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Supplemental Material

Towards Consistent Methodology to Quantify Populations in Proximity to Oil and Gas Development: A National Spatial Analysis and Review

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This Supplemental Appendix provides detailed tables of results from the proximal population study across all buffer distances, as well as a detailed discussion of the caveats and advantages of various population allocation methods.

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PART I: RESULTS TABLES

Buffer Distance	100 m		400 m		800 m		1000 m		1600 m		2000 m	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Total	320,000	–	3,710,000	–	8,890,000	–	11,300,000	–	17,600,000	–	21,300,000	–
Age 5 and under	23,400	7.3	280,000	7.6	686,000	7.7	875,000	7.8	1,370,000	7.8	1,660,000	7.8
Age under 18	75,600	23.6	891,000	24.0	2,150,000	24.2	2,730,000	24.2	4,270,000	24.2	5,160,000	24.2
Age 75 and older	20,600	6.4	239,000	6.4	558,000	6.3	700,000	6.2	1,080,000	6.2	1,300,000	6.1
Hispanic	34,000	10.6	432,000	11.6	1,240,000	13.9	1,660,000	14.8	2,900,000	16.5	3,680,000	17.3
Non-Hispanic Minority	36,400	11.4	422,000	11.4	1,150,000	12.9	1,520,000	13.5	2,560,000	14.5	3,200,000	15.0
Minority	51,700	16.2	610,000	16.4	1,680,000	18.9	2,240,000	19.9	3,820,000	21.7	4,810,000	22.6

Supplemental Material, Table S1. National population living in proximity to a confirmed-active oil and/or gas well, all buffer distances, by demographic.

Well Data Category	100 m		400 m		800 m		1000 m		1600 m		2000 m	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
Producing	318,000	99.5	3,690,000	99.3	8,790,000	98.9	11,100,000	98.7	17,300,000	98.2	20,900,000	98.0
Recently drilled	5,690	1.8	108,000	2.9	462,000	5.2	726,000	6.4	1,830,000	10.4	2,740,000	12.9
Oil	110,000	34.3	1,130,000	30.3	3,140,000	35.3	4,290,000	38.1	8,000,000	45.4	10,600,000	49.7
Wet gas	56,400	17.6	864,000	23.3	2,420,000	27.2	3,180,000	28.2	5,400,000	30.7	6,880,000	32.3
Dry gas	158,000	49.4	2,020,000	54.5	4,940,000	55.6	6,280,000	55.7	9,710,000	55.1	11,600,000	54.6

Supplemental Material, Table S2. National population living in proximity to a confirmed-active oil and/or gas well, all buffer distances, by well type and primary production category.

Note: Percentages sum to greater than 100 due to proximal overlap in well type buffers.

State	400 m	800 m	1600 m	State	400 m	800 m	1600 m
Ohio	762,000	2,090,000	2,800,000	***Virginia***	26,800	44,700	67,200
Texas	729,000	1,690,000	4,520,000	***Mississippi***	13,000	34,300	90,500
Pennsylvania	504,000	964,000	1,650,000	***Tennessee***	7,840	19,500	41,800
West Virginia	316,000	601,000	919,000	***Wyoming***	4,730	13,500	34,300
Oklahoma	312,000	868,000	1,750,000	***Utah***	4,020	13,000	31,900
California	273,000	762,000	2,090,000	***Montana***	3,620	9,980	27,700
Kentucky	133,000	261,000	407,000	***N. Dakota***	3,080	12,400	40,900
Colorado	131,000	255,000	429,000	***Florida***	680	2,350	7,620
New York	119,000	333,000	790,000	***Nebraska***	600	2,190	6,830
Louisiana	94,1000	255,000	639,000	***Missouri***	110	750	4,350
New Mexico	86,900	150,000	195,000	***Maryland***	38	140	610
Arkansas	64,000	175,000	302,000	***Oregon***	18	56	190
Kansas	50,800	154,000	373,000	***S. Dakota***	12	36	77
Michigan	45,400	117,000	297,000	***Arizona***	9	14	73
Alabama	28,800	54,000	97,100	***Nevada***	0	1	2

Supplemental Material, Table S3. Populations living in proximity to a confirmed-active oil and/or gas well, 400 m, 800 m, and 1600m buffers by state.

PART II. WELL TYPE UNCERTAINTY

The range of well type counts reflects uncertainty in the count of unconventional wells as classified according to producing formation. This method classifies 772 coalbed methane wells (CBM; as reported by state agencies) as unconventional and 38,990 CBM wells as conventional.

Coalbed methane has traditionally been defined as an unconventional resource, but in recent years is more commonly viewed as conventional. The unconventional category also includes 21,045 wells completed prior to commercial economic viability of high-volume hydraulic fracturing, horizontal drilling methods, and clustered development on multi-well pads (circa 2001; Wang and Krupnick 2013). While these wells may target unconventional geologic resources, they cannot be considered modern unconventional wells from a technological standpoint. The low end of the unconventional range (86,016 wells) is equal to the count of horizontal wellbores which report a producing formation matched to the EIA listing of tight formations. The high end of the unconventional count (106,428 wells) is equal to the number of wells classified, as per producing target, as unconventional which are not reported as a CBM well and/or completed prior to 2001. Conventional well counts are reported as the difference between total well count and unconventional well count.

PART III. POPULATION ALLOCATION METHODS

The method used in allocating population data to well spatial data can also cause large variance in reported results. The simplest method for allocating populations is spatial coincidence, whereby if an environmental health hazard is located within a population aggregation unit (census block, block group, tract), then the entire population of the block is assumed to be at risk. This method is limited and inflates the count of population at risk. Vector proximity apportionment and dasymetric mapping are more commonly used and result in relatively less error.

Vector proximity analysis overlays population aggregation units and a buffered distance surrounding environmental health hazard points to determine the population count within the buffer area of the hazard source. The most basic method is complete apportionment, wherein if any part of an aggregated population unit intersects the buffer, then the entire population of the unit is allocated to the buffer. This method differs slightly from spatial coincidence in that more than one population aggregation unit is potentially counted. Like the spatial coincidence method, this method also tends to overestimate the affected population, as demonstrated in results from Gold and McGinty (2013). Slightly improved versions allocate the entire population aggregation units only if a substantial portion of the population unit overlays the source buffer, or if residential portions of population aggregation unit, as determined by land-use maps, intersect the source buffer, as done in various ways by Ogneva-Himmelberger and Huang (2015). A significantly improved method is proportional population apportionment, used by Srebotnjak et al (2014), Ridlington et al. (2015), and the current study. This method assumes that populations are evenly distributed across aggregated population units, and allocates population based on the measured proportion of area intersection. A caveat to this method is that the assumption of an evenly distributed population is rarely valid, although the effect of this population heterogeneity is most limited at the smallest-level census unit, the block, used in this study.

Population can also be allocated by dasymetric mapping techniques. Dasymetry is an alternative aerial apportionment method that uses additional ancillary information, such as road networks, impervious surfaces, or, most commonly, land cover data to infer more granular information on where people live (Mennis 2003, 2015; Saporito et al. 2007; Sleeter 2004). This technique was incorporated in previous oil and gas proximity analyses by Slonecker and Milheim (2015), and Clough and Bell (2016). Their approach to dasymetry involved reclassifying a continuous surface of land cover data as residential or non-residential using binary coding. Counts attributed to aggregated population units were then transferred to the portion of the unit that was classified as residential, and from this point the analysis continued with proportional population apportionment. Using this type of dasymetry produces population allocation results that align with areas categorized in land cover datasets as developed. Hence, we could have applied dasymetric data to census enumeration units, in this case census blocks, to gain insight into where populations are distributed within each block, to address the common (but overly restrictive) assumption that populations are evenly distributed throughout census units. As census block data is already presented at a fine-grained scale, dasymetry is not as beneficial as it would have been had we used larger census units, such as block groups or census tracts, that inherently have greater heterogeneity, and thus we did not use dasymetry. One downside to dasymetry is that the ancillary data in most cases does not distinguish between types of developed urban land, and can therefore not differentiate between residential land and commercial or industrial land (Mennis 2003), which can result in the mis-allocation of populations to developed non-residential areas. In addition, raster land cover datasets are classified into land cover types by computer algorithms and are known to misclassify land use types in some cases (Hollister et al. 2004; Wickham et al. 2013). Also, land cover data provide no information on demographic distributions, such as age, race, or ethnicity. We could assume that demographics are distributed evenly throughout the populated areas of a census unit, but considering the history of racial and ethnic segregation geographically in this country (Fischer et al. 2004; Lee et al. 2008), that assumption would be unlikely to hold true.

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