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ABSTRACT

Introduction: There is increasing evidence of an association between individual long-term $PM_{2.5}$ exposure and human health. Mortality and morbidity data collected at the area-level are valuable resources for investigating corresponding population-level health effects. However, $PM_{2.5}$ monitoring data are available for limited periods of time and locations, and are not adequate for estimating area-level concentrations. We developed a general approach to estimate county-average concentrations representative of population exposures for 1980-2010 in the continental U.S.

Methods: We predicted annual average $PM_{2.5}$ concentrations at about 70,000 census tract centroids, using a point prediction model previously developed for estimating annual average $PM_{2.5}$ concentrations in the continental U.S. for 1980-2010. We then averaged these predicted $PM_{2.5}$ concentrations in all counties weighted by census tract population. In sensitivity analyses, we compared the resulting estimates to four alternative county average estimates using MSE-based R^2 in order to capture both systematic and random differences in estimates. These estimates included crude aggregates of regulatory monitoring data, averages of predictions at residential addresses in Southern California, and two sets of averages of census tract centroid predictions unweighted by population and interpolated from predictions at 25-km national grid coordinates.

Results: The county-average mean $PM_{2.5}$ was 14.40 (standard deviation=3.94) µg/m^3 in 1980 and decreased to 12.24 (3.24), 10.42 (3.30), and 8.06 (2.06) µg/m^3 in 1990, 2000, and 2010, respectively. These estimates were moderately related with crude averages in 2000 and 2010 when monitoring data were available (R^2= 0.70-0.82) and almost identical to the unweighted averages in all four decennial years. County averages were also consistent with the county averages derived from residential estimates in Southern California (0.95-0.96). We found grid-based estimates of county-average $PM_{2.5}$ were more consistent with our estimates when we also included monitoring data (0.95-0.98) than grid-only estimates (0.91-0.96); both had slightly lower concentrations than census tract-based estimates.

Conclusions: Our approach to estimating population representative area-level $PM_{2.5}$ concentrations is consistent with averages across residences. These exposure estimates will allow us to assess health impacts of ambient $PM_{2.5}$ concentration in datasets with area-level health data.

INTRODUCTION

There has been increasing evidence of the association between individual long-term exposures to $PM_{2.5}$ and human health developed from cohort studies (Beelen et al. 2014; Kaufman et al. 2016; Laden et al. 2006; Pope et al. 2004). Mortality and morbidity data available at the area level, such as county and district areas, are valuable resources for investigating health effects of long-term $PM_{2.5}$ exposures. Some previous studies performed population-level health analyses of air pollution using aggregated $PM_{2.5}$ data mostly from a few regulatory monitoring sites in the areas where monitoring data were available within the sampling period (Correia et al. 2011; Eftim et al. 2008; Pope et al. 2009; Zeger et al. 2008).

Regulatory monitoring data for $PM_{2.5}$, limited in time and space, may be inadequate for estimating area-level $PM_{2.5}$ concentrations. For example, the nationwide and population-focused monitoring for $PM_{2.5}$ in U.S. was established in 1999 (U.S. EPA 2004). Available $PM_{2.5}$ monitoring data are sparse before 1999. For the spatial coverage, only 567 counties (18 %) out of 3,109 in the continental U.S. in 2000 had at least one regulatory monitoring site where there are sufficient daily measurements to provide representative annual averages (Figure S1). Ninety-three percent of these 567 counties contained one to three monitoring sites, which may not be sufficient to accurately represent population exposures for the county.

We recently developed a $PM_{2.5}$ historical prediction model, which could address the limitations of the historical regulatory monitoring data. This pointwise spatio-temporal prediction model was developed for estimating annual average concentrations of $PM_{2.5}$ at arbitrary point locations in the continental U.S. for 1980-2010 including the years when extensive spatial monitoring data are unavailable (Kim et al. 2016a). In our validation with external $PM_{2.5}$ data that measured before 1999 from the Interagency Monitoring of Protected Visual Environments (IMPROVE) network and the Southern California Children's Health Study, the model generally performed well with high R^2s over 0.7.

We aimed to develop an approach to estimate county averages of annual average $PM_{2.5}$ concentrations representative of population exposures for 1980-2010 in the continental U.S. based on our pointwise historical prediction model. For illustration, we report four decennial years: 1980, 1990, 2000, and 2010. We focused on counties rather than other administrative units because most publicly available health data in U.S. provide aggregated attributes at the county level. We also carried out extensive sensitivity analyses in order to gain insights into the performance of our approach in comparison with alternatives.

METHODS

Locational data

We downloaded boundary data for census tracts and counties as shapefiles for 1980, 1990, 2000, and 2010 from the National Historical Geographic Information System website (https://www.nhgis.org/) (Table S1). Given the boundary changes over time, we used different boundary maps for each year instead of aggregating to the largest boundary in the earliest year. Since census tract boundary data in 1980 were available only for limited areas, we replaced these with the 1990 boundaries. Two new counties were established between 1980 and 1990 as subdivisions of the original. To get accurate county boundaries in 1980, we merged these counties, keeping the original county names. Then we created centroids for the 72,271 2010 census tracts using ArcGIS 10.2 Geographic Information System software (Figure S2). For our sensitivity analyses, we obtained locations of 1,466 $PM_{2.5}$ regulatory monitoring sites from the U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) database (Figure S3). These sites were from two networks: Federal Reference Method (FRM) sites mostly located in largely populated urban areas and IMPROVE sites deployed in national parks and rural areas (U.S. EPA 2004; Hand et al. 2011). In addition, we took advantage of 12,501 coordinates on a 25-km national grid in the continental U.S. and 3,319 geocoded residential addresses in Southern California from our previous work.

$PM_{2.5}$ concentration data

We downloaded daily measurements of $PM_{2.5}$ at 1,466 FRM and IMPROVE monitoring sites from the U.S. EPA AQS database and computed annual averages for sites which provided sufficient daily measurements to meet our minimum inclusion criteria. We included annual averages from monitoring sites which had daily measurements for more than one fourth of the sampling days and no missing measurements for more than 45 consecutive days.

Population data

We downloaded population in census tracts for 1990, 2000, and 2010 and in counties for all four years from the National Historical Geographic Information System website (Table S1). These data were generated from the population and housing census carried out in decennial years since 1970 (U.S. Census Bureau 2002). Since census tract population was unavailable for 1980, we used the data for 1990 multiplied by an adjustment factor (the ratio of county population in 1980 to that of 1990).

Geographic variables

We computed about 900 geographic variables at 72,271 census tract centroids, 1,466 regulatory monitoring sites, 12,501 national grid coordinates, and 3,319 residential addresses. The geographic variables represent geographic characteristics representing $PM_{2.5}$ pollution sources such as traffic, land use, population, emissions, vegetation, and elevation (Table S2). For example, traffic variables include the distances to the nearest major roads and the sums of road lengths within circular buffer areas from the coordinate location, whereas land use variables are percentages of areas for land use categories such as residential and commercial areas within the areas of circular buffers.

County-average estimation procedure

Using the pointwise historical $PM_{2.5}$ prediction model we developed (Kim et al.

2016a), we estimated $PM_{2.5}$ annual average concentrations at all 72,271 census tract centroids. This spatio-temporal prediction model uses the same $PM_{2.5}$ prediction model framework used in the Multiethnic Study of Atherosclerosis and Air Pollution (Keller et al. 2015; Sampson et al. 2011; Szipro et al. 2010). Whereas this previous work predicted 2-week average concentrations in six U.S. metropolitan cities using monitoring data from both regulatory monitoring networks and a cohort-focused monitoring campaign, the historical model relied only on regulatory monitoring data to predict annual average concentrations in the continental U.S. between 1980 and 2010. In brief, this model consists of three components to characterize temporal and spatial patterns of annual average concentrations of $PM_{2.5}$: a spatially-varying long-term mean, a spatially-varying temporal trend, and temporally-independent and spatially-dependent spatio-temporal residuals. We estimated the single temporal trend using the data for 1999-2010 and extrapolated to the period prior to 1999. The temporal trend was scaled by a spatially-varying trend coefficient to reflect spatial heterogeneity of the temporal trend. We characterized the spatial structures of the long-term mean and the trend coefficient in a universal kriging framework with dimension-reduced summary predictors. These summary predictors were estimated from hundreds of geographic variables by partial least squares (PLS). PLS finds the linear combination of geographic variables which is most correlated with $PM_{2.5}$ annual averages (Sampson et al. 2013).

We averaged predicted $PM_{2.5}$ annual averages in 1980, 1990, 2000, and 2010 at 72,271 census tract centroids, weighted by census tract populations, to obtain year-specific county annual averages. The population weight was the ratio of the year-specific population in the census tract to the population of all census tracts in the county for the corresponding year.

Sensitivity analysis

We performed four sensitivity analyses to compare to our population-weighted county average estimates. First, we computed county averages using regulatory monitoring data only. We restricted this comparison to the two decennial years after 1999 when spatially-extensive and population-focused regulatory monitoring networks were established. We also restricted to the counties containing at least one monitoring site that met our site inclusion criteria for computing annual averages. This reduced the number of counties to 567 and 578 for 2000 and 2010, respectively. Second, we averaged $PM_{2.5}$ predictions at census tract centroids without population weight. Third, to address whether we could reduce the computational burden of our approach, we computed county averages from 12,501 grid coordinates on the 25-km national grid, roughly one sixth the number of census tract centroids. We estimated $PM_{2.5}$ annual averages at grid coordinates using the historical prediction model, interpolated grid predictions to census tract centroids by ordinary kriging, and computed county averages. To further determine whether county averages based on the grid were underestimated because some grid coordinates fall in non-residential areas, we expanded this sensitivity analysis to include regulatory monitoring sites mostly located in urban areas. We then compared these two sets of county average estimates based on national grid coordinates (only and with regulatory monitoring sites) to our original census tract-based estimates. For this comparison, we used county average estimates without population weight to focus on the effect of prediction location alone. As with national grid coordinates, census tract centroids may also be located in where few people live and may not provide population-representative exposures. Thus in our fourth sensitivity analysis we explored the population representativeness of census tract centroids compared to county-averages developed from home addresses. We randomly sampled one cohort address in each census tract, estimated historical predictions, and computed residence-based county averages. For feasibility reasons, we restricted this comparison to 9 counties in Southern California. In all sensitivity analyses we evaluated performance by computing the mean square error-based R-squared statistic

(MSE-based R^2) to compare the estimate pairs (Keller et al. 2015; Kim et al. 2016b). This statistic captures both systematic and random differences between estimates.

RESULTS

Mean county-wise annual average $PM_{2.5}$ concentrations estimated from census tract centroid predictions from the historical prediction model were 14.40, 12.24, 10.42, and 8.06 µg/m^3 in 1980, 1990, 2000, and 2010, respectively (Table 1). Variability also decreased over time (standard deviation (SD) = 3.94, 3.24, 3.30, and 2.06 µg/m^3). County average estimates were higher in the East and Southern California than other regions (Figure 1). These high concentrations decreased dramatically over time between 1980 and 2010 although there was slow improvement in some counties. In 2000 and 2010 respectively, estimated county averages from counties with at least one regulatory monitoring site were generally higher and more variable (mean=11.73 (SD=3.50) and 8.46 (2.59) µg/m^3) than those from counties without any regulatory monitoring sites (10.12 (3.19) and 7.97 (1.91) µg/m^3) (Table S3).

Figure 2 to 5 show the four sensitivity analysis comparisons to those based on our historical predictions at census tract centroids. Census tract-based county average estimates were moderately related to those based on the monitoring data only across counties in 2000 and 2010 (R^2=0.70 and 0.82, respectively) (Figure 2). The R^2s were similar when we restricted to the counties where more than 10 sites contributed to computing county averages (data not shown). Population weighted census tracts gave almost identical county average estimates to those without population weight (Figure 3). County average estimates based on interpolating the national grid were generally lower than our estimates (R^2=0.91-0.96). Regression slopes for all four years were less than and significantly different from one (slope= 0.97-0.99). However, these estimates became more consistent with our primary estimates and were not different from one except for 2000, when we added regulatory monitoring sites (R^2=0.95-0.98; slope=1.00-1.01) (Figure 4). We found county average estimates based on cohort home addresses in 9 counties in Southern California were generally consistent with our primary estimates, suggesting averages based on census tract centroids provide good representation of population exposures (Figure 5, Figure S4). In all sensitivity analyses, estimates were more consistent in recent than in early years.

DISCUSSION

This study developed an approach for estimating population-representative county averages of annual average $PM_{2.5}$ concentrations in the continental U.S. from 1980 to 2010. We averaged pointwise spatio-temporal predictions at census tract centroids to represent county-level population exposures; this allowed us to develop high quality estimates across the continental U.S. over three decades. Our county average estimates are much more comprehensive than simple county-level regulatory monitor averages, and they are consistent with those derived directly from residential locations.

By expanding the temporal and spatial scales of county-average $PM_{2.5}$ estimates to cover the entire continental U.S back to 1980, this work will allow many new high-quality policy-relevant analyses of PM health impacts to be conducted. Mortality and morbidity data are often available much earlier than 1999 when the extensive spatial monitoring of $PM_{2.5}$ began. These limited data have hampered investigations of the association between $PM_{2.5}$ and health by not allowing all existing health data to be used. Our estimates linked to administrative health data will allow the health benefits achieved from the reduction of $PM_{2.5}$ over time to be evaluated. In addition, areas where there are no nearby regulatory monitoring sites have been shown to have different demographic characteristics than those represented by monitors (Bravo et al. 2012). This suggests that it may be inadequate to rely on simpler county-level averages computed directly from regulatory monitoring sites to capture county-level differences in susceptibility. Our estimates allow the 82% of counties without any regulatory monitors in 2000 to be included in health analyses; this will provide better insight into $PM_{2.5}$-attributable health effects in all U.S. sub-populations.

Our approach is slightly better than and generally consistent with a much less computationally demanding alternative approach that averages census tract centroid estimates obtained from interpolating (via ordinary kriging) a national grid of predictions supplemented with predictions at regulatory monitoring sites. The total number of national grid coordinates and regulatory monitoring sites is about 13,000, which is less than one fifth of the approximately 70,000 census tract centroids. This reduction in computational burden is meaningful since not only are five-fold fewer historical model predictions required, but this alternative approach also avoids the burden of computing hundreds of geographic variables that accompanies each new location. We used census tracts which are the largest geographic units in the census. It would be even more computationally expensive to consider smaller units; there are about 0.2 million block groups and 11 million blocks in the continental U.S. We believe that the estimates based only on the national grid gave lower county average estimates because grid locations do not adequately represent locations where people live. The improvement to our predictions after adding monitoring data suggests the regulatory monitoring networks provide good population representation. However, regulatory monitoring network designs may not sufficiently represent population exposures in all areas.

County average estimates with and without population weighting gave almost identical estimates. Census tracts, as subdivision of counties, were designed to be relatively homogeneous units in terms of population characteristics, economic status, and living conditions (U.S. Department of Commerce 1994). Our result suggests population weighting is not necessary because the relative homogeneity within and heterogeneity across census tracts adequately represents county-level population exposures.

Some previous studies developed approaches for estimating county average estimates by combining photochemical model outputs on a grid with monitoring data at points

(Barrocal et al. 2009; Brindley et al. 2005; McMillan et al. 2010). The U.S. EPA provides $PM_{2.5}$ annual average concentrations estimated at census tract centroids for 2001-2008 (https://www.epa.gov/air-research/fused-air-quality-surfaces-using-downscaling-tool-predicting-daily-air-pollution), using a Bayesian space-time downscaling fusion model derived from regulatory monitoring data and Community Multiscale Air Quality model output (U.S. EPA 2012). These estimates have been applied to county-level health analyses of air pollution (Hao et al. 2015). However, because photochemical models rely on input data including emissions and meteorology, the time period for these estimates are limited to the period when input data are available. This is much shorter than the three decades we were able to capture.

Our approach, though developed primarily for area-level health analyses, can be applied to epidemiological studies that wish to use individual exposures but need to rely on area-average estimates for logistical reasons. For instance, several previous cohort studies of air pollution assigned an area average air pollution concentration to all individuals residing in the area, when addresses were only available at a crude level (Hoek et al. 2013). Typically exposure assessment in these studies was based on one or a few monitoring sites in an area and restricted to the study regions where regulatory monitoring sites were available. Our approach provides population-representative area-average exposures on the national scale for an extended time period.

One limitation of this study is that while our estimates are conceptually preferable, validation is challenging. While the sensitivity analysis we performed using available cohort data in Southern California indicates that our estimates are representative of population exposures, the geographic area of this work was very limited. Future validation studies should expand the geographic coverage and consider using residential parcel data.

CONCLUSIONS

Our approach to estimating area-level $PM_{2.5}$ concentrations will enhance epidemiological research using area- and individual-level health data, and allow much more extensive policy-relevant assessments of health effects and air quality interventions.

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Table 1. Summary statistics of county-wide annual average estimates of $PM_{2.5}$ (ug/m^3) in 1980, 1990, 2000, and 2010 from our primary estimation approach

Year	N	Min	Percentile					Max	Mean	SD
			10%	25%	50%	75%	90%			
1980	3,109	3.16	8.42	11.90	15.06	17.19	18.66	25.47	14.40	3.94
1990	3,111	3.03	7.39	10.16	12.76	14.51	15.99	21.70	12.24	3.24
2000	3,109	1.71	5.77	7.76	10.84	13.08	14.35	19.84	10.42	3.30
2010	3,109	1.32	4.99	6.71	8.41	9.51	10.49	13.73	8.06	2.06

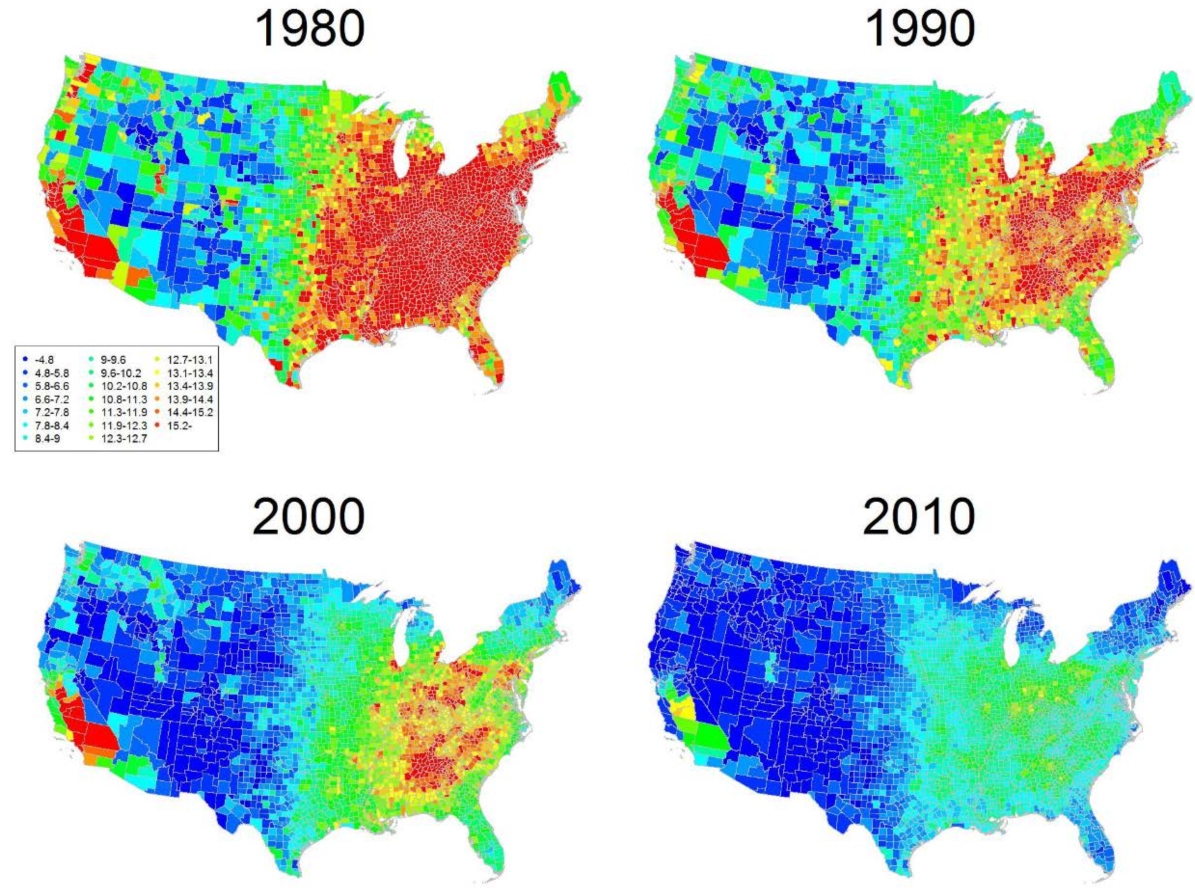

Figure 1. Maps of county-level annual average estimates of $PM_{2.5}$ in 1980, 1990, 2000, and 2010

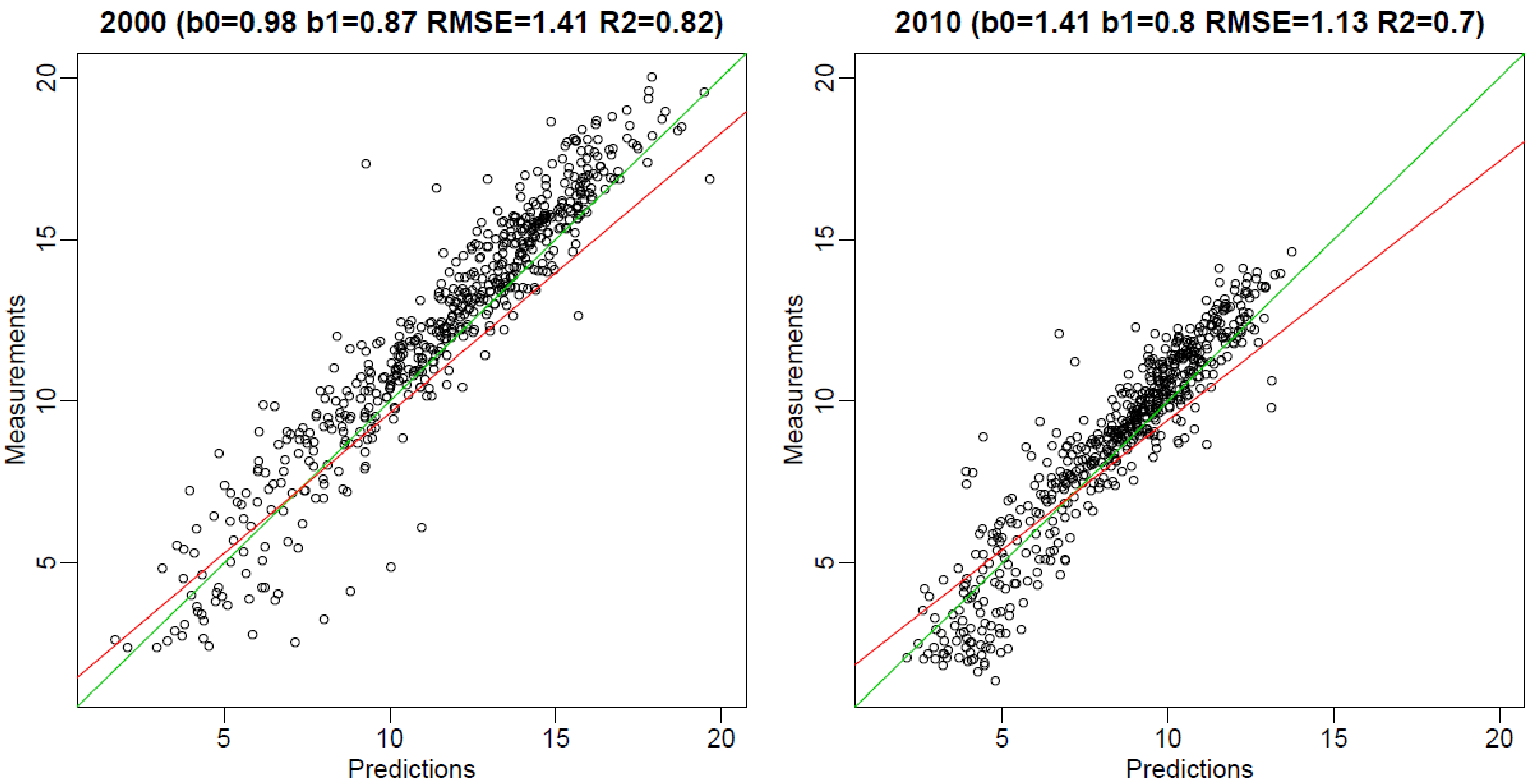

Figure 2. Scatter plots of county-level annual averages of $PM_{2.5}$ (ug/m^3) from predictions estimated by the historical exposure prediction model and from measurements at regulatory monitoring sites across 567, and 578 counties containing at least one monitoring site in 2000 and 2010, respectively

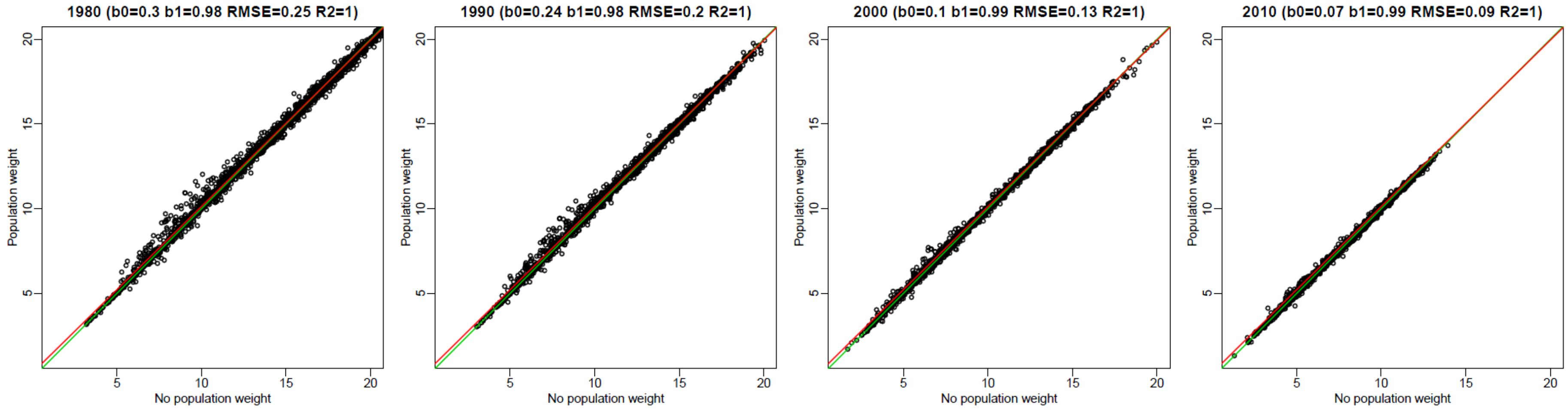

Figure 3. Scatter plots of county-level annual average estimates of $PM_{2.5}$ (ug/m^3) comparing population weight and no weight for census tracts in 1980, 1990, 2000, and 2010

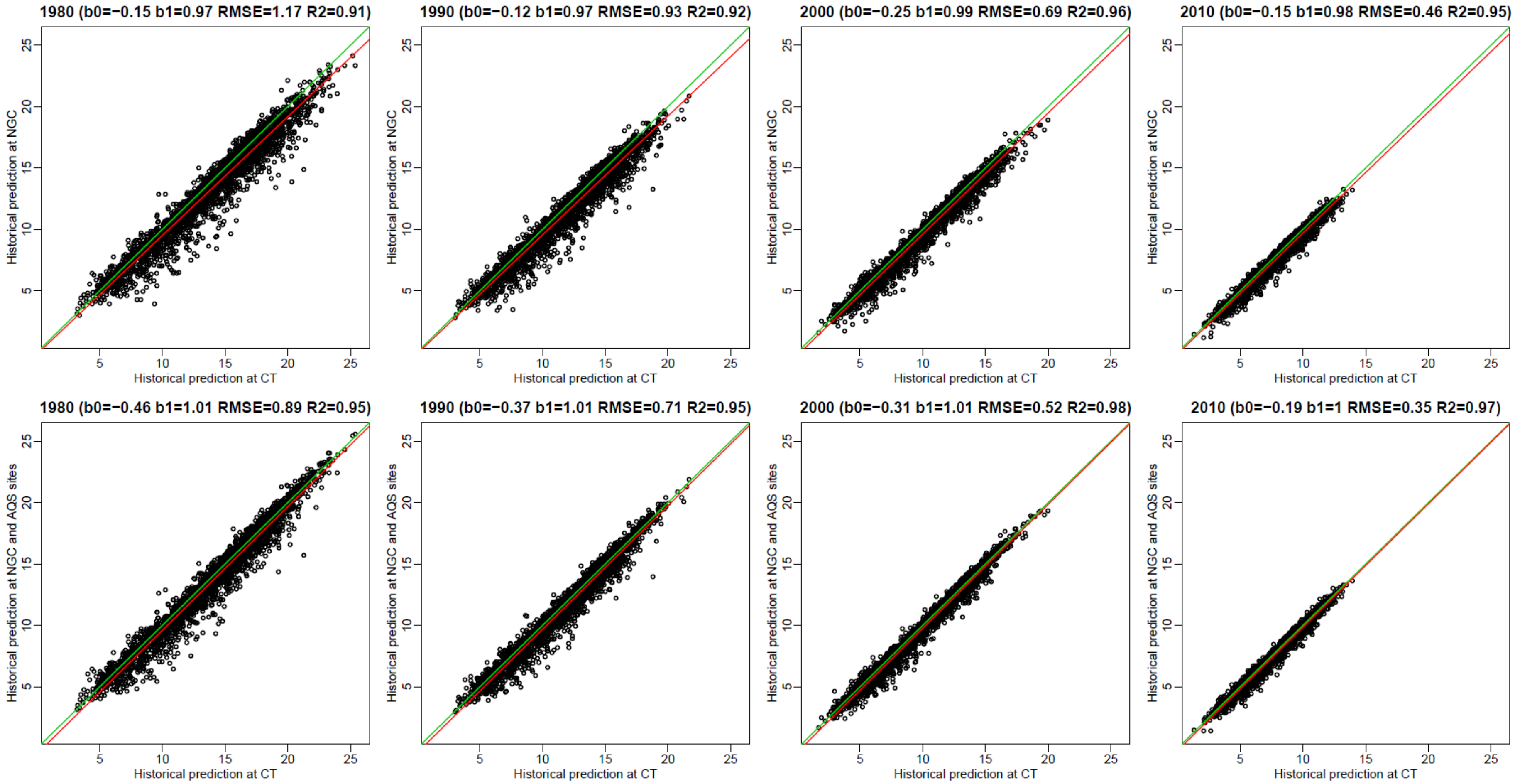

Figure 4. Scatter plots of count-level annual average estimates of $PM_{2.5}$ (ug/m^3) comparing predictions directly at census tract (CT) centroids vs. predictions at centroids interpolated from national grid coordinates (NGC) (top) and from national grid coordinates and regulatory monitoring sites (NGC + AQS) (bottom) in 1980, 1990, 2000, and 2010

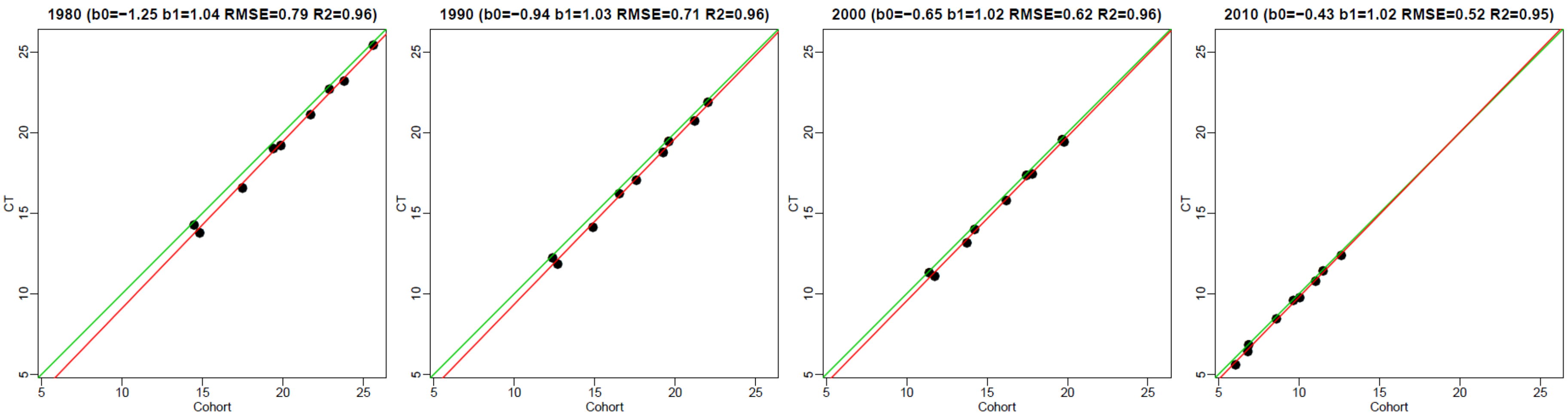

Figure 5. County-level annual average estimates of $PM_{2.5}$ (ug/m^3) based on census tract centroids and cohort residential addresses across 9 counties in Southern California in 1980, 1990, 2000, and 2010

SUPPLEMENTAL MATERIALS

Table S1. Data availability of GIS boundary and population data in the U.S. continent in 1980, 1990, 2000, and 2010

	GIS boundary			Population		
Year	Data source	Census tract[b]	County	Data source	Census tract[b]	County
1980	2000 TIGER/Line[a]	42,643	3,109	1980 census 100% data	46,433	3,109
1990	2000 TIGER/Line[a]	60,513	3,111	1990 census 100% data	60,803	3,111
2000	2000 TIGER/Line[a]	64,866	3,109	2000 census 100% data	64,999	3,109
2010	2010 TIGER/Line	72,271	3,109	2010 census P & H data	72,539	3,109

a. NHGIS modified the 2000 TIGER/Line definitions only by erasing coastal water areas.

b. Some census tracts do not match for the same year-geographic level, typically because those cannot be mapped (like crew-on-vessel census tracts) or the coastline clip done to GIS files might has removed a few areas that had no population but were still in the census tables.

Table S2. List of geographic variables

Category	Measure	Variable description
Traffic	Distance to the nearest road	Any road, A1, intersection
	Sum within buffers of 0.05-15 km	A1, A2+A3, truck route, intersections
Population	Sum within buffers of 0.5-3 km	Population in block groups
Land use (Urban)	Percent within buffers of 0.05-15 km	Urban or Built-Up land (residential, commercial, industrial, transportation, urban)
		Developed low, medium, and high density
		Developed open space
Land use (Rural)	Percent within buffers of 0.05-15 km	Agricultural land (cropland, groves, feeding)
		Rangeland (herbaceous, shrub)
		Forest land (deciduous, evergreen, mixed)
		Water (streams, lakes, reservoirs, bays)
		Wetland
		Barren land (beaches, dry salt flats, sand, mines, rock)
		Tundra
		Perennial snow or Ice
Position	Coordinates	Longitude, latitude
Source	Distance to the nearest source	Coastline, Coastline (rough)
		Commercial area

		Railroad
		Railyard
		Airport
		Major airport
		Large port
		City hall
Emissions	Sum within buffers of 3-30 km	$PM_{2.5}$
		PM_{10}
		CO
		SO2
		NOx
Vegetation	Quantiles within buffers of 0.5-10 km	Normalized Difference Vegetation Index (NDVI)
Imperviousness	Percent within buffers of 0.05-5 km	Impervious surface value
Elevation	Elevation above sea levels	Elevation value
	Counts of points above or below a threshold within buffers of 1-5 km	

Table S3. Summary statistics of county-level annual average estimates of $PM_{2.5}$ (ug/m^3) from counties with and without regulatory monitoring sites in 2000 and 2010

	Counties with at least one regulatory monitoring site						Counties without any regulatory monitoring sites					
Year	N	Min	Median	Max	Mean	SD	N	Min	Median	Max	Mean	SD
2000	567	1.71	12.25	19.64	11.73	3.50	2,542	2.24	10.47	19.84	10.12	3.19
2010	578	2.13	9.00	13.73	8.46	2.59	2,531	1.32	8.31	12.53	7.97	1.91

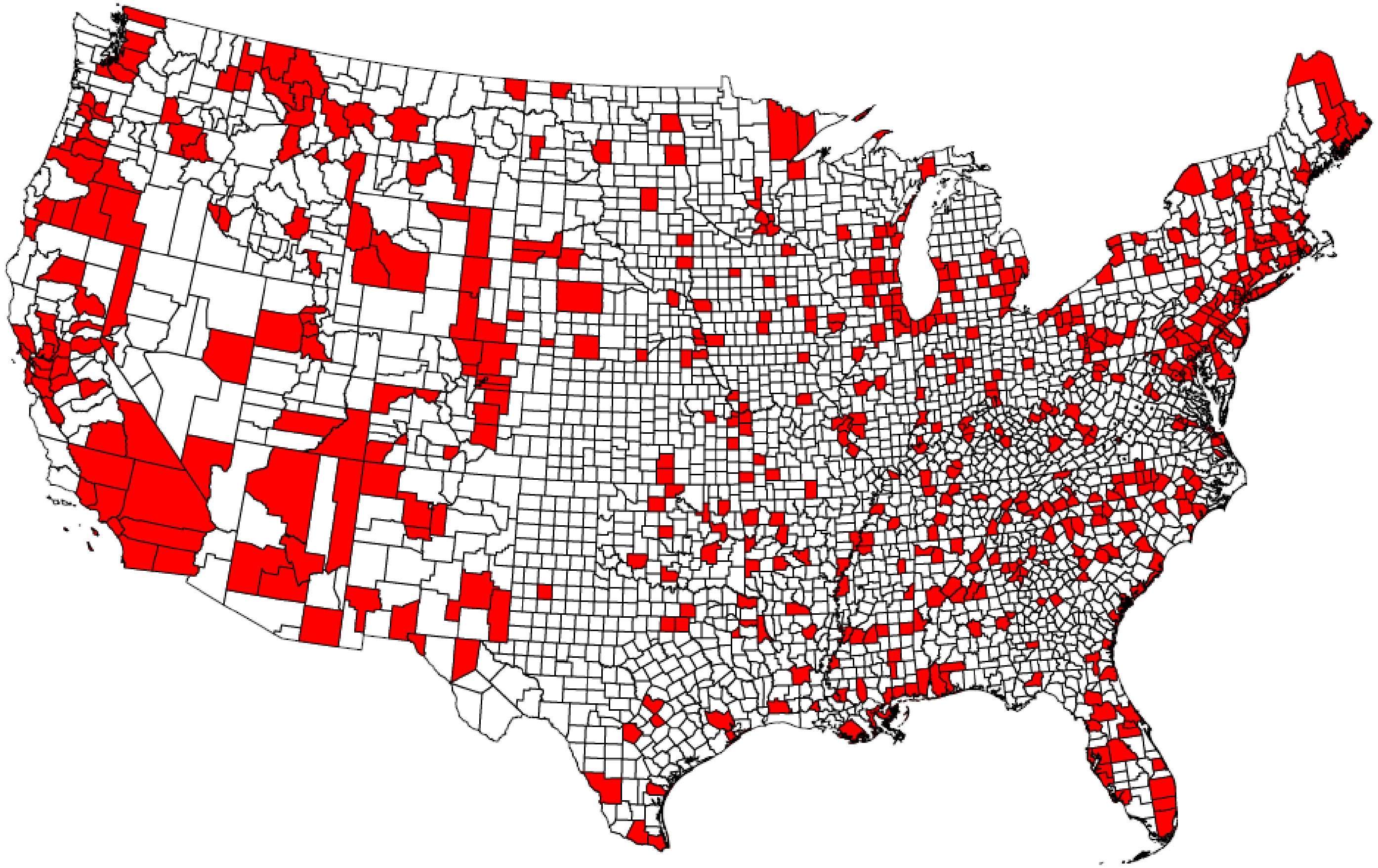

Figure S1. Map of 567 counties where there is at least one regulatory monitoring site after applying the minimum inclusion criteria for computing annual averages in 2000

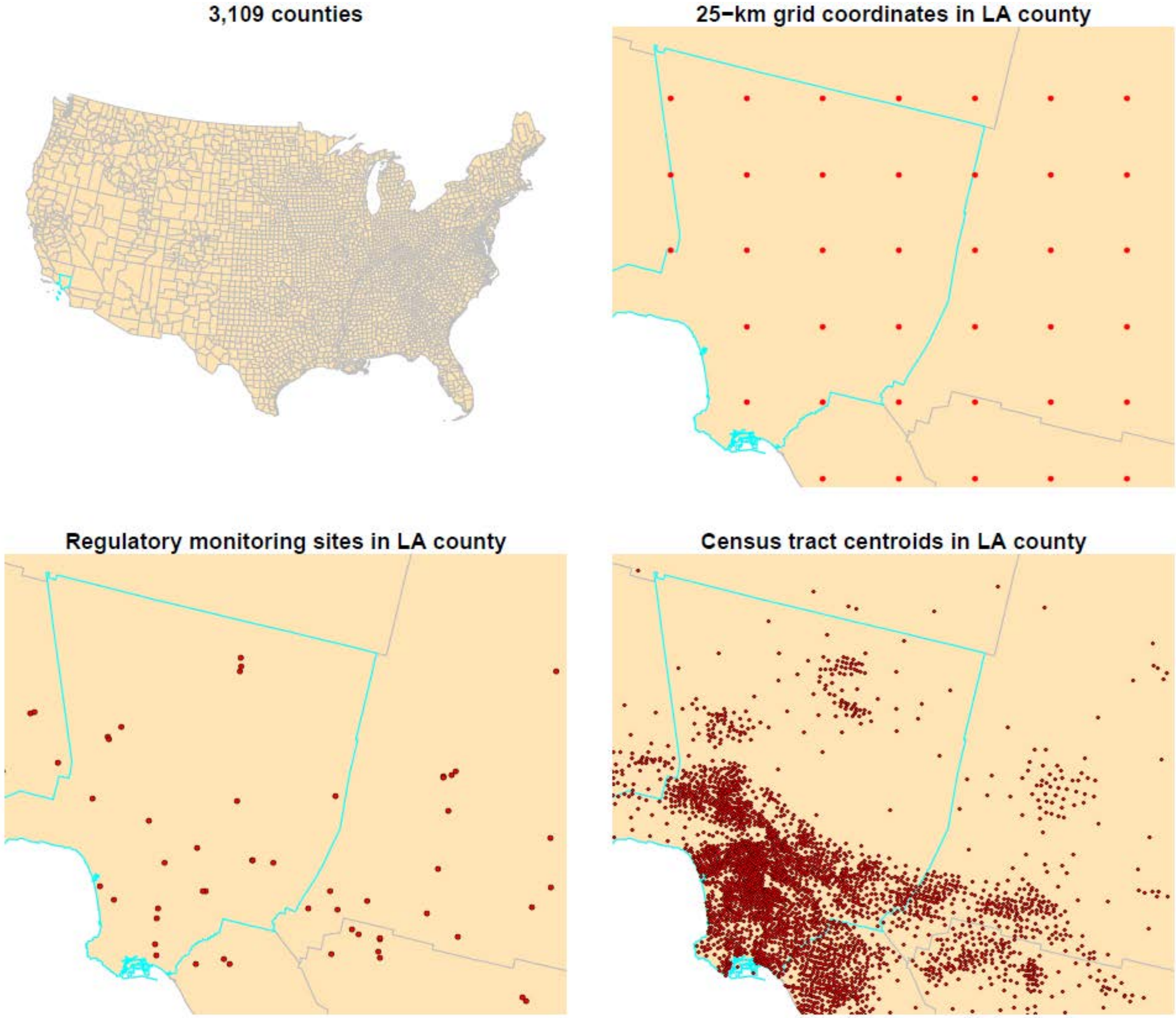

Figure S2. Maps of 3,109 counties in the continental U.S., and 25-km grid coordinates, regulatory monitoring sites, and census tract centroids in Los Angeles county in 2010

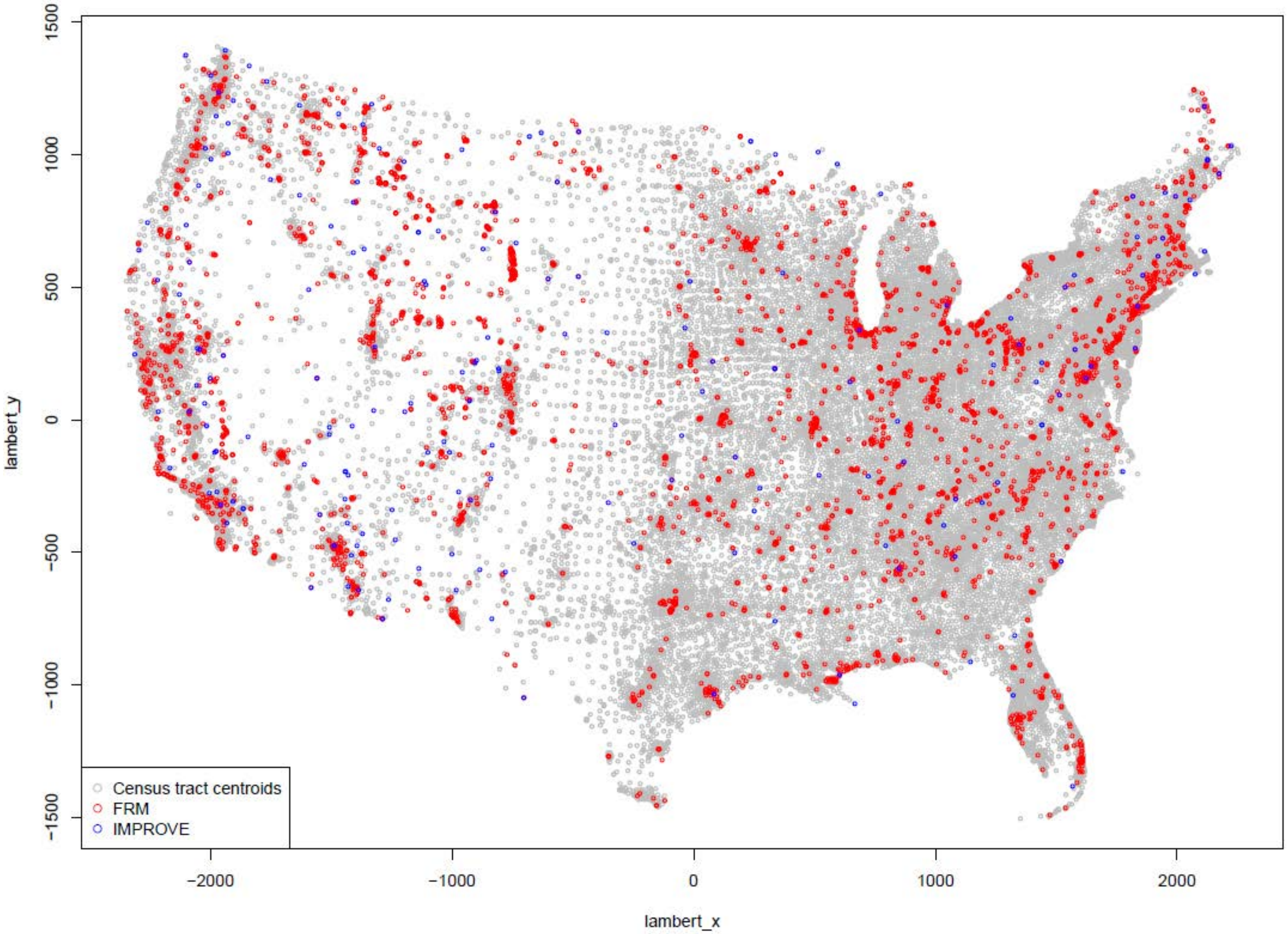

Figure S3. 72,271 census tract centroids from the year 2010 census, and 3,873 U.S EPA Federal Reference Method (FRM) and 195 Interagency Monitoring of Protected Visual Environments (IMPROVE) regulatory monitoring sites in the continental U.S.

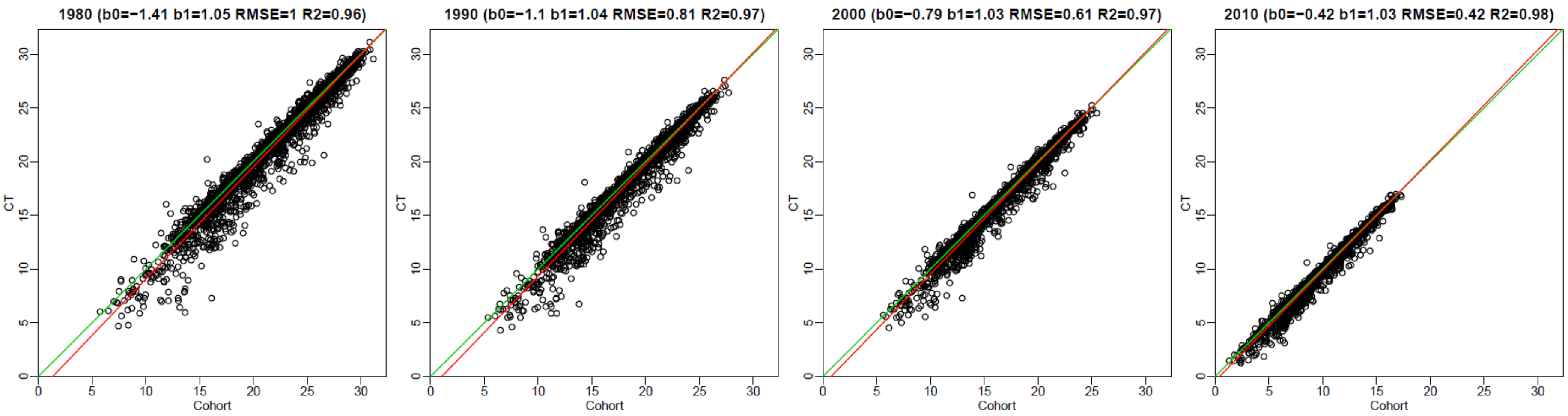

Figure S4. $PM_{2.5}$ annual average predictions across the year 2010 census tracts based on estimation at census tract centroids and at cohort residential addresses in 9 counties of Southern California in 1980, 1990, 2000, and 2010