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Spatial Modeling to Identify Sociodemographic Predictors of Hydraulic Fracturing Wastewater Injection Wells in Ohio Census Block Groups

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Background: Hydraulically fractured wells produce 2–14 million liters of wastewater, which may contain toxic and radioactive compounds. The wastewater is predominantly disposed of using Class II injection wells.

Objective: Our objective was to evaluate the relationship between sociodemographic characteristics and injection well locations in Ohio.

Methods: Using state and federal data sources, we classified Ohio census block groups by presence of injection wells, number of hydraulically fractured wells, sociodemographic factors (median household income, % white, population density, % ≥high school education, median age, voter turnout), and geographic information (land area, water area, situated over shale). We modeled the odds of having at least one injection well within a block group with respect to all covariates using three multivariable models incorporating different spatial components to account for similarities in neighboring block groups.

Results: In bivariate analyses, block groups with injection wells ($n = 156$) compared with those without ($n = 9{,}049$) had lower population density (71 vs. 2,210 people/mi^2 or 27 vs. 854 people/km^2), larger median area (43.5 vs. 1.35 km^2), higher median age (42.8 vs. 40.2 y), and higher % white (98.1% vs. 92.1%). After adjustment using a spatial logistic regression model, the odds of a block group containing an injection well were 16% lower per \$10,000 increase in median income [odds ratio(OR) = 0.837; 95% credible interval (CI): 0.719, 0.961] and 97% lower per 1,000 people/mi^2 (or per 386 people/km^2) increase (OR = 0.030; 95% CI = 0.008, 0.072). Block groups on shale and those containing fewer hydraulically fractured wells were more likely to include an injection well. Percentage white, median age, % ≥high school education, and % voter turnout were not significant predictors of injection well presence.

Conclusion: In Ohio, injection wells were inversely associated with block groups' median incomes after adjusting for other sociodemographic and geographic variables. Research is needed to determine whether residents in census blocks with injection wells face increased risk of chemical exposures or adverse health outcomes. https://doi.org/10.1289/EHP2663

Introduction

The production of natural gas has been increasing in the United States due to advances in drilling technologies, fluctuating oil prices, and a desire to replace coal with a cleaner-burning fuel (de Gouw et al. 2014). In 2015, approximately 430 billion cubic meters of natural gas were produced in the United States from shale rock formations, and production volumes are projected to continue increasing through 2050 (U.S. EIA 2016a, 2017). Natural gas is extracted from low-permeable, organic-rich shale using hydraulic fracturing, that is, the injection of large volumes of pressurized fluids and proppants ~2,500 m underground to create fissures in the rock and release the gas stored within (Jackson et al. 2015). After completion of the fracturing process, pressure is released and wastewater, composed of residual fracturing fluids and water from the geologic formations, flows up the well along with the gas.

Each hydraulically fractured unconventional natural gas (UNG) well yields 1.7 to 14.3 million liters of wastewater over the first 5–10 y of production (Kondash et al. 2017). Within the first 2 wk, the wastewater primarily consists of residual fracturing fluids, which contain anti-corrosive agents, biocides, surfactants, and lubricants (Stringfellow et al. 2017). These fluids ultimately account for a relatively small percentage (4–8%) of the total volume of wastewater produced, given that the composition of the wastewater becomes dominated by the formation brine. This highly saline formation water may contain radioactive materials, dissolved hydrocarbons, shale minerals, and metal ions originating from the surrounding rock (Kondash et al. 2017; Shih et al. 2015; Shrestha et al. 2017; Thacker et al. 2015; Warner et al. 2013). Overall, UNG fracturing fluids and wastewater can contain hazardous constituents, including chemicals classified as endocrine disrupting compounds (Kassotis et al. 2016), reproductive and developmental toxicants (Elliott et al. 2017a; Webb et al. 2014), and carcinogens (Elliott et al. 2017b).

In many regions, the primary method of UNG wastewater disposal is via Class II (CII) underground injection wells (NRC 2013). CII injection wells, designed for brine and energy extraction fluid disposal, have less stringent requirements in terms of permitting, depth, and construction than do Class I injection wells, which are designed for hazardous waste (U.S. EPA 2016b). In the CII method, wastewater is injected through a well pipe drilled vertically into underground rock formations. The inner injection tubing carrying the wastewater is enclosed by varying degrees of protective steel and cement casing, dependent on the pipe depth (NRC 2013). Wastewater is released through openings in the casing at the final "injection zone." The wastewater flows out between layers of rock, which act as natural containment barriers for the waste.

The prevalence of CII injection wells and the implementation and enforcement of their regulation varies by state. Ohio, the focus of our analysis, sits partially above the Marcellus and Utica Shales and receives wastewater from both its own UNG wells and those in Pennsylvania (Lutz et al. 2013; ODNR Division of Oil & Gas Resources 2016b). The Ohio Department of Natural Resources states that the wastewater injection zone must be located at least (50 ft or 15 m) below the deepest potential underground source of drinking water (water containing <10,000 mg/L of chlorides) (State of Ohio 2009). However, potential pathways of contamination include spills at the surface during the transport or initial

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injection of the wastewater, subsurface leaks if the injection pipe casing deteriorates over time, and permeation of wastewater through the confining rock layers (U.S. EPA 2015; Shrestha et al. 2017; Vengosh et al. 2014).

There is a significant history of disproportionate placement of hazardous facilities, particularly waste disposal facilities, in communities with a lower average income and a higher proportion of minority residents (Agyeman et al. 2016); however, little is known with respect to the characteristics of populations living near CII injection wells in particular. To our knowledge, only one study in one state has evaluated sociodemographic profiles specifically in regions of CII injection well siting (Johnston et al. 2016). In that Texas-based study, Johnston et al. (2016) found that CII injection wells were disproportionately permitted in areas with greater proportions of minority populations and residents living in poverty. Racial disparities persisted after adjustment for income.

The objective of our research was to evaluate the association between the spatial locations of CII injection wells and sociodemographic characteristics at the block group level in Ohio. To meet this objective, we applied different multivariable statistical models to estimate associations between predictors defined at the block group level, while also accounting for spatial correlation among characteristics of neighboring block groups.

Methods

Data Sources

We conducted all analyses at Ohio's census block group level, the smallest geographic unit for which the required sociodemographic data could be obtained. Working at the block group level allowed us to investigate associations of interest using data at a localized spatial scale and allowed for spatial alignment with the majority of our predictor and outcome variables. We linked the block group geographic boundary information with data from multiple sources to provide information on four critical areas: (*a*) geographic coordinates and waste volume of CII injection wells, (*b*) sociodemographic factors and voter turnout data as indicators of population vulnerability, (*c*) geographic coordinates of UNG wells as a possible predictor of where CII injection wells may be placed, and (*d*) geospatial data related to block group land and water areas and boundaries of the Marcellus and Utica Shales.

Class II Injection Wells

Geographic coordinates and quarterly volumes of wastewater injected in all Ohio CII injection wells that were active at some point between July 2010 and March 2016 (Figure 1) were provided by FracTracker Alliance (2016) and T. Auch (written communication, September 2016). FracTracker Alliance is an organization that compiles existing data on oil and gas facilities. FracTracker obtained data on CII injection well locations and quarterly waste volumes from the Ohio Department of Natural Resources (ODNR) Underground Injection Control program and the ODNR's Risk-Based Data Management System Microsoft Access Database. We linked these location and volume data with geospatial data for Ohio's block groups, based on the 2010 U.S. Census, from the TIGER/Line Shapefiles database (U.S. Census Bureau 2016b) and identified each block group by the presence or absence of a CII injection well. We also calculated the cumulative volume of waste received by each of the 257 CII injection wells across the study period of 2010–2016 by summing the quarterly volumes from July (Quarter 3) 2010 to March (Quarter 1) 2016. Each CII injection well was classified as high volume or low volume, based on whether the cumulative waste volume was $>$ or $\leq$ the median across all wells analyzed.

Sociodemographic Characteristics

A critical aspect of environmental justice, as delineated by the U.S. Environmental Protection Agency, is that no group of people, including a racial, ethnic, or socioeconomic group, should bear a disproportionate environmental health burden resulting from industrial, municipal, or commercial operations (Brulle and Pellow 2006; Cushing et al. 2015; U.S. EPA 2017). To address this, we examined variables describing social vulnerability, which we define as sociodemographic characteristics that increase an individual's susceptibility to health detriments from exposure to potential environmental hazards (Molitor et al. 2011; Morello-Frosch et al. 2011; Solomon et al. 2016). We included six sociodemographic variables from the 2010–2014 American Community Survey 5-y estimates (U.S. Census Bureau 2016a) at the block group level: median household income (U.S. dollars), median household value (U.S. dollars), percentage of population identifying as white only, population density (population per square mile), percentage of population with a high school education/GED or higher, and median age of the population.

We also obtained voter turnout percentages for 2012 from the State of Ohio (2017) and 2012 voter turnout district boundaries from the U.S. Census Bureau (2012). Because voting districts did not align with census block group boundaries, we calculated the average voting percentage for all voting districts intersecting a block group, weighted by the area of the intersecting segment. If data were completely unavailable for a block group (561 of the 9,205 block groups, or 6%), we assigned it the corresponding county voter turnout percentage.

Collectively, these variables serve as proxies for susceptibility to biases in healthcare treatment; limited financial resources to fund better medical care, legal power, infrastructure, or relocation; decreased knowledge about environmental exposures; and limited access to resources to advocate on one's behalf or mobilize political change (Institute of Medicine 2003; Molitor et al. 2011; Morello-Frosch et al. 2011; Solomon et al. 2016; Su et al. 2012). Prior environmental justice studies evaluating spatial components of environmental risk factors have included similar variables as metrics of community disadvantage (Johnston et al. 2016; Lamichhane et al. 2013; Ogneva-Himmelberger and Huang 2015).

UNG Wells and Other Spatial Variables

We calculated the number of UNG wells within a block group using data from the Ohio Department of Natural Resources [in North American Datum of 1983 (NAD 83) format] for all UNG wells permitted through March 2016 (ODNR Division of Oil & Gas Resources 2016a). Each block group was assigned an indicator value representing whether or not it was at least partially situated on a shale formation (Marcellus or Utica) using boundary shapefiles for the Marcellus and Utica Shales obtained from the U.S. Energy Information Administration (U.S. EIA 2016b). We included the Marcellus and Utica Shales as separate predictors to allow for the relationship with CII injection well presence to differ by formation. We also created variables representing the land area and water surface area (squared kilometers) covered by each block group.

We eliminated 7 of Ohio's 9,238 census block groups (0.08%) because they were completely covered by water or had no neighboring block groups containing land area (a criterion for our spatial models). A total of 26 additional block groups (0.30%) were also removed due to missing information for median age and/or median income, leaving $n = 9{,}205$ (99.6%) block groups for statistical analysis. None of the removed block groups contained a CII injection well within their bounds; their removal should have a negligible impact on results, because the number of block groups with CII injection wells is small relative to the total.

Statistical Analyses

We first conducted two-sample *t*-tests to evaluate individual differences in sociodemographic characteristics between block groups with and without CII injection wells. We then performed multivariable regression analyses to jointly investigate associations between the predictors and the presence of CII injection wells. For the multivariable models, we first evaluated the correlation among all independent variables using Spearman's rank correlation ($r_{Spearman}$). Results showed relatively high correlation between two sets of variables: median household value/median income ($r_{Spearman} = 0.77$) and population density/land area ($r_{Spearman} = -0.94$). Based on these findings, we excluded median household value and land area from the final set of multivariable analyses. Given the small number of independent variables and the large number of block groups, we opted to retain all other covariates in the final models regardless of effect magnitude or statistical significance.

To correctly estimate the relationships between CII injection well presence and the sociodemographic predictors, we applied three statistical models that used different approaches for jointly (*a*) modeling associations with all block group–level predictors, (*b*) accounting for spatial correlation among the block group data, and (*c*) reducing the impact of spatial confounding that may arise as a result of modeling the spatial correlation (Clayton et al. 1993; Hodges and Reich 2010; Reich et al. 2006). Accounting for spatial correlation is necessary to accurately quantify uncertainty in estimated associations and, therefore, to determine whether associations are statistically significant (Hodges and Reich 2010). In addition, spatial confounding may occur when spatially correlated random effects are also correlated with model covariates; failure to correct for spatial confounding can bias estimated associations and inflate standard errors (Hodges and Reich 2010). We applied the following three models: (*a*) NSGLM: nonspatial generalized linear model, (*b*) SGLMM: spatial generalized linear mixed model, and (*c*) Sparse SGLMM: sparse version of the SGLMM, as introduced by Hughes and Haran (2013).

In brief, NSGLM represents a standard multivariable logistic regression model in which the log of the odds of a block group containing a CII injection well is modeled as a function of the available covariates. NSGLM does not directly account for any spatial correlation that may be present in the data (i.e., beyond the available spatially varying covariates). The model is given as $Y_i|p_i \sim \text{Bernoulli}(p_i), i = 1, \ldots n$ and $\text{logit}(p_i) = \mathbf{x}_i^{\mathrm{T}}\boldsymbol{\beta}$, in which Y_i is equal to one if block group i contains at least one CII injection well and is equal to zero otherwise; n is the number of block groups in the analysis; p_i represents the probability that block group i contains a CII injection well; logit(.) represents the logit link function; $\mathbf{x}_i$ is the vector of available covariates; and $\boldsymbol{\beta}$ is the vector of unknown regression parameters describing the associations between the covariates and the probability of interest.

SGLMM extends NSGLM to directly account for spatial correlation through the introduction of spatially correlated random effects. The logistic regression model is given as $\text{logit}(p_i) = \mathbf{x}_i^{\mathrm{T}}\boldsymbol{\beta} + \theta_i$, in which θ_i is the random effect specific to block group i. We modeled these random effects using the intrinsic conditional autoregressive (CAR) model (Besag et al. 1991). The CAR model accounts for similarities among the neighboring block groups (i.e., those sharing a border) by assuming that the conditional mean of one of the normally distributed random effects is equal to the average of its neighbors' random effect values.

Sparse SGLMM further extends NSGLM by both accounting for spatial correlation and controlling for potential spatial confounding between the introduced random effects and the fixed effects of interest (Hughes and Haran 2013). Sparse SGLMM is given as $\text{logit}(p_i) = \mathbf{x}_i^{\mathrm{T}}\boldsymbol{\beta} + \boldsymbol{m}_i^{\mathrm{T}}\boldsymbol{\delta}_s$, in which $\boldsymbol{m}_i^{\mathrm{T}}\boldsymbol{\delta}_s$ represents the block group–specific random effect. This model is denoted as "sparse" because the specification of the random effect results in a model with fewer parameters than SGLMM given that $\boldsymbol{m}_i$ is the ith row of an $n \times q$ matrix $\boldsymbol{M}$ ($q \ll n$) in which $\boldsymbol{M}$ contains the first q eigenvectors of the Moran operator. The $\boldsymbol{\delta}_s$ vector (length q) is modeled using a modified intrinsic CAR model, in which the original CAR precision matrix is multiplied by the matrix $\boldsymbol{M}^{\mathrm{T}}$ (on the left side) and $\boldsymbol{M}$ (on the right side). We set $q = 250$ based on exploratory analyses of our data set and results from Hughes and Haran (2013).

All models were fit in the Bayesian framework to facilitate model comparisons. Posterior means of odds ratios (OR) and quantile-based 95% credible intervals (CIs) were obtained from each model. We considered estimates with 95% CIs that did not include 1.00 to be significant associations. We preferentially specified weakly informative prior distributions to enable the data, rather than our prior beliefs, to drive the inference. Specifically, across each model, the β_j parameters that describe the association between covariate j and the response were given independent and identically normally distributed prior distributions centered at zero with a variance of 1,000. In SGLMM, the intrinsic CAR random effect variance parameter was given an inverse-gamma (3, 1) prior distribution. In Sparse SGLMM, the comparable variance parameter was given an inverse-gamma (0.50, 0.0005) prior distribution.

We fit the three models using packages within R statistical software (version 3.4.1; R Development Core Team). NSGLM was fit using "rjags" (Plummer 2016), SGLMM was fit using "CARBayes" (Lee 2013), and Sparse SGLMM was fit using "ngspatial" (Hughes and Cui 2017). For each model, we obtained 1,000 approximately independent posterior samples from all model parameters after a lengthy burn-in period (i.e., before convergence of the model), which were used to make inferences on the associations of interest. Approximate independence of the posterior samples was achieved by thinning the complete set of correlated posterior samples. The length of burn-in and amount of thinning were model specific. We assessed convergence through visual inspection of trace plots as well as the calculation of the Geweke convergence diagnostic for each parameter individually (Geweke 1991). There were no obvious signs of nonconvergence for any of the models.

Model Evaluation

We compared the three models using four criteria. We assessed (*a*) the deviance information criterion (DIC) to evaluate fit to the data [smaller values preferred (Spiegelhalter et al. 2002)], (*b*) overall complexity of the model by effective number of parameters (Spiegelhalter et al. 2002), (*c*) changes in estimated ORs and 95% CIs between the different models, and (*d*) maps of the estimated spatially correlated random effects to evaluate spatial confounding.

Sensitivity Analyses

We carried out several sensitivity analyses to test our modeling assumptions and examine the robustness of our findings to the different modeling choices. We repeated our statistical modeling while defining the outcome as having at least one CII injection well within 5 km of a block group's centroid to examine whether associations changed using a buffer-zone definition versus using an administratively defined unit. We only included CII injection wells within Ohio in this analysis. We also examined the associations of interest while restricting the outcome to block groups

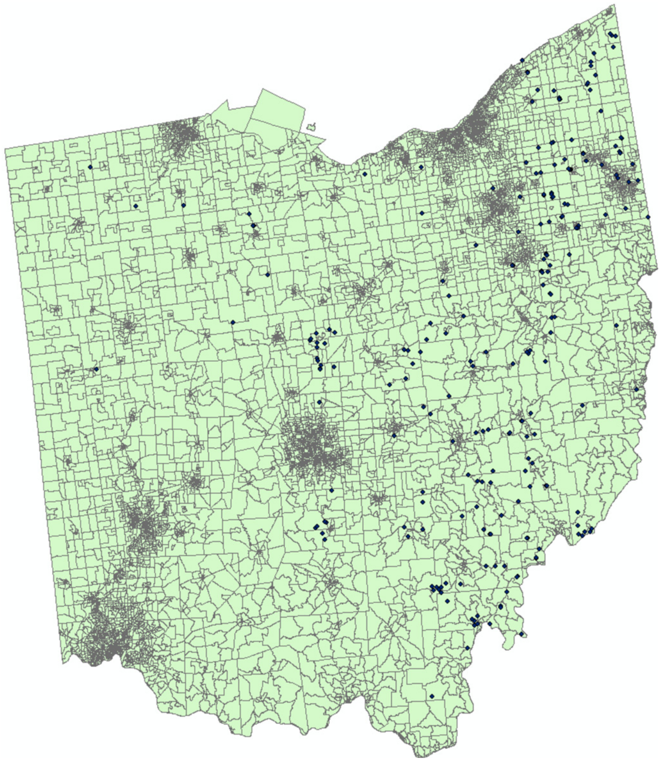

Figure 1. Locations of Class II injection wells in Ohio (2010–2016), delineated by census block group. Data obtained from the U.S. Census Bureau (2016b) and FracTracker Alliance (2016).

that contained at least one high-volume (≥141,367 barrels, the median volume) waste wells, which could represent greater potential for water contamination or seismic activity. In addition, we conducted our analyses within the subset of block groups classified as rural (<1,000 people/mi^2 or <386 people/km^2) (U.S. Census Bureau 2000) to determine if the associations with the sociodemographic predictors remained when urbanized areas of the state were excluded. Finally, we evaluated the consistency of the Sparse SGLMM by varying the value of q (50, 150, and 250), a term that controls the complexity of the model.

Results

Bivariate Analyses

During our study period, 257 CII injection wells were identified in Ohio (Figure 1). Of the 9,205 block groups, only 2% ($n = 156$ contained a CII injection well (Table 1). Compared with block groups without CII injection wells, block groups with CII injection wells had a slightly older median age [median 42.8 y; interquartile range (IQR): 39.5, 47.5 vs. 40.2 y; IQR: 33.9, 46.2, respectively] and were substantially less densely populated (median population density of 71.2 people/mi^2; IQR: 40.1, 157 vs. 2,210 people/mi^2; IQR: 433, 4,750) (Table 1). Further illustrating the marked differences in population density, block groups containing CII injection wells had densities ranging from 11.93 people/mi^2 to 1,703.01 people/mi^2, whereas over half of block groups without CII injection wells had population densities greater than 1,703.01 people/mi^2.

Median land area was greater in block groups with CII injection wells (43.5 km^2; IQR: 25.4, 74.3) than in those without (1.35 km^2; IQR: 0.51, 7.43) (Table 1). The median percentage of the population identifying as white was higher in census block groups with a CII injection well (98%) compared with without a CII injection well (92%). Median income, median household value, percentage of the population with a high school education and above, and percentage voter turnout were not significantly different between the two block group types based on these bivariate analyses (Table 1). Both median income and median household value were higher in block groups with CII injection wells ($49,097 vs. $46,250 and $118,750 vs. $109,800, respectively), although these differences were not statistically significant.

Multivariable Analyses

In multivariable regression analyses, the odds of a block group containing a CII injection well decreased 13–17% for each $10,000 increase in median income across the models (e.g., OR = 0.837, 95% CI: 0.719, 0.961 for Sparse SGLMM), although this association did not reach statistical significance in SGLMM (Table 2). The estimated OR for a CII injection well in relation to population density was far below 1, indicating a strong inverse relationship (Sparse SGLMM OR = 0.030, 95% CI: 0.008, 0.072), consistent with the pronounced difference in population density between block groups with and without CII injection wells. The percentage of block group residents with a high school degree or greater, percentage who were white only, voter turnout, and median age were not statistically significant predictors of CII injection well status in any model. The odds of a block group having a CII injection well decreased ∼3% with the addition of one UNG well across all models (e.g., OR = 0.967; 95% CI: 0.939, 0.989 for Sparse SGLMM). Block groups with greater water surface area were also less likely to have a CII injection well. Associations between CII injection well presence and whether a block group was located on the Marcellus or Utica Shale varied across the models, with significant positive associations for both shales based on NSGLM and Sparse

Table 1. Characteristics of Ohio census block groups by the presence of Class II (CII) injection wells ($n = 9,205$), from 2010 to 2016. Data are medians (25th–75th percentiles) or n (%).

Characteristic	CII Well within Block Group ($n = 156$)	No CII Well within Block Group ($n = 9,049$)	p-Value[a]
Median age (y)	42.8 (39.5–47.5)	40.2 (33.9–46.2)	2.1×10^{-6}
Population density (people/mi^2)[b]	71.2 (40.1–157)	2,210 (433–4,750)	$<2.2 \times 10^{-16}$
Median income ($)	49,097 (41,333–57,050)	46,250 (33,100–61,944)	0.36
Education ≥high school (%)	88.6 (84.3–92.6)	89.9 (82.6–94.9)	0.58
White only (%)	98.1 (95.3–100.0)	92.1 (74.7–97.7)	2.2×10^{-16}
Voter turnout (%)	71.6 (68.1–75.2)	71.8 (64.1–76.4)	0.0017
Median household value ($)	118,750 (91,625–147,700)	109,800 (78,600–153,800)	0.36
Land area (km^2)	43.5 (25.4–74.3)	1.35 (0.51–7.43)	$<2.2 \times 10^{-16}$
Water area (km^2)	0.16 (0.02–0.58)	0.00 (0.00–0.04)	0.041
Utica Shale	124 (79.5%)	3,979 (44.0%)	$<2.2 \times 10^{-16}$
Marcellus Shale	42 (26.9%)	456 (5.0%)	6.9×10^{-9}
Any UNG well	23 (14.7%)	161 (1.8%)	1.1×10^{-5}

[a]Difference between block groups with and without CII injection wells, two-sample t-tests.
[b]Each unit of people/mi^2 is equivalent to 0.386 people/km^2.

Table 2. Odds ratios (posterior means) and 95% credible intervals for associations between block group–level sociodemographic and geographic characteristics and the presence of Class II injection wells in Ohio (2010–2016), based on three models ($n = 156$ block groups with CII injection well; $n = 9{,}049$ without CII injection well).

Characteristic	NSGLM (DIC: 1095.89, p_D: 10.13)	SGLMM (DIC: 985.72, p_D: 114.13)	Sparse SGLMM ($q = 250$) (DIC: 1049.71, p_D: 47.50)
UNG well (per 1 count)	0.968 (0.943, 0.988)[a]	0.974 (0.947, 0.994)[a]	0.967 (0.939, 0.989)[a]
Median age (per 1 y)	0.987 (0.964, 1.01)	0.980 (0.952, 1.01)	0.984 (0.959, 1.01)
Education ≥high school (per 1%)	1.01 (0.991, 1.04)	1.01 (0.986, 1.04)	1.01 (0.988, 1.04)
Median income (per \$10,000)	0.834 (0.727, 0.939)[a]	0.867 (0.733, 1.01)	0.837 (0.719, 0.961)[a]
White only (per 1%)	1.01 (0.986, 1.04)	1.01 (0.982, 1.04)	1.02 (0.990, 1.05)
Voter turnout (per 1%)	0.993 (0.961, 1.02)	1.01 (0.965, 1.05)	0.994 (0.959, 1.03)
Population density (per 1,000 people/mi^2)[b]	0.023 (0.006, 0.050)[a]	0.017 (0.004, 0.045)[a]	0.030 (0.008, 0.072)[a]
Water area (per 1 km^2)	0.933 (0.815, 1.00)	0.903 (0.751, 1.00)	0.904 (0.761, 1.00)
Utica Shale (yes vs. no)	6.13 (4.08, 9.07)[a]	1.18 (0.350, 2.93)	5.06 (2.76, 8.36)[a]
Marcellus Shale (yes vs. no)	1.76 (1.14, 2.63)[a]	1.49 (0.577, 3.12)	2.58 (1.29, 4.45)[a]

Note: All posterior summaries were generated using models that included all characteristics shown in Table 2. DIC, deviance information criterion; NSGLM, non-spatial generalized linear model; p_D, effective number of parameters; q, model complexity; SGLMM, spatial generalized linear mixed model; Sparse SGLMM, sparse version of the SGLM; UNG, hydraulically fractured unconventional natural gas well.
[a]Indicates statistical significance; 95% credible interval does not include 1.00.
[b]Each unit of people/mi^2 is equivalent to 0.386 people/km^2.

SGLMM, but near-null ORs for both shale formations based on SGLMM.

Model Evaluation

SGLMM had the smallest DIC, followed by Sparse SGLMM, indicating that the spatially adjusted models fit the data better than the nonspatial model (NSGLM), consistent with the presence of spatial correlation (Table 2). Of the two spatial models, Sparse SLGMM had a smaller effective number of parameters (p_D: 47.50 vs. 114.13), indicating less complexity than SGLMM. Large differences in the estimated ORs and statistical significance for the Utica and Marcellus Shale predictors were observed between NSGLM and SGLMM, potentially indicating the presence of spatial confounding (Table 2). Additionally, the map of posterior means of the spatial random effects from SGLMM (Figure 2B) shows larger estimated random effects overlaying the Utica and Marcellus Shale locations, even after including the shale predictors in the model. The ORs and 95% CIs for the Utica Shale location variable for Sparse SGLMM were consistent with NSGLM, and the map of estimated spatial random effects (Figure 2C) does not suggest any obvious spatial patterning. Therefore, we concluded that Sparse SGLMM had the best overall performance because it provided a better fit than NSGLM, was less complex than SGLMM, and, in contrast with SGLMM, could reduce spatial confounding caused by the introduction of spatially correlated random effects.

Sensitivity Analyses

Using the presence of a CII injection well within a 5-km buffer from the block group centroid for classification, 718 block groups were classified as containing a CII injection well, compared with 156 block groups with a CII injection well located within their boundaries (see Table S1). Using the buffer-based outcome metric, statistically significant associations for median income, number of UNG wells, and block group overlying the Marcellus Shale were similar to, but farther from, the null than ORs estimated using the CII injection within block group boundary outcome metric, based on the Sparse SGLMM model (see Table S1). For example, the OR for a block group overlying the Utica Shale increased to 33.7 (95% CI: 18.3, 56.2) compared with the OR of 5.06 (95% CI: 2.76, 8.36) for the buffer versus block group boundary metrics. The odds of a Class II injection well within 5 km of a block group centroid were significantly lower with a 1% increase in voter turnout (OR = 0.974; 95% CI: 0.954, 0.993) as compared with the null association estimated for a Class II injection well within a block group's bounds (OR = 0.994; 95% CI: 0.959, 1.03) (see Table S1). Significant associations with population density were not observed when using this buffer-based outcome metric.

A total of 90 block groups had at least one high-volume CII injection well within their bounds. Population density was the only socioeconomic variable statistically significantly associated with siting of the higher waste volume CII injection wells, and the OR was similar to that estimated in our primary model (OR = 0.037; 95% CI: 0.007, 0.096 vs. OR = 0.030; 95% CI: 0.008, 0.072). Results restricted to the rural block groups ($n = 3{,}237$; $n = 152$ containing a CII injection well) were consistent with those for all block groups except for the relationship with the Marcellus Shale, which became null. Finally, estimated associations based on Sparse SGLMM with $q = 50$ and 150 were similar to those from the primary model ($q = 250$) (see Table S2).

Discussion

Our Ohio-based study addresses one of the many public health concerns raised about hydraulic fracturing: the placement of waste disposal sites. Results from our primary model, including multiple sociodemographic and geographic predictors and controlling for spatial correlation and confounding, indicated an inverse association between CII injection well presence and median income within census block groups. This association was robust to the different sensitivity analyses conducted. In addition, block groups with at least one CII injection well had fewer UNG wells, were more likely to be located on a shale formation, and had substantially lower population densities than Ohio block groups without a CII injection well. Although estimated associations with sociodemographic characteristics were generally consistent among the three models, we found evidence of both spatial correlation and spatial confounding, which may be important to address in other settings.

The inverse association between block group median income and the presence of waste disposal sites in Ohio suggests a pattern of environmental inequity and is consistent with findings from a study in Texas that reported a greater proportion of disposal wells in high poverty block groups (those with a mean percentage of residents living in poverty above the regional mean of 18.6%) (Johnston et al. 2016). Populations with lower income may be at increased vulnerability to potential exposures and risks posed by CII waste sites due to limited financial resources to support medical care, legal questions, exposure mitigation strategies, and relocation expenses.

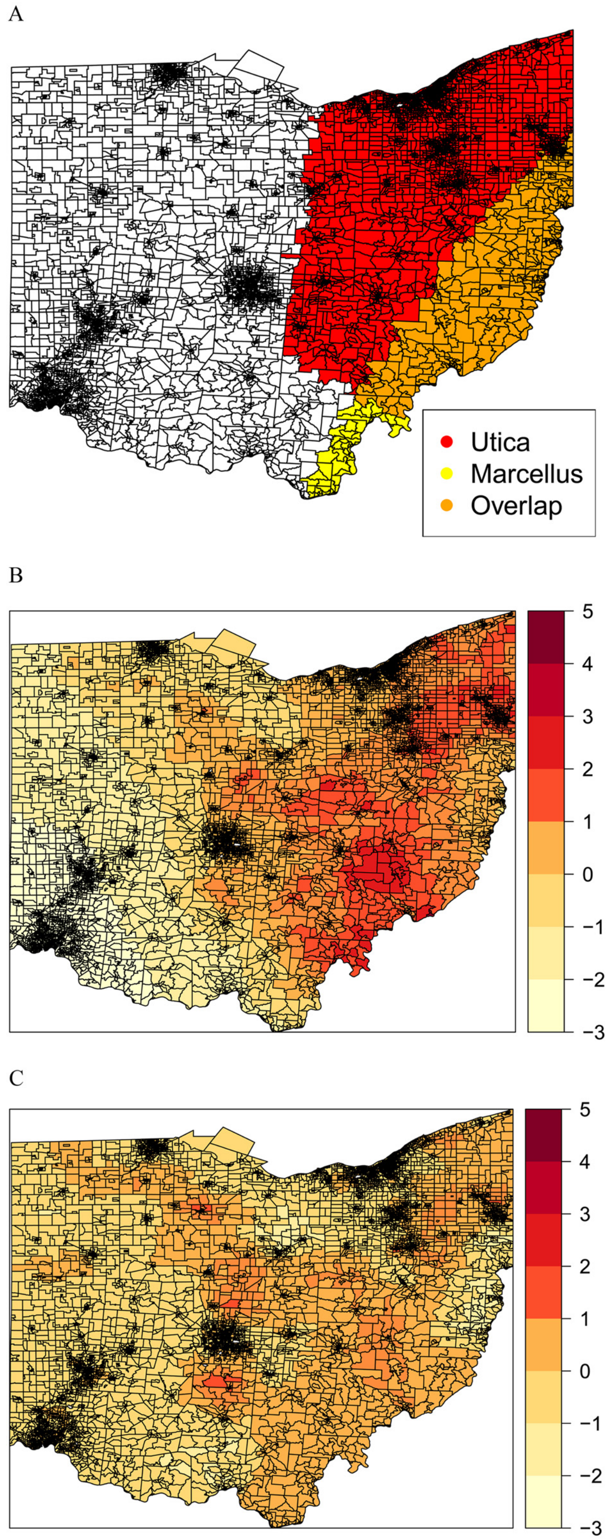

Figure 2. Utica Shale, Marcellus Shale, and their (*A*) overlapping areas in Ohio; (*B*) posterior mean spatial random effects (magnitude and direction indicated by color gradation) from SGLMM; and (*C*) posterior mean spatial random effects (magnitude and direction indicated by color gradation) from Sparse SGLMM. Large positive random effect values represent elevated risk of CII injection well after adjustment for the considered predictors, whereas large negative values indicate the opposite. Images represent random effects from models of presence/absence of a CII injection well within a block group (dependent variable) against the following independent predictor variables: UNG wells, median age, % ≥high school educated, % white only, % voter turnout, population density, and water area.

The association between low population density and the likelihood of the presence of a CII injection well was expected given the impracticality of establishing a wastewater disposal facility in a densely populated urban center. Although this suggests that fewer people could be potentially exposed to suspected hazards posed by CII injection wells, some of the disadvantages of rurality, such as distance from high-staffed healthcare facilities, could serve to exacerbate the exposure and health risks potentially faced by residents of block groups with a waste disposal facility.

Race was not associated with the presence of CII injection wells. However, race was a difficult determinant to examine, due to the overwhelming majority of white-only populations across Ohio's block groups (IQR: 75.1%, 97.8%); any deviations were clustered in urban centers of the state, which are not generally suitable for construction of CII injection wells. These results contrasted with those reported by Johnston et al. (2016); however, the study by Johnston et al. (2016) was conducted in Texas, which has extensive drilling in densely populated areas with substantial racial and ethnic diversity (Whitworth et al. 2017). Interestingly, our study found that the number of UNG wells within a block group's bounds was negatively associated with the presence of a CII injection well. This inverse relationship between UNG well count and CII injection well presence could exist because oil and gas companies may prioritize a region of shale that is accessible and productive enough to merit multiple UNG wells for shale gas extraction rather than for injecting wastewater, which would consume valuable surface area. However, CII injection wells are sited overwhelmingly over the eastern half of Ohio overlying the Utica and Marcellus Shale formations, indicating that wastewater is still disposed of relatively close to the location of drilling into the shale.

Our analyses using three different models demonstrated the presence of spatial correlation and confounding in our data set. Spatial confounding biased SGLMM estimates of associations with location over the Utica and Marcellus Shales toward the null, whereas strong positive associations with shale locations were estimated when Sparse SGLMM was used. Our spatial analysis enabled visualization of the estimated spatially correlated random effects (Figure 2). Block groups with large positive random effect estimates (Figure 2C) had a greater risk of having CII injection wells than can be explained by the covariates alone. This information could be used to focus attention on these block groups to determine what common features they have that may be leading to this increased probability of CII injection well presence.

We used the defined geographic boundary of the census block group as our primary unit of analysis to ensure spatial alignment of the majority of our data sources. We found some differences when defining our outcome as presence of a CII injection well within 5 km of the block group centroid, which had the advantage of capturing CII injection wells located across block group borders. For instance, there was a statistically significant inverse relationship between voter turnout and presence of CII injection well only when using this buffer-based metric. This finding could indicate a link between reduced civic engagement capacity and siting of CII disposal wells, which warrants follow-up. Population density was not associated with the buffer-based outcome, potentially due to spatial misalignment between the outcome metric and census data, leading to greater land area, and therefore a potentially more heterogeneous population distribution. Another limitation of the buffer-based metric is that we did not have data on injection well locations in bordering states. However, injection wells are less prevalent in Ohio's neighboring states of Pennsylvania and West Virginia (U.S. EPA 2016a).

Data on CII injection well locations and other data attributes are available from other data sources, such as the commercially available DrillingInfo (https://info.drillinginfo.com/). Future analyses could evaluate the agreement in CII injection well coordinate data among different published databases.

It is important to note that, although we estimated significant associations between sociodemographic and other factors and CII injection well presence in this ecologic analysis, we cannot claim causation or a temporal relationship from our results. One must consider whether income values decreased following placement of CII injection wells or whether the CII injection wells were placed disproportionately in regions with already lower income values. Irrespective of the temporality or intentionality of the placement of CII injection wells, our findings suggest a pattern of environmental injustice, in which block groups of lower median income could have a greater likelihood of facing deleterious impacts from containing a wastewater disposal facility. Data regarding those potential health impacts are still sparse, but recent studies comparing surface water samples collected upstream and downstream of a West Virginia CII injection well facility suspected of a contamination event observed in the downstream samples elevated concentrations of a range of inorganic and organic pollutants (Akob et al. 2016; Orem et al. 2017) and increased antagonist hormonal activities for estrogen, progesterone, glucocorticoid, and thyroid hormone receptors assessed with mammalian and yeast reporter gene assays (Kassotis et al. 2016). Furthermore, there is increasing evidence of the seismic activity induced from CII injection wells (Ellsworth 2013; Frohlich et al. 2011, 2014; Horton 2012; Kim 2013; McGarr et al. 2015; Zoback 2012). These microearthquakes could cause physical harm, structural property damage, anxiety, and fear in the affected communities (Bommer et al. 2015). They may occur up to several kilometers from the injection point (Horton 2012; Justinic et al. 2013; Keranen et al. 2014), and therefore the impact may not be confined to block groups containing the disposal facility. More water sampling, human exposure, and health studies in communities with CII injection wells would provide further insights into the potential environmental health impacts of living in proximity to these disposal wells.

Conclusions

Our analysis presents evidence of an inverse association between median income, population density, and number of UNG wells and CII injection well presence in Ohio census block groups after adjusting for other sociodemographic and geographic variables and spatial correlation and confounding. Although we observed positive, significant associations between median age and % population white and CII injection well presence in bivariate analyses, these associations did not remain after adjustment for other factors in the multivariable regression analyses. Our findings advance understanding of the sociodemographic characteristics of Ohio populations living in census areas with higher likelihoods of containing CII injection wells, and they demonstrate the importance of examining hydraulic fracturing activities in terms of waste disposal and the surrounding communities. More studies must still be conducted to determine specific exposures, health risks, and economic impacts that may be associated with CII injection well presence. These types of findings can inform future public health regulations and wastewater management and siting policies, both in Ohio and in all regions in which hydraulic fracturing occurs.

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References

Agyeman J, Schlosberg D, Craven L, Matthews C. 2016. Trends and directions in environmental justice: from inequity to everyday life, community, and just sustainabilities. Annu Rev Environ Resour 41(1):321–340, https://doi.org/10.1146/annurev-environ-110615-090052.

Akob DM, Mumford AC, Orem W, Engle MA, Klinges JG, Kent DB, et al. 2016. Wastewater disposal from unconventional oil and gas development degrades stream quality at a West Virginia injection facility. Environ Sci Technol 50(11):5517–5525, PMID: 27158829, https://doi.org/10.1021/acs.est.6b00428.

Besag J, York J, Mollié A. 1991. Bayesian image restoration, with two applications in spatial statistics. Ann Inst Stat Math 43(1):1–20, https://doi.org/10.1007/BF00116466.

Bommer JJ, Crowley H, Pinho R. 2015. A risk-mitigation approach to the management of induced seismicity. J Seismol 19(2):623–646, PMID: 28190961, https://doi.org/10.1007/s10950-015-9478-z.

Brulle RJ, Pellow DN. 2006. Environmental justice: human health and environmental inequalities. Annu Rev Public Health 27:103–124, PMID: 16533111, https://doi.org/10.1146/annurev.publhealth.27.021405.102124.

Clayton DG, Bernardinelli L, Montomoli C. 1993. Spatial correlation in ecological analysis. Int J Epidemiol 22(6):1193–1202, PMID: 8144305, https://doi.org/10.1093/ije/22.6.1193.

Cushing L, Morello-Frosch R, Wander M, Pastor M. 2015. The haves, the have-nots, and the health of everyone: the relationship between social inequality and environmental quality. Annu Rev Public Health 36:193–209, PMID: 25785890, https://doi.org/10.1146/annurev-publhealth-031914-122646.

de Gouw JA, Parrish DD, Frost GJ, Trainer M. 2014. Reduced emissions of CO_2, NOx, and SO_2 from U.S. power plants owing to switch from coal to natural gas with combined cycle technology. Earths Future 2(2):75–82, https://doi.org/10.1002/2013EF000196.

Elliott EG, Ettinger AS, Leaderer BP, Bracken MB, Deziel NC. 2017a. A systematic evaluation of chemicals in hydraulic-fracturing fluids and wastewater for reproductive and developmental toxicity. J Expo Sci Environ Epidemiol 27(1):90–99, PMID: 26732376, https://doi.org/10.1038/jes.2015.81.

Elliott EG, Trinh P, Ma X, Leaderer BP, Ward MH, Deziel NC. 2017b. Unconventional oil and gas development and risk of childhood leukemia: assessing the evidence. Sci Total Environ 576:138–147, PMID: 27783932, https://doi.org/10.1016/j.scitotenv.2016.10.072.

Ellsworth WL. 2013. Injection-induced earthquakes. Science 341(6142):1225942, PMID: 23846903, https://doi.org/10.1126/science.1225942.

FracTracker Alliance. 2016. Ohio oil and gas activity. https://www.fractracker.org/map/us/ohio/ [accessed 28 September 2016].

Frohlich C, Ellsworth W, Brown WA, Brunt M, Luetgert J, MacDonald T, et al. 2014. The 17 May 2012 *M*4.8 earthquake near Timpson, east Texas: an event possibly triggered by fluid injection. J Geophys Res Solid Earth 119(1):581–593, https://doi.org/10.1002/2013JB010755.

Frohlich C, Hayward C, Stump B, Potter E. 2011. The Dallas–Fort Worth earthquake sequence: October 2008 through May 2009. Bull Seismol Soc Am 101(1):327–340, https://doi.org/10.1785/0120100131.

Geweke J. 1991. "Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments." Staff report 148. Minneapolis, MN:Federal Reserve Bank of Minneapolis, Research Department.

Hodges JS, Reich BJ. 2010. Adding spatially-correlated errors can mess up the fixed effect you love. Am Stat 64(4):325–334, https://doi.org/10.1198/tast.2010.10052.

Horton S. 2012. Disposal of hydrofracking waste fluid by injection into subsurface aquifers triggers earthquake swarm in central Arkansas with potential for damaging earthquake. Seismol Res Lett 83(2):250–260, https://doi.org/10.1785/gssrl.83.2.250.

Hughes J, Cui X. 2017. ngspatial: fitting the centered autologistic and sparse spatial generalized linear mixed models for areal data. R package version 1.1–3.

Hughes J, Haran M. 2013. Dimension reduction and alleviation of confounding for spatial generalized linear mixed models. J R Stat Soc Series B Stat Methodol 75(1):139–159, https://doi.org/10.1111/j.1467-9868.2012.01041.x.

Institute of Medicine. 2003. *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. Smedley BD, Stith AY, Nelson AR, eds. Washington, DC:National Academies Press.

Jackson RB, Lowry ER, Pickle A, Kang M, DiGiulio D, Zhao K. 2015. The depths of hydraulic fracturing and accompanying water use across the United States. Environ Sci Technol 49(15):8969–8976, PMID: 26196164, https://doi.org/10.1021/acs.est.5b01228.

Johnston JE, Werder E, Sebastian D. 2016. Wastewater disposal wells, fracking, and environmental injustice in southern Texas. Am J Public Health 106(3):550–556, PMID: 26794166, https://doi.org/10.2105/AJPH.2015.303000.

Justinic AH, Stump B, Hayward C, Frohlich C. 2013. Analysis of the Cleburne, Texas, earthquake sequence from June 2009 to June 2010. Bull Seismol Soc Am 103(6):3083–3093, https://doi.org/10.1785/0120120336.

Kassotis CD, Iwanowicz LR, Akob DM, Cozzarelli IM, Mumford AC, Orem W, et al. 2016. Endocrine disrupting activities of surface water associated with a West Virginia oil and gas industry wastewater disposal site. Sci Total Environ 557–558:901–910, PMID: 27073166, https://doi.org/10.1016/j.scitotenv.2016.03.113.

Keranen KM, Weingarten M, Abers GA, Bekins BA, Ge S. 2014. Sharp increase in central Oklahoma seismicity since 2008 induced by massive wastewater injection. Science 345(6195):448–451, PMID: 24993347, https://doi.org/10.1126/science.1255802.

Kim WY. 2013. Induced seismicity associated with fluid injection into a deep well in Youngstown, Ohio. J Geophys Res Solid Earth 118(7):3506–3518, https://doi.org/10.1002/jgrb.50247.

Kondash AJ, Albright E, Vengosh A. 2017. Quantity of flowback and produced waters from unconventional oil and gas exploration. Sci Total Environ 574:314–321, PMID: 27639468, https://doi.org/10.1016/j.scitotenv.2016.09.069.

Lamichhane AP, Warren J, Puett R, Porter DE, Bottai M, Mayer-Davis EJ, et al. 2013. Spatial patterning of supermarkets and fast food outlets with respect to neighborhood characteristics. Health Place 23:157–164, PMID: 23933445, https://doi.org/10.1016/j.healthplace.2013.07.002.

Lee D. 2013. CARBayes: an R package for Bayesian spatial modeling with conditional autoregressive priors. J Stat Soft 55(13):1–24, https://doi.org/10.18637/jss.v055.i13.

Lutz BD, Lewis AN, Doyle MW. 2013. Generation, transport, and disposal of wastewater associated with Marcellus Shale gas development. Water Resour Res 49(2):647–656, https://doi.org/10.1002/wrcr.20096.

McGarr A, Bekins B, Burkardt N, Dewey J, Earle P, Ellsworth W, et al. 2015. Coping with earthquakes induced by fluid injection. Science 347(6224):830–831, PMID: 25700505, https://doi.org/10.1126/science.aaa0494.

Molitor J, Su JG, Molitor N-T, Rubio VG, Rubio VG, Richardson S, et al. 2011. Identifying vulnerable populations through an examination of the association between multipollutant profiles and poverty. Environ Sci Technol 45(18):7754–7760, PMID: 21797252, https://doi.org/10.1021/es104017x.

Morello-Frosch R, Zuk M, Jerrett M, Shamasunder B, Kyle AD. 2011. Understanding the cumulative impacts of inequalities in environmental health: implications for policy. Health Aff (Millwood) 30(5):879–887, PMID: 21555471, https://doi.org/10.1377/hlthaff.2011.0153.

NRC (National Research Council). 2013. "Induced Seismicity Potential in Energy Technologies." Washington, DC:National Academies Press.

ODNR Division of Oil & Gas Resources. 2016a. Shale well drilling & permitting. http://oilandgas.ohiodnr.gov/shale [accessed 22 June 2017].

ODNR Division of Oil & Gas Resources. 2016b. Underground injection control (UIC). http://oilandgas.ohiodnr.gov/regulatory-sections/underground-injection-control [accessed 13 June 2018].

Ogneva-Himmelberger Y, Huang L. 2015. Spatial distribution of unconventional gas wells and human populations in the Marcellus Shale in the United States: vulnerability analysis. Appl Geogr 60:165–174, https://doi.org/10.1016/j.apgeog.2015.03.011.

Orem W, Varonka M, Crosby L, Haase K, Loftin K, Hladik M, et al. 2017. Organic geochemistry and toxicology of a stream impacted by unconventional oil and gas wastewater disposal operations. Appl Geochem 80:155–167, https://doi.org/10.1016/j.apgeochem.2017.02.016.

Plummer M. 2016. rjags: Bayesian graphical models using mcmc. R package version 4–6.

Reich BJ, Hodges JS, Zadnik V. 2006. Effects of residual smoothing on the posterior of the fixed effects in disease-mapping models. Biometrics 62(4):1197–1206, PMID: 17156295, https://doi.org/10.1111/j.1541-0420.2006.00617.x.

Shih JS, Saiers JE, Anisfeld SC, Chu Z, Muehlenbachs LA, Olmstead SM. 2015. Characterization and analysis of liquid waste from Marcellus Shale gas development. Environ Sci Technol 49(16):9557–9565, PMID: 26140412, https://doi.org/10.1021/acs.est.5b01780.

Shrestha N, Chilkoor G, Wilder J, Gadhamshetty V, Stone JJ. 2017. Potential water resource impacts of hydraulic fracturing from unconventional oil production in the Bakken Shale. Water Res 108:1–24, PMID: 27865434, https://doi.org/10.1016/j.watres.2016.11.006.

Solomon GM, Morello-Frosch R, Zeise L, Faust JB. 2016. Cumulative environmental impacts: science and policy to protect communities. Annu Rev Public Health 37:83–96, PMID: 26735429, https://doi.org/10.1146/annurev-publhealth-032315-021807.

Spiegelhalter DJ, Best NG, Carlin BP, van der Linde A. 2002. Bayesian measures of model complexity and fit. J R Stat Soc Series B Stat Methodol 64(4):583–639, https://doi.org/10.1111/1467-9868.00353.

State of Ohio (Ohio Division of Mineral Resources Management, Oil and Gas). 2009. 1501:9-3-05 Construction of and conversion to saltwater injection wells. http://codes.ohio.gov/oac/1501:9-3-05v1 [accessed 6 June 2018].

State of Ohio (Ohio Secretary of State). 2017. 2012 Official Results by Precinct: Office of the Ohio Secretary of State; election results and data. https://www.sos.state.oh.us/elections/election-results-and-data/2012-elections-results/ [accessed 10 January 2018].

Stringfellow WT, Camarillo MK, Domen JK, Sandelin WL, Varadharajan C, Jordan PD, et al. 2017. Identifying chemicals of concern in hydraulic fracturing fluids used for oil production. Environ Pollut 220(pt A):413–420, PMID: 27743793, https://doi.org/10.1016/j.envpol.2016.09.082.

Su JG, Jerrett M, Morello-Frosch R, Jesdale BM, Kyle AD. 2012. Inequalities in cumulative environmental burdens among three urbanized counties in California. Environ Int 40:79–87, PMID: 22280931, https://doi.org/10.1016/j.envint.2011.11.003.

Thacker JB, Carlton DD Jr, Hildenbrand ZL, Kadjo AF, Schug KA. 2015. Chemical analysis of wastewater from unconventional drilling operations. Water 7(4):1568–1579, https://doi.org/10.3390/w7041568.

U.S. Census Bureau. 2000. Census 2000 urban and rural classification. https://www.census.gov/geo/reference/ua/urban-rural-2000.html [accessed 21 December 2017].

U.S. Census Bureau. 2012. 2012 Ohio voting districts.TIGER/Line Shapefile. https://www2.census.gov/geo/tiger/TIGER2012/VTD/ [accessed 10 January 2018].

U.S. Census Bureau. 2016a. American FactFinder. https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml [accessed 1 November 2016].

U.S. Census Bureau. 2016b. TIGER/Line® shapefiles and TIGER/Line® files. https://www.census.gov/geo/maps-data/data/tiger-line.html [accessed 1 November 2016].

U.S. EIA (U.S. Energy Information Administration). 2016a. Oil- and gas-related maps, geospatial data, and geospatial software. https://www.eia.gov/maps/maps.htm [accessed 29 April 2017].

U.S. EIA. 2016b. Shale gas production (billion cubic feet). https://www.eia.gov/dnav/ng/ng_prod_shalegas_s1_a.htm [accessed 1 August 2017].

U.S. EIA. 2017. Annual energy outlook 2017. https://www.eia.gov/outlooks/aeo/pdf/0383%282017%29.pdf [accessed 10 May 2018].

U.S. EPA (U.S. Environmental Protection Agency). 2015. Assessment of the potential impacts of hydraulic fracturing for oil and gas on drinking water resources (external review draft). EPA/600/R-15/047. Washington, DC:U.S. EPA.

U.S. EPA. 2016a. National underground injection control inventory-federal fiscal year 2016 state and tribal summary. Washington, DC:U.S. EPA. https://www.epa.gov/sites/production/files/2017-06/documents/state_fy_16_inventory_format_508.pdf [accessed 10 May 2018].

U.S. EPA. 2016b. Underground injection control (UIC). https://www.epa.gov/uic/class-ii-oil-and-gas-related-injection-wells [accessed 29 April 2017].

U.S. EPA. 2017. Learn about environmental justice. https://www.epa.gov/environmentaljustice/learn-about-environmental-justice [accessed 22 January 2018].

Vengosh A, Jackson RB, Warner N, Darrah TH, Kondash A. 2014. A critical review of the risks to water resources from unconventional shale gas development and hydraulic fracturing in the United States. Environ Sci Technol 48(15):8334–8348, PMID: 24606408, https://doi.org/10.1021/es405118y.

Warner NR, Christie CA, Jackson RB, Vengosh A. 2013. Impacts of shale gas wastewater disposal on water quality in western Pennsylvania. Environ Sci Technol 47(20):11849–11857, PMID: 24087919, https://doi.org/10.1021/es402165b.

Webb E, Bushkin-Bedient S, Cheng A, Kassotis CD, Balise V, Nagel SC. 2014. Developmental and reproductive effects of chemicals associated with unconventional oil and natural gas operations. Rev Environ Health 29(4):307–318, PMID: 25478730, https://doi.org/10.1515/reveh-2014-0057.

Whitworth KW, Marshall AK, Symanski E. 2017. Maternal residential proximity to unconventional gas development and perinatal outcomes among a diverse urban population in Texas. PLoS One 12(7):e0180966, PMID: 28732016, https://doi.org/10.1371/journal.pone.0180966].

Zoback MD. 2012. Managing the seismic risk posed by wastewater disposal. Earth Mag 57(5).