Spatial Estimation of Radon Exposure for Epidemiologic Risk Assessment

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Introduction

Problem

- Radon levels are rising across North America, linked to trends in climate change
- Radon exposure is associated with lung cancer, strokes and other cardiovascular events
- Current estimates of radon exposure are limited, classified into three levels at low spatial resolution

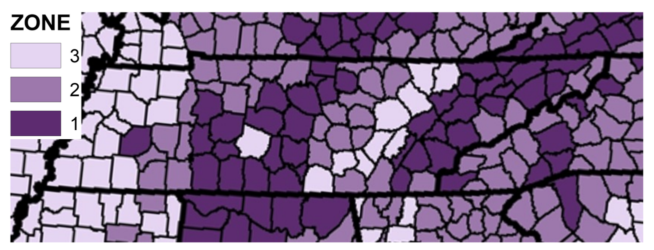


Figure 1: example of county-level resolution US EPA map of GRP radon zones in TN

Aim

- Create a spatial model for the geographic distribution of radon with some quantification of uncertainty
- Incorporate data accounting for geologic, atmospheric, and residential factors
- Provide improved, granular estimates of radon exposure

Solution

- Kriging, latent process modeling, alternative approaches
- Zip-code level model validation

Background

Radon

- Chemical element with symbol Rn, number 86
- Radioactive, colorless, odorless, and invisible gas
- Naturally occurring product of the decay of uranium

Exposure to radon

- Second leading cause of lung cancer
- Linked to strokes and other cardiovascular events
- Evidence of recent increases in North America

Radon and climate change - climate change may indirectly influence rises in radon exposure due to…

- Increased HVAC use
- Recycling of indoor air

Kriging

- Popular spatial modeling algorithm
- Model is a Gaussian process with…
  - Mean – function of covariates
  - Covariance – function of the spatial coordinates

Spatial dependence structure

- Nearby data is more similar than distant data
- Can cause artificially optimistic estimates of model performance

Spatial blocking cross-validation

- Folds from standard k-fold CV → geographically distinct regions
- Provides more realistic measure of model performance

Data

SRRS - EPA's State Residential Radon Survey

- Series of household-level short-term surveys
- 63,291 homes, 42 US states and six US territories
- Conducted between 1986 and 1992

GRP - USGS and EPA's Geologic Radon Potential

- Constructed from geologic, atmospheric and residential survey data
- Three levels:
  - "high" (estimated radon level > 4 picocuries per liter, or pCi/L) – zone 1
  - "moderate/variable" (2–4 pCi/L) – zone 2
  - "low" (< 2 pCi/L) – zone 3

Methods

Subset selection for example analysis

- 3 by 3 coordinate region in middle Tennessee
- 1247 homes across 256 zip-codes
- Relatively high spatial variability in GRP
  - Suggests that we may see sharper fluctuations in radon concentration across space

Kriging

- One of the most common methods for linear interpolation
  - Mean – linear function of covariates
  - Covariance – nonlinear function of spatial coordinates
- Two analyses: one for SRRS, one for integrated SRRS+GRP

Latent process modeling

- Highly flexible modeling approach that allows for robust integration of other data sources
  - Specified in a Bayesian hierarchical formulation
  - Allows us to condition the observed values on the so-called latent process values
- Two analyses: one for SRRS, one for integrated SRRS+GRP

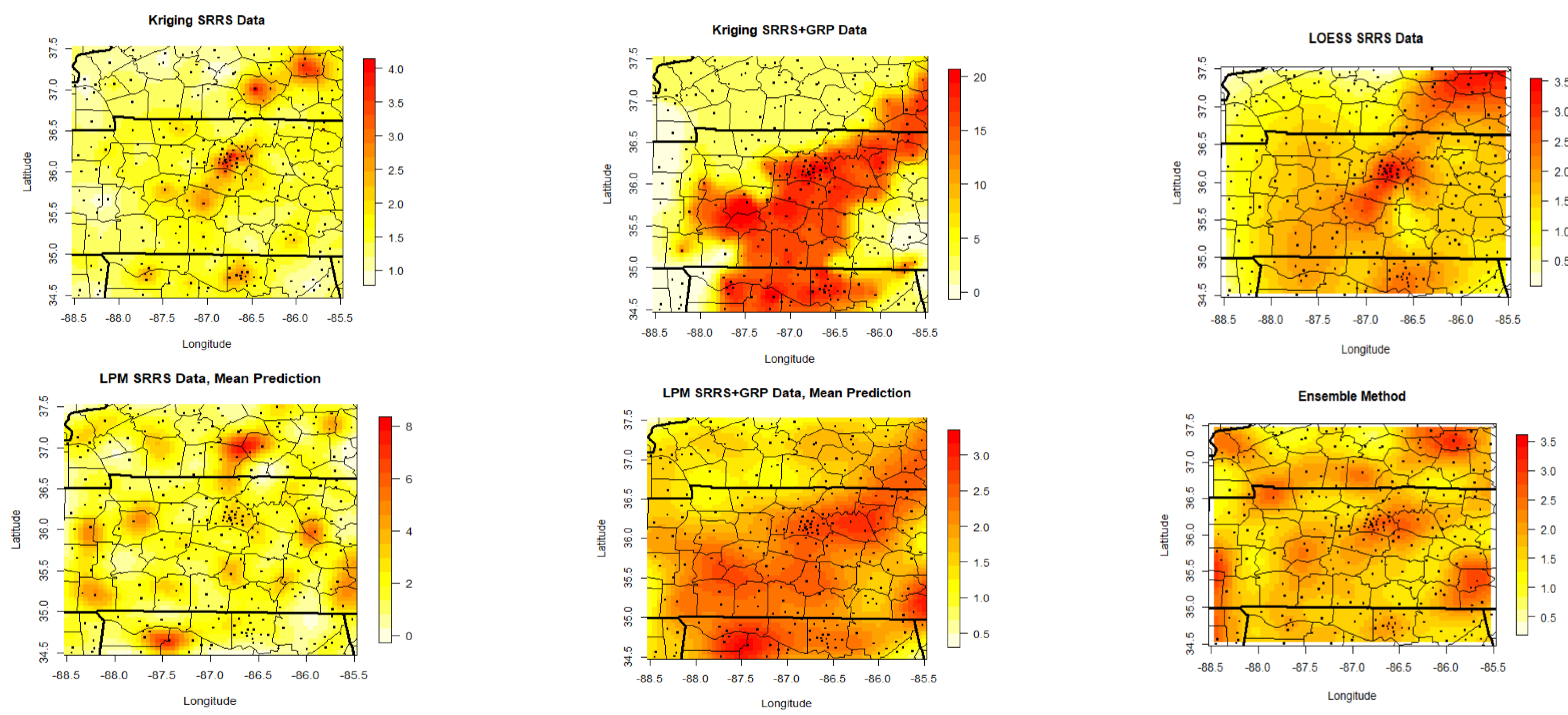
Alternative methods

- Locally estimated scatter plot smoothing (LOESS)
- Ensemble estimation
  - Simple average of predicted values across all models above

Model validation

- 80/20 training/test split on the level of zip-code, rather than individual observation
  - Ensures that our training and test sets are independent and eliminates concerns with spatial dependence
- Mean absolute error (MAE) used to compare accuracy and bias used to compare the direction of average error in predicted values

Results



Model	MAE (pCi/L)	Bias (pCi/L)
Kriging (SRRS)	2.112	-0.397
Kriging (SRRS+GRP)	9.941	+4.325
LPM (SRRS+GRP)	2.209	-0.416
LPM (SRRS+GRP)	2.071	-0.462
LOESS	2.329	-1.044
Ensemble estimation	2.059	-0.579

Future Work and Recommendations

Integration of additional data sets

- Base has been established for integrating additional data sets
- Could extend the latent process modeling approach to include other data sets accounting for the individual factors used to construct the GRP

Temporal component

- More recent radon measurement data exists, including the National Residential Radon Survey (NRRS)
- May allow for forecasting of changes in radon concentration across time

Bias in the sampling design, sampling weights

- We have not yet corrected for is the effect of the biased sampling design of SRRS
- Could leverage sampling weights to limit the effects of strong outliers

Other modeling approaches

- Nearest neighboring measure
- Inverse distance weighted mean

Further development of second-stage model

- Ensemble approach currently uses a simple mean as the second stage
- More complex modeling techniques have been applied in multi-stage models for spatial data with promising results

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