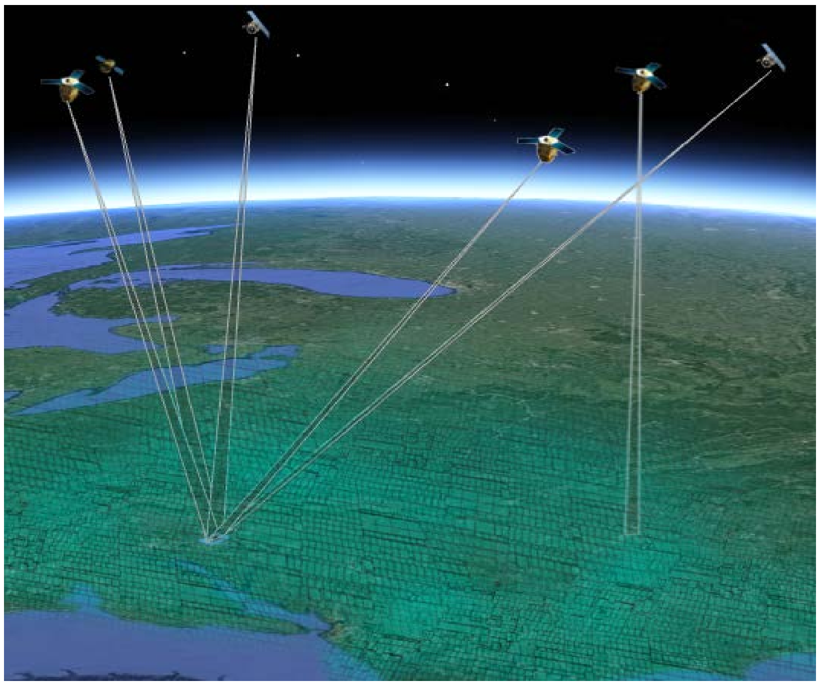


Fisher JA et al., in prep

Estimate stack height for dispersion models



3D surface extraction with paired satellite images



Cerro de Pasco, Peru
Open-Pit Mine

Opportunities and Challenges

Opportunities

- GIS-based linkage/modeling to estimate exposure at specific locations – approach is the same
- Estimating exposure over the lifetime, across key microenvironments may be simplified for animals
- Shorter latency/lifetime exposure period of interest for animals vs. humans
- Add companion animals to existing cohorts

connect for cancer prevention study

Challenges

- Disparities in exposure opportunity / potential / burden
- Regulatory data – not collected for health studies
- Secondary datasets – spatial and temporal gaps in information
- Modeled estimates may be difficult to validate

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Our Research Changes Lives

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