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A community-based evaluation of proximity to unconventional oil and gas wells, drinking water contaminants, and health symptoms in Ohio

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ABSTRACT

Over 4 million Americans live within 1.6 km of an unconventional oil and gas (UO&G) well, potentially placing them in the path of toxic releases. We evaluated relationships between residential proximity to UO&G wells and (1) water contamination and (2) health symptoms in an exploratory study. We analyzed drinking water samples from 66 Ohio households for 13 UO&G-related volatile organic compounds (VOCs) (e.g., benzene, disinfection byproducts [DBPs]), gasoline-range organics (GRO), and diesel-range organics. We interviewed participants about health symptoms and calculated metrics capturing proximity to UO&G wells. Based on multivariable logistic regression, odds of detection of bromoform and dibromochloromethane in surface water decreased significantly as distance to nearest UO&G well increased (odds ratios [OR]: 0.28–0.29 per km). Similarly, distance to nearest well was significantly negatively correlated with concentrations of GRO and toluene in ground water ($r_{Spearman}$: −0.40 to −0.44) and with concentrations of bromoform and dibromochloromethane in surface water ($r_{Spearman}$: −0.48 to −0.50). In our study population, those with higher inverse-distance-squared-weighted UO&G well counts within 5 km around the home were more likely to report experiencing general health symptoms (e.g. stress, fatigue) (OR: 1.52, 95%CI: 1.02–2.26). This exploratory study, though limited by small sample size and self-reported health symptoms, suggests that those in closer proximity to multiple UO&G wells may be more likely to experience environmental health impacts. Further, presence of brominated DBPs (linked to UO&G wastewater) raises the question of whether UO&G activities are impacting drinking water sources in the region. The findings from this study support expanded studies to advance knowledge of the potential for water quality and human health impacts; such studies could include a greater number of sampling sites, more detailed chemical analyses to examine source attribution, and objective health assessments.

1. Introduction

Unconventional oil and gas (UO&G) development, the extraction of oil and gas from low-permeability rock formations using directional drilling and hydraulic fracturing, has rapidly expanded in the United States with an estimated 25,000–35,000 UO&G wells drilled and hydraulically fractured from 2011 to 2014 (U.S. Environmental Protection Agency, 2015). Consequently, more than 4 million people live within 1.6 km (one mile) of an UO&G well (Czolowski et al., 2017) and more than 9 million people have drinking water sources within 1.6 km of an UO&G well (U.S. Environmental Protection Agency, 2015), potentially placing them in the path of hazardous agents. Data are critically needed to better understand potential water quality and health impacts in communities near UO&G development.

Pathways of groundwater and surface water contamination from UO&G activities include leaks from deteriorating or improperly constructed UO&G wells, surface spills, and improper wastewater storage and disposal (U.S. Environmental Protection Agency, 2015). Chemicals used in or produced by hydraulic fracturing include biocides (Kahrilas et al., 2015), endocrine disruptors (Kassotis et al., 2014), reproductive/developmental toxicants (Elliott et al., 2017a), and carcinogenic compounds (Elliott et al., 2017b). Several studies have detected more than a dozen health-relevant compounds in ground and surface water near UO&G extraction sites (Drollette et al., 2015; Fontenot et al., 2013; Hildenbrand et al., 2015; Llewellyn et al., 2015; McMahon et al., 2017). However, they represent only a small fraction of the hazardous

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chemicals known to exist in hydraulic fracturing fluids and UO&G wastewaters. Additionally, existing studies have primarily been conducted in Pennsylvania, Texas, Colorado, and West Virginia, while Ohio remains under-studied, and the types and concentrations of contaminants may vary geographically. Though studies have examined the chemical constituents of drinking water samples, they often use distance to nearest well as a surrogate for proximity to UO&G activity, but do not consider the presence of multiple UO&G wells surrounding a drinking water source. Further, they generally do not have individual-level demographic or health information to complement the water monitoring data.

Epidemiologic studies of UO&G development have observed associations with increased risk of perinatal outcomes (Casey et al., 2016; Currie et al., 2017; McKenzie et al., 2014; Stacy et al., 2015; Whitworth et al., 2017), self-reported dermal and respiratory irritation (Rabinowitz et al., 2015), asthma symptom exacerbations (Rasmussen et al., 2016), respiratory, migraine, and fatigue symptoms (Tustin et al., 2016), childhood leukemia (McKenzie et al., 2017), and increased hospitalization rates (Jemielita et al., 2015). These studies have relied on proximity-based metrics and models to assess potential exposure rather than on environmental or biological measurements. These models do capture proximity and density of multiple UO&G wells around the home, and often include other well attributes, such as production volume and well depth, as surrogates of UO&G activity (Allshouse et al., 2017; Rasmussen et al., 2016). Measurements in large epidemiologic investigations of UO&G development are not yet practical due to the lack of knowledge of specific etiologic agents and the varying sampling methods, analysis procedures, and costs required to examine the wide-ranging potential contaminants. However, there is a need to measure environmental contaminants to inform exposure and environmental health studies on UO&G development.

Our primary objective was to explore whether there were associations between residential proximity to UO&G wells and detection and concentrations of health-relevant drinking water contaminants in a community-based setting in Ohio. As a secondary objective, we evaluated whether there were relationships between residential UO&G proximity and prevalent health symptoms to complement the exposure assessment and obtain a preliminary indication of health status and concerns in the community.

2. Materials and methods

2.1. Study population

We recruited 66 residents of Belmont County, Ohio, the county with the highest number of permitted shale wells in Ohio (Fig. 1) (Ohio Department of Natural Resources, 2018), as part of the Ohio Water and Air Quality Study, a multi-media exposure and health study. Participants were recruited using mailed informational flyers, local newspaper and television news stories, and social media. Eligible participants were required to be: ≥ 21 years old, a head of household, and English-speaking. We enrolled participants living at varying distances to UO&G wells (Fig. 2), and preferentially enrolled participants with groundwater (private well or spring) as their primary drinking water source, as compared to surface water (municipal reservoirs or creek water). We prioritized groundwater sources because our proximity metrics would be most relevant for evaluating potential impacts, as these sources are co-located with the home, where drinking water samples were collected. We included homes serviced by surface water also because surface water may be vulnerable to UO&G activity either at the source or via the distribution system. Home visits were completed during June-August 2016. All participants provided informed consent prior to study activities. Protocols were approved by the Yale Institutional Review Board.

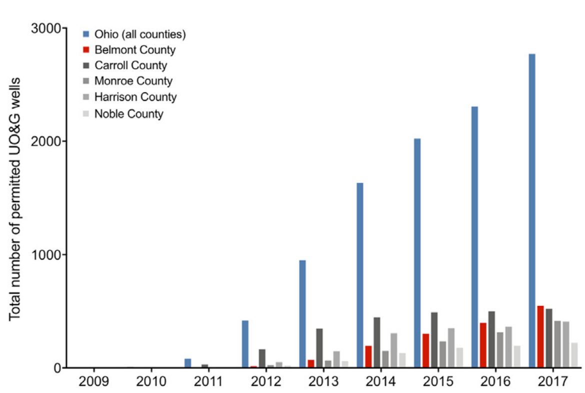

Fig. 1. Unconventional oil and gas (UO&G) well permits in Ohio over time. Total number of permitted UO&G wells in Belmont County (N [%]), by year: 2009: 2 (67%), 2010: 4 (44%), 2011: 5 (6%), 2012: 15 (4%), 2013: 70 (7%), 2014: 195 (12%), 2015: 302 (15%), 2016: 398 (17%), 2017: 548 (20%).

2.2. Interviewer-administered questionnaire

Trained interviewers queried participants about demographics and housing and drinking water source characteristics. Using a questionnaire adapted from a previous community health study (Rabinowitz et al., 2015), interviewers also asked participants about prevalent health symptoms to assess potential health concerns in the community. We considered health outcomes that could be related to environmental exposures and with relatively short latencies: respiratory (e.g., allergies, wheezing), dermal (e.g., skin rash ≥ 3 days, burning skin), neurologic (e.g., severe headaches, dizziness), gastro-intestinal (e.g., stomach ulcers, nausea), and general (e.g., stress, fatigue).

2.3. Residential proximity to UO&G Wells

ArcGIS 10.1 (ESRI, Redlands, CA) was used to geocode residential street addresses and calculate residential proximity to UO&G wells. We obtained data on latitude, longitude, and permit date of all "active" shale wells (in the drilling, drilled, or production phase at the time of the home visit) in Belmont County from the Ohio Department of Natural Resources (Ohio Department of Natural Resources, 2018). We constructed three proximity metrics based on the different types of metrics used in the geochemical and epidemiologic literature. We calculated distance to nearest active UO&G well (km), consistent with the geochemical literature identifying increased methane, metals, gasoline range organic compounds (GRO), and diesel range organic compounds (DRO) concentrations in drinking water samples 1–2 km from the nearest UO&G well (Drollette et al., 2015; Fontenot et al., 2013; Jackson et al., 2013; Osborn et al., 2011). We also calculated an inverse-distance weighted (IDW, Eq. (1)) well count and inverse-distance-squared weighted (ID^{2}W, Eq. (2)) well count for all wells within 5 km of a residence, similar to some of the epidemiologic literature (McKenzie et al., 2014; Stacy et al., 2015).

$$IDW\ well\ count = \sum_{i=1}^{n} \frac{1}{d_i} \tag{1}$$

$$ID^2W\ well\ count = \sum_{i=1}^{n} \frac{1}{d_i^2} \tag{2}$$

where distance (d) in km between the wellhead (i) to the ~~maternal~~ residence, and n is the number of UO&G wells within 5 km around the residence; giving more weight to wells closer to the residence and less weight to wells further from the residence. For use in sensitivity analyses, we calculated metrics specific to the drilling/drilled or production phases and explored all inverse-distance weighted metrics with alternative buffer sizes of 1 km and 2 km.

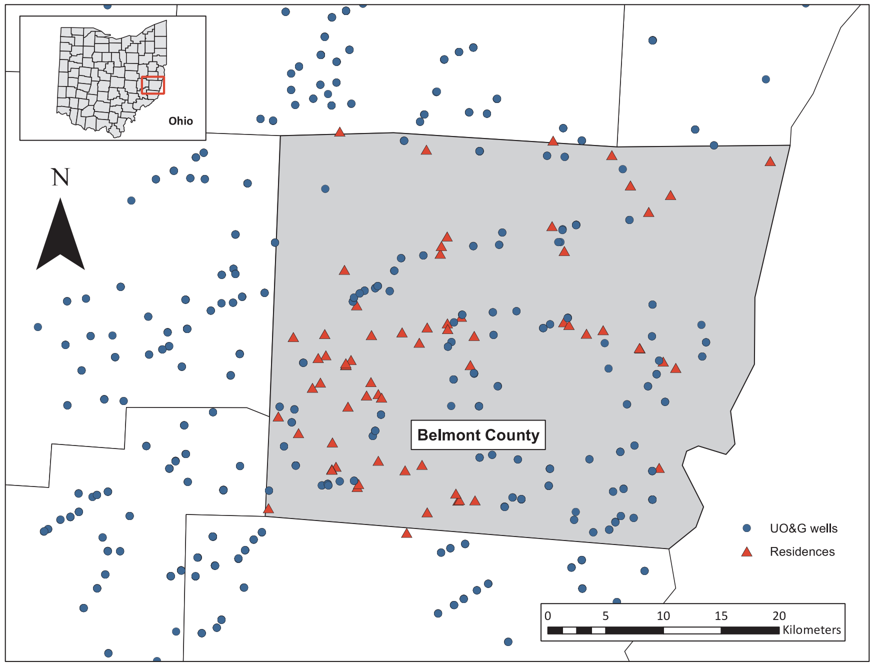

Fig. 2. Unconventional oil and gas (UO&G) wells and participant's residences in Belmont County, Ohio.

2.4. Water sample collection and analysis

We collected drinking water samples from all 66 homes and used a targeted approach focusing on compounds present in hydraulic fracturing fluids and/or wastewater with potential for causing reproductive toxicity, developmental toxicity, and/or cancer (Table S1). We analyzed samples for 15 health-relevant volatile organic compounds (VOCs), including benzene, toluene, ethylbenzene, xylene-like (BTEX-like) compounds and trihalomethanes, and GRO, an integrative measure of hydrocarbons ranging from C_6 to C_{10}. In a random subset of 39 homes, we collected additional samples for analysis of DRO, an integrative measure of hydrocarbons from C_{10} to C_{28}.

All water samples were collected in precombusted, clear vials containing 1 mL of 50% (v/v) hydrochloric acid as a preservative (final pH < 2) with less than 0.5 mL of headspace and stored on ice at 4 °C prior to analysis within four weeks. Samples were collected upstream of drinking water treatment systems from the kitchen tap or, if a filter was installed, the bathroom tap or outdoor spigot. Field blanks were collected in a random 20% subset of homes.

For analysis of VOCs and GRO, we followed U.S. Environmental Protection Agency (EPA) Method 624, with minor modifications previously described by Getzinger et al. (2015). Some compounds co-eluted and could not be distinguished (e.g., o-xylene and styrene). Therefore, our final analyte list included 13 individual or pairs of VOCs. Concentrations of compounds below method detection limits were set to half the detection limit. For DRO, we used a dichloromethane methanol solution (90:10 v/v) for liquid-liquid extraction followed by gas chromatography with flame ionization detection, in accordance with U.S. EPA Method 8015D, with minor modifications previously described by Getzinger et al. (2015). After completion of the water analyses, we mailed result reports to each participant, that placed their individual results into context with existing U.S. EPA water quality standards and included information on resources for further information on water quality and testing. Reports were also explained in a Town Hall-style community meeting.

2.5. Statistical analysis

For the analysis of water samples, we constructed multivariable logistic regression models for each of the 13 analytes using compound detection (yes/no) as the dependent variable and the three continuous proximity metrics (distance to nearest well, IDW, and ID^{2}W well count) as independent variables. We considered several other potential predictors of water contamination in these models: phase of the nearest gas well (i.e., drilled/drilling versus producing), report of unusual changes in drinking water, at home drinking water treatment (i.e. sampled water untreated versus collected downstream of a sediment or lime filter), and water well depth; however, none were associated with compound detection at the $\alpha = 0.05$ level and therefore none were included in final regression models. We also examined the relationship between drinking water source (groundwater versus surface water) and detection of individual compounds in univariable analyses using X^2 or Fisher's exact tests. Next, we calculated Spearman correlation coefficients for concentrations of the 13 analytes and UO&G residential proximity metrics. All analyses were performed stratified by sampled water source (ground [n = 46] or surface water [n = 20]), due to differences in water source location, potential contamination pathways, and treatment.

For examination of health symptoms, we conducted multivariable logistic regression analysis considering our three continuous proximity metrics (distance to nearest well, IDW, and ID^{2}W well count) and considering *a priori* identified potential confounders that are predictors for health and that could also be associated with residential proximity to UO&G wells: age, sex, body-mass index, smoking status, educational status, marital status, and employment status. For example, several sociodemographic factors are known to be related to health and could be linked to UO&G well placement (Ogneva-Himmelberger and Huang, 2015). In adjusted analyses, we considered the most parsimonious regression models using backward logistic regression analysis to retain only the proximity metric and covariates with $p < 0.05$. We used proximity metrics rather than concentrations of compounds in drinking water as our exposure metrics in these health analyses because the proximity metrics could capture both water and other UO&G-related exposures (e.g., air emissions, noise) and not all participants were consuming the sampled drinking water piped to their homes. Health analyses were also conducted stratified by sampled water source (ground versus surface).

In sensitivity analyses, we explored whether there were any

Table 1
Demographic characteristics of the Ohio Water and Air Quality Study population (n = 66).

Characteristic	Mean ± SD
Age (years)	59.8 ± 13.7
Years lived in current home	19.5 ± 17.1
	N (%)
Sex (male/female)	
Male	37 (56)
Race	
White	64 (97)
Other/unknown	2 (3)
Educational level	
< High school	8 (12)
High school diploma	17 (26)
Some higher education/associate's degree	18 (27)
Bachelor's degree	12 (18)
Postgraduate's degree	11 (17)
Marital status	
Married/domestic partnership	52 (79)
Single, never married	6 (9)
Separated/divorced	4 (6)
Widowed	4 (6)
Employment status	
Employed/self-employed	38 (58)
Retired	24 (36)
Homemaker	2 (3)
Unemployed	2 (3)
Smoking status	
Never smoker	40 (61)
Former smoker	16 (24)
Current smoker	10 (15)
Current smoker in the home (yes/no)	
Yes	10 (15)
Home owner/renter	
Owner	63 (96)
Type of home	
Single-family home	66 (100)

differences in associations using phase-specific metrics (drilling/drilled or production). Metrics presented in final analyses were selected based on best fit to the data using the Akaike information criterion (AIC). All analyses were performed in SAS 9.3 (SAS Institute, Cary, NC).

3. Results

3.1. Population and home characteristics

The study population was predominantly white, married, nonsmoking, home-owning, older, and living in a single-family home, while levels of education and employment varied (Table 1). The mean distance ± standard deviation to the nearest UO&G well was 2.1 ± 1.2 km (Table 2). The number of UO&G wells within a 5-km radius of homes ranged from 0 to 43 with an average of 17 (Table 2). By design, groundwater (private well or spring) was the main drinking water source for the greater proportion of participants (61%). Those on surface water were predominantly served by municipally treated surface waters (95%). Most participants did not use any tap or house water treatment system (65%). A total of eight (12%) participants reported a new unnatural taste, appearance, or odor to their drinking water (4 [20%] on surface water, 4 [9%] on groundwater). Of these eight participants reporting a change, five reported that the change prevented them from using the water as usual.

3.2. Organic drinking water contaminants

All homes had at least one VOC or GRO above detection limits; 62% of the homes sampled for DRO had these compounds detected (Table 3). The profile of contaminants differed between drinking water sources, with statistically significantly higher detection rates of toluene among groundwater samples and statistically significantly higher detection rates of halogenated compounds among surface water samples ($p < 0.0001$, Table 3). Detection rates of trihalomethanes in particular were higher among surface water compared to groundwater samples: among homes served by surface water, detection rates of bromodichloromethane, bromoform, chloroform, and dibromochloromethane ranged from 55% to 85%, but ranged from 0% to 9% for homes served by groundwater (Table 3). All contaminant concentrations were below U.S. EPA enforceable Maximum Contaminant Levels (MCLs); however, four of the detected VOCs (benzene, bromodichloromethane, bromoform, and tetrachloroethylene) have Maximum Contaminant Level Goals (MCLG) of 0 µg/L (Table 4, Table S1). Furthermore, six of the detected VOCs (benzene, ethylbenzene, styrene, bromodichloromethane, chloroform, and tetrachloroethylene) are classified as

Table 2
Characteristics related to residential proximity to unconventional oil and gas (UO&G) wells and residential drinking water (n = 66).

Characteristic	Mean ± SD	Range
Distance to nearest unconventional oil and gas (UO&G) well (km)	2.1 ± 1.2	0.17–5.1
Drilled/drilling	3.3 ± 2.1	0.17 – 8.9
Producing	2.7 ± 2.1	0.18–15
Number of UO&G wells within radius		
2 km	3.0 ± 3.8	0–13
5 km	17 ± 8.9	0–43
Inverse-distance weighted UO&G well counts within 5 km (wells/km)	7.1 ± 5.2	0–29
Inverse-distance^2 weighted UO&G well counts within 5 km (wells/km^2)	6.2 ± 16	0–127
	N (%)	
Phase of nearest UO&G well		
Drilled/drilling	20 (30)	
Producing	46 (70)	
Private water well (yes/no)		
Yes	44 (67)	
Main source of drinking water		
Ground	40 (61)	
Surface	13 (20)	
Bottled	13 (20)	
Main source of water used for other purposes		
Ground	38 (58)	
Surface	23 (35)	
Rain barrel/cistern	5 (8)	
Water source sampled[a]		
Ground	46 (70)	
Surface	20 (30)	
Use of drinking water treatment		
None	43 (65)	
Sediment filter	11 (17)	
Water softener	9 (14)	
Carbon filter	3 (5)	
Lime filter	2 (3)	
UV filter	2 (3)	
Reverse osmosis	2 (3)	
Treatment of sampled water[b]		
None	60 (91)	
Sediment filter	5 (8)	
Water softener	0 (0)	
Carbon filter	0 (0)	
Lime filter	1 (2)	
UV filter	0 (0)	
Reverse osmosis	0 (0)	
New unnatural taste, appearance, or water odor over past 6 months (yes/no)		
Yes	8 (12)	
New unnatural taste, appearance, or water odor prevented use (n = 8) (yes/no)		
Yes	5 (63)	

[a] Sampled groundwater sources were 35 private wells and 11 springs; sampled surface water sources were 19 municipal reservoirs and 1 creek.
[b] Drinking water samples were collected upstream of any water treatment systems expected to impact target analytes.

Table 3
Unadjusted odds of detection of organic compounds in drinking water in relation to distance to nearest unconventional oil and gas well (km) (n = 66).

	Ground water (N = 46)			Surface water (N = 20)			
Organic compounds	Detect N (%)	OR	95% CI	Detect N (%)	OR	95% CI	P[a]
Gasoline range organic compounds	45 (98)	0.38	(0.059, 2.5)	20 (100)	–	(-, -)	
Diesel range organic compounds[b]	19 (59)	1.1	(0.66, 1.9)	5 (71)	2.1	(0.32, 14)	
BTEX & Related Compounds							
Benzene	3 (7)	0.39	(0.094, 1.6)	2 (10)	1.1	(0.28, 4.6)	0.63
Cumene	0 (0)	–	(-, -)	0 (0)	–	(-, -)	–
Ethylbenzene	2 (4)	0.50	(0.11, 2.3)	0 (0)	–	(-, -)	0.99
Toluene	43 (94)	0.49	(0.18, 1.4)	7 (35)	2.2	(0.77, 6.0)	< 0.0001
m-Xylene, *p*-Xylene	6 (13)	0.69	(0.32, 1.5)	1 (5)	1.1	(0.17, 7.8)	0.67
o-Xylene, Styrene	3 (7)	0.94	(0.36, 2.4)	0 (0)	–	(-, -)	0.55
Halogenated Compounds							
Bromodichloromethane	4 (9)	0.38	(0.11, 1.4)	17 (85)	0.29	(0.069, 1.2)	< 0.0001
Bromoform	0 (0)	–	(-, -)	11 (55)	0.28	(0.076, 1.0)	< 0.0001
Chloroform	3 (7)	0.64	(0.22, 1.9)	17 (85)	0.58	(0.18, 1.9)	< 0.0001
Dibromochloromethane	0 (0)	–	(-, -)	12 (60)	0.29	(0.080, 1.0)	< 0.0001
Tetrachloroethylene	0 (0)	–	(-, -)	1 (5)	1.1	(0.17, 7.8)	0.30
1,2,4-Trichlorobenzene	0 (0)	–	(-, -)	0 (0)	–	(-, -)	–

BTEX: Benzene, toluene, ethylbenzene, xylene, CI: Confidence interval, OR: Odds ratio.
[a] p-values are for X^2 or Fisher's exact text for drinking water source and detection of individual compounds.
[b] Diesel Range Organic Compounds ground water: n = 32, surface water: n = 7.

known, probable, or possible human carcinogens by the International Agency for Research on Cancer and are assumed not to have safe levels of exposure (Table S1) (Elliott et al., 2017b).

In logistic regression analyses for compound detection, increasing distance to nearest well, the best-fitting metric, was statistically significantly associated with decreasing odds of detection of trihalomethanes (bromoform and dibromochloromethane) in surface water samples (Table 3). Among groundwater samples, as distance to nearest well increased, odds of organic compound detection tended to decrease, though relationships were not statistically significant (Table 3). Distance to nearest well was statistically significantly negatively correlated with concentrations of GRO ($r_{Spearman} = -0.40$; p = 0.008) and toluene ($r_{Spearman} = -0.44$; p = 0.003) among ground water samples and bromoform ($r_{Spearman} -0.50$; p = 0.03) and dibromochloromethane ($r_{Spearman} = -0.48$; p = 0.03) among surface water samples (Table 4, Fig. S1).

3.3. Self-reported health symptoms

In the study population, the most frequently reported health symptoms were respiratory symptoms (85%; e.g. wheezing), general (77%; e.g., stress, fatigue), and neurologic (76% e.g., headaches), with 61 (92%) participants reporting at least one health symptom (Table 5). In logistic regression models, ID^2W well count was the best-fitting UO&

Table 4
Concentrations of organic compounds in drinking water in relation to distance to nearest unconventional oil and gas well (km) (n = 66).

	Total (N = 66)		Ground Water (N = 46)						Surface Water (N = 20)					
	Mean Detection Limit (DL)	Samples > DL	Samples > DL	Concentration (μg/L)[a]					Samples > DL	Concentration (μg/L)[a]				
Organic compounds	(μg/L)	N (%)	N (%)	Min	Median	Max	$r_{Spearman}$[b]	*p*[c]	N (%)	Min	Median	Max	$r_{Spearman}$[b]	*p*[c]
Gasoline range organic compounds	0.1	65 (98)	45 (98)	0.20	1.6	31	−0.40	0.008	20 (100)	0.54	4.1	44	0.03	0.90
Diesel range organic compounds[d]	18	24 (62)	19 (59)	28	62	184	0.04	0.82	5 (71)	21	57	187	0.63	0.13
BTEX & Related Compounds														
Benzene	0.1	5 (8)	3 (7)	0.30	1.0	1.2	−0.19	0.21	2 (10)	1.1	1.4	1.6	0.11	0.63
Cumene	0.1	0 (0)	0 (0)	–	–	–	–	–	0 (0)	–	–	–	–	–
Ethylbenzene	0.1	2 (3)	2 (4)	0.1	0.17	0.24	−0.13	0.40	0 (0)	–	–	–	–	–
Toluene	0.1	48 (73)	43 (94)	0.08	0.76	14	−0.44	0.003	7 (35)	0.17	0.31	22	0.39	0.11
m-Xylene, *p*-Xylene	0.1	7 (11)	6 (13)	0.11	0.14	0.87	−0.14	0.36	1 (5)	0.19	0.19	0.19	0.1	0.68
o-Xylene, Styrene	0.1	3 (5)	3 (7)	0.10	0.12	0.51	−0.02	0.91	0 (0)	–	–	–	–	–
Halogenated Compounds														
Bromodichloromethane	1.4	21 (32)	4 (9)	2.3	5.6	12	−0.25	0.10	17 (85)	4.0	10	44	−0.36	0.12
Bromoform	2.5	11 (17)	0 (0)	–	–	–	–	–	11 (55)	4.6	7.0	8.7	−0.50	0.03
Chloroform	0.9	20 (30)	3 (7)	0.83	1.1	3.1	−0.09	0.56	17 (85)	0.51	5.4	52	0.01	0.95
Dibromochloromethane	2.0	12 (18)	0 (0)	–	–	–	–	–	12 (60)	9.9	15	22	−0.48	0.03
Tetrachloroethylene	0.5	1 (2)	0 (0)	–	–	–	–	–	1 (5)	0.43	0.43	0.43	0.12	0.64
1,2,4-Trichlorobenzene	0.3	0 (0)	0 (0)	–	–	–	–	–	0 (0)	–	–	–	–	–

BTEX: Benzene, toluene, ethylbenzene, xylene, DL: Detection limit.
[a] Minimum, median, and maximum concentrations for detected compounds.
[b] $r_{Spearman}$ for compound concentration and distance to nearest unconventional oil and gas well.
[c] p-value is for $r_{Spearman}$.
[d] Diesel Range Organic Compounds total: n = 39, ground water: n = 32, surface water: n = 7.

Table 5
Unadjusted and adjusted odds of self-reported health symptoms in relation to inverse-distance-squared weighted unconventional oil and gas well counts within 5 km (wells/km^2) (n = 66).

Health symptoms	N (%)	Unadjusted N (%)		Adjusted[a] N (%)	
		OR	95% CI	OR	95% CI
Respiratory[b]	56 (85)	1.07	(0.90, 1.27)	1.07	(0.90, 1.27)
Neurologic[c]	50 (76)	0.98	(0.95, 1.02)	0.98	(0.95, 1.02)
Dermal[d]	29 (44)	1.08	(0.98, 1.19)	1.08	(0.98, 1.18)
Gastro-intestinal[e]	18 (27)	0.99	(0.93, 1.04)	0.96	(0.86, 1.07)
General[f]	51 (77)	1.41	(0.98, 2.03)	1.52	(1.02, 2.26)

CI: Confidence interval, OR: Odds ratio.
[a] Adjusted for age and employment status (dermal symptoms), smoking status (gastro-intestinal symptoms), and body mass index (general health symptoms) using backward logistic regression analysis.
[b] Respiratory symptoms included: allergies, eye irritation, metallic taste, wheezing, shortness of breath, chest tightness, cough, sore throat, or cold, frequent nose bleeds, hearing problems.
[c] Neurologic symptoms included: frequent headaches or migraines, dizziness or balance problems, feeling down, difficulties with concentration or memory, difficulty sleeping or insomnia, feeling anxious or nervous, seizures).
[d] Dermal symptoms included: skin rash, burning skin, itchy skin, dermatitis).
[e] Gastro-intestinal symptoms (stomach ulcers, nausea, vomiting, or diarrhea, abdominal pain, other digestive issues).
[f] General health symptoms (stress, fatigue, muscle or joint pain, any other health symptoms).

G proximity metric. After adjusting for potential confounders, an increase in ID^{2}W well count was statistically significantly associated with increased odds of reporting general symptoms; for each additional UO&G well per km^2 the odds of experiencing general health symptoms was 1.5 times as high (95% confidence interval: 1.02–2.26) (Table 5). No statistically significant associations were observed for the other symptoms. Associations did not differ by water source; therefore, results are presented for the full population.

Sensitivity analyses with the inverse-distance-weighted proximity metrics, phase-specific metrics, and 1 km and 2 km buffer sizes did not reveal any differences in relationships with water contaminants or health symptoms.

4. Discussion

In our Ohio Water and Air Quality Study, residential proximity to UO&G wells was associated with higher detection rates and concentrations of drinking water contaminants, particularly for GRO, bromoform, and dibromochloromethane. Although all contaminant concentrations were below U.S. EPA MCLs, four VOCs were present in excess of the MCLGs. After adjusting for potential confounders, residential proximity to UO&G wells was associated with experiencing general health symptoms. To our knowledge, this is the only study to date to concurrently collect drinking water samples, health information, and proximity data in relation to UO&G development and is one of the few exposure studies conducted in Ohio. These data do not specifically indicate that UO&G activities are the source of contaminants and do not provide direct evidence for a link to health symptoms. However, the results provide support for further analyses and additional monitoring in a larger population and raise the question of whether UO&G activities are impacting municipal drinking water treatment plants in the region.

The increased prevalence of contaminants in drinking water samples from homes located closer to UO&G wells compared to those farther away is consistent with a growing number of studies across a range of compounds, such as methane/ethane (Jackson et al., 2013; Osborn et al., 2011), DRO (Drollette et al., 2015), and inorganics (Fontenot et al., 2013), though not all studies observed such associations (McMahon et al., 2017). In contrast with Drollette et al. (2015), we did not observe associations between residential proximity to UO&G wells and DRO detection and concentrations (Drollette et al., 2015). However, subsurface transport of DRO is slow due to sorptive interactions with the aquifer solids, and our sampling may not have accounted for a sufficient lag between development activities at the well pad and sampling. Additionally, previous studies identified surface spills and activities as the likely source of observed DRO in groundwater (Drollette et al., 2015), and data on surface spills were not available for our study area.

The presence of genotoxic brominated disinfection byproducts (DBPs) bromodichloromethane, bromoform, and dibromochloromethane in surface water was notable because their formation occurs at higher frequencies in water impacted by shale gas activities (Parker et al., 2014) and is consistent with studies of brine-impacted surface waters near wastewater treatment and discharge facilities (Hildenbrand et al., 2015; Parker et al., 2014; Regli et al., 2015). Though there are more than 250 Class II injection wells in Ohio (Ohio Department of Natural Resources, 2018), at the time of sample collection, only two were located in Belmont County, and 55 (83%) participants were farther than 5 km from either of them, and 35 (53%) were farther than 10 km away, indicating spills, rather than discharge of inadequately treated wastewater, would be more likely possible sources of surface water contamination in the study area.

The observed increasing detection and concentration of some organic contaminants with decreasing distance between the residence and nearest UO&G well was somewhat unexpected for homes served by surface water, as the source water is not co-located with the home. However, it is possible that organic contaminants may enter the drinking water distribution system from UO&G sites located in the vicinity of the home. Future efforts could obtain locations of drinking water reservoirs, distribution systems, and spill data to examine the relationship between proximity of UO&G facilities to reservoirs on municipal water quality and to investigate the potential for contamination of drinking water during transport to homes.

In our community-based study, we observed relatively high proportions of participants reporting health symptoms, particularly respiratory (e.g. wheezing), neurologic (e.g., headaches), and general symptoms (e.g., fatigue), possibly due to the older average age of the study population or that people with health problems may have been more likely to participate. These types of symptoms have been linked to UO&G development in prior studies (Rabinowitz et al., 2015; Tustin et al., 2016), though we only observed a link between residential proximity to UO&G wells and general health symptoms, such as stress and fatigue. Our findings support further investigation of these symptoms with more directed stress- and fatigue-related questions, such as the Daily Inventory of Stressful Events (Almeida et al., 2002) or fatigue-related questions from the Patient-Reported Outcomes Measurement Information System (PROMIS®) (2018) used by Tustin et al. (2016), or measurement of biological indicators of stress, such as salivary cortisol.

We examined several types of UO&G metrics that accounted for both the number and proximity of UO&G wells to the home, hypothesizing that more refined metrics could illuminate previously obfuscated relationships. However, distance to nearest well fit the water monitoring data better than the IDW and ID^{2}W metrics. Distance to nearest well may be a better predictor of vulnerability of water resources to contamination because source water located closer to UO&G sites will be more vulnerable sooner, due to contaminant travel times, dilution, and degradation reactions. In contrast, ID^{2}W well count had a better fit to the health data, which may be because it better reflects dispersion of air pollutants or other environmental hazards linked to UO&G activities (Adgate et al., 2014).

Several limitations should be considered in the interpretation of this exploratory study. The sample size of 66 homes was moderate, and therefore we had limited statistical power, particularly for analysis of the less common contaminants. Due to the self-selection design in our community-based study, our study population likely included a higher proportion of participants concerned about their water quality and/or health, and therefore results may not be generalizable to the broader area. Although differential reporting bias cannot be excluded due to potential participant knowledge about proximity to UO&G wells, the results with health symptoms were mostly null, which does not support the presence of bias. Furthermore, self-selection would not be expected to impact associations between proximity to UO&G wells and levels of drinking water contaminants, which are objective measures. Assessment of drinking water contaminants could be improved upon by considering hydrogeological and temporal factors, such as groundwater flow patterns, soil characteristics, and compound transport time in addition to UO&G well proximity and density. Because VOCs, GRO, and DRO could be naturally occurring or present due to contamination from other industrial activity historically occurring in the region, incorporation of geochemical tracers in conjunction with VOCs, GRO, and DRO would enhance understanding of whether observed contaminants can be linked to UO&G activity (Darrah et al., 2014; Harkness et al., 2017). Finally, our analyses compared residential proximity to UO&G wells to 13 water contaminants and five categories of health symptoms. Although multiple comparisons may have impacted the observed statistically significant relationships, we observed consistent patterns of increased water contaminants with distance to nearest UO&G well.

Our study also has several strengths. To our knowledge, this is the only study to date to concurrently collect drinking water samples, health information, and proximity data in relation to UO&G development. Self-reported information about perceived health in the community may serve as a useful complement to monitoring data (Gallagher et al., 2016). In addition, our study is one of the few exposure studies conducted in the Appalachian basin in Ohio. Our study focused its chemical analysis on UO&G-related health-relevant compounds and our sensitive laboratory analyses enabled us to investigate target compounds at lower levels than conventional techniques, which are focused on the MCLs. Although we observed associations between residential proximity to UO&G wells and drinking water contaminants, these data do not specifically indicate that UO&G activities are the source of contaminants and do not provide direct evidence for a link to health symptoms. However, the observed trends are consistent with and expand the literature on UO&G development and environmental health impacts. These findings underscore the need for further investigation and additional monitoring in a larger population and raise the question of whether UO&G activities are impacting municipal drinking water sources in the region.

5. Conclusion

In this community-based study in Belmont County, Ohio, we observed associations between residential proximity to UO&G wells and drinking water contaminants, particularly bromoform, dibromochloromethane, and GRO. We observed limited evidence of links between residential proximity to UO&G wells and health symptoms. Although these data do not definitively indicate UO&G activities as the source of the contaminants or health symptoms, the observed trends are consistent with and expand the literature on UO&G development and environmental health impacts. These findings underscore the need for further investigation and additional monitoring in a larger population and raise the question of whether UO&G activities are impacting municipal drinking water sources in the region.

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Associated contentSupporting information

Organic compound concentrations in drinking water and distance to nearest UO&G well, additional health information on target VOCs.Author contributions

EGE and NCD designed and implemented the study with input from DLP, XM, and BPL. CJP, CW, and CJG collected the field data under the supervision of NCD. EGE, TJW, and MB, performed the laboratory analyses under the supervision of DLP, with method development and analysis support provided by AJS. EGE, NCD led the statistical analyses with input from LAM, JLW, and GS. EGE and NCD drafted the initial manuscript. All authors provided input into data interpretation and reviewed and approved the manuscript.

Declaration of interest

We declare no competing financial interests.

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This work was partially funded by Yale Institute of Biospheric Studies and the Jan A. J. Stolwijk Fellowship, which had no role in the research.

Protection of human subjects

Protocols were approved by the Yale Institutional Review Board (HIC 1605017742). All participants provided informed consent prior to study activities.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at 10.1016/j.envres.2018.08.022.

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