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Mapping County-Level Exposure and Vulnerability to the US Energy Transition

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1. Introduction

The urgent challenge of climate change necessitates an energy transition at unprecedented speed and scale (National Academies of Science, Engineering, and Medicine 2021). As the United States seeks to deeply reduce greenhouse gas emissions, and as public policies coupled with innovation accelerate the deployment of clean energy and associated technologies, economic changes will occur across the nation. But where are those economic changes likely to be concentrated, and which communities might be most vulnerable to disruptions?

This analysis seeks to help answer those questions by combining a near-comprehensive view of fossil fuel activities at the county level with a range of socioeconomic, environmental, and public health indicators. The results can help policymakers better understand and prioritize which communities may be most vulnerable, and which may be most resilient, to accelerating changes in the US energy economy.

Several recent analyses have sought to achieve related goals. In the scholarly literature, Carley et al. (2018) develop a framework to evaluate county-level vulnerability associated with the energy transition, incorporating measures of exposure (e.g., job losses), sensitivity (e.g., share of population living in poverty), and adaptive capacity (e.g., institutional capacity). They apply the framework to the case of renewable portfolio standards, which reduce emissions but increase electricity costs, and focus on communities that are vulnerable to these higher costs.

Other recent work has reviewed the social outcomes of climate mitigation policies (Lamb et al. 2020), assessed transition-related socioeconomic and environmental risks for communities around the world (Sovacool et al. 2021), examined the vulnerability of low-income US households to higher energy costs (Brown et al. 2020), and proposed principles to guide policymakers (Muttitt and Kartha 2020; Bazilian et al. 2021). Scholars have also provided case studies of US coal communities, identifying challenges and proposing policy pathways to improve transition planning (Haggerty et al. 2018; Jolley et al. 2019; Roemer and Haggerty 2021). A recent analysis examines Appalachian communities, seeking to identify the main factors that help enable economic resilience as coal production has declined (Lobao et al. 2021).

Taking a similar approach to this analysis, Snyder (2018) combines fossil fuel employment data from the Bureau of Labor Statistics (BLS) with socioeconomic measures to create an index of energy transition vulnerability for US counties. The paper provides an analogue to the current analysis but is limited in two ways. First, it aggregates all fossil fuel employment into a single category. As discussed in more detail below, the risks from climate policies vary considerably across fuels and technologies, a dynamic that Snyder does not take into account. As a result, for example, counties in Wyoming, which dominates US coal production, do not appear near the top of the index. Second, the rationale for including and weighting various metrics in the index is not clear, making it difficult to know whether the most important contributors to vulnerability are truly reflected in the index.

In recent months, government entities and policy researchers have produced analyses to provide more practical guidance for policymakers. The White House Interagency Working Group on Coal and Power Plant Communities and Economic Revitalization recently identified 25 US regions where fossil energy activities are concentrated, grouping regions by BLS metropolitan and nonmetropolitan classifications (Interagency Working Group on Coal and Power Plant Communities and Economic Revitalization 2021). These groupings provide a useful starting point for understanding which regions are likely to be affected, but they offer limited geographic specificity and limited detail on socioeconomic and environmental risk factors.

To develop a more granular geographically picture of which communities are most dependent on fossil energy as an economic driver, I produced a series of maps identifying the counties where fossil energy accounts for large shares of employment and wages (Raimi 2021). However, these maps were incomplete because the BLS data that underpin them are often suppressed for low-population (typically rural) counties, which may be particularly vulnerable to the effects of the energy transition. In addition, that analysis did not incorporate additional measures of socioeconomic or environmental vulnerability.

The purpose of this analysis is to produce a tool that can guide policymakers in focusing attention and resources on the appropriate places at the appropriate time. To that end, it makes three main contributions. First, it identifies all US counties (or equivalent governmental units) that are heavily dependent on fossil energy as an economic driver, ranking them by the scale of the relevant energy activity. Second, it provides a high level of geographic specificity (county level). Third, it includes not only measures of energy activity but also metrics to assess the socioeconomic and environmental risk factors present in each county. Taken together, these metrics should give policymakers practical guidance on which US communities are most vulnerable to the economic effects of a transition away from fossil fuels. While this paper does not address the anticipated county-by-county benefits of a transition to clean energy, I do note that counties will experience different benefits from an energy transition.

Importantly, this analysis can (and will) be improved in the months ahead. Future work will seek to refine the relevant socioeconomic and environmental indicators, perhaps developing an index to more easily prioritize counties (though, as noted above and discussed more below, index creation presents methodological issues). In addition, it will seek to better characterize how effects may evolve over time in different locations. For example, ambitious climate policies are likely to cause more rapid declines in coal production than natural gas production, leading to differential timing between coal-producing and natural gas–producing communities. What's more, there is variation within fuels: coals, oils, and natural gases produced in different locations have different life-cycle emissions characteristics, and those with lower life-cycle emissions, better access to markets, and other economic advantages are likely to be most resilient, at least in the near to medium term.

2. Data and Methods

I gather energy data from multiple sources to create a near-comprehensive county-level database of fossil fuel extraction, oil refining, and electricity production capacity in the United States. Coal extraction data come from the US Energy Information Administration (EIA 2021c), which in turn sources its data from the US Department of Labor's Mine Safety and Health Administration. County-level oil and gas extraction data are more difficult to gather: information must be aggregated from multiple state agencies and private data providers. For this analysis, I collected 2019 oil and natural gas production data from state agencies in Alaska, Arkansas, California, Colorado, Mississippi, Montana, North Dakota, New Mexico, Ohio, Pennsylvania, Texas, Utah, and Wyoming. Gathering county-level production data from state agencies for Kansas, Oklahoma, Louisiana, and West Virginia proved more challenging, so I use 2018 data (complete 2019 data were not available) collected and processed by Upton and Yu (2021). In 2020, these 17 states accounted for more than 99 percent of US crude oil and natural gas production (excluding federal offshore production) (EIA 2021b, 2021a). Oil refining and electricity capacity data are from EIA.

Socioeconomic and environmental data come from a variety of sources. Data from the Appalachian Regional Commission (ARC), US Census, and USDA's Economic Research Service are provided at the county level and merged with the energy activity data. Data from the Environmental Protection Agency's EJScreen tool are provided at the census block level. To make these data comparable, I aggregate the census block data up to the county level, weighting each census block by population.

Many variables and data sources could be used to identify socioeconomic and environmental vulnerability, and choosing among the options is not straightforward. After reviewing dozens of candidate variables, analyzing correlations, and speaking with experts, I settled on 12 measures, each of which provides relevant information on vulnerability and most of which are weakly correlated with one another (discussed more below). This information is presented as a "dashboard" alongside metrics of energy activity, population, and energy activity per capita. Aggregate population figures are important because, all else equal, it would be logical to prioritize locations with larger numbers of people who may be affected by the energy transition. Of course, all else is not equal, so I include per capita measures, which are crucial to understanding the concentration of the energy activity for a given community.

I considered developing an index to aggregate these measures into a single score to reflect county-level vulnerability to the energy transition, but chose not to for the primary reason that it is unclear which metrics should be included and how one would assign weights to different elements of an index to accurately reflect vulnerability. As noted above, an index will be considered for future versions of this analysis, and research is available to guide the development of such an index (e.g., Flanagan et al. 2011; Cutter et al. 2013; Stafford and Abramowitz 2017). However, because policymakers are seeking quality information to help inform their decisionmaking today, I felt it was appropriate to publish the analysis in its current form.

Table 1 describes each variable, briefly notes the rationale for its inclusion, and identifies the underlying data source. The complete data set is available freely and publicly on RFF's website. You can access it at **https://www.rff.org/publications/data-tools/mapping-vulnerable-communities/.**

Table 1. Socioeconomic and Environmental Vulnerability Metrics

	Metric	Description	Rationale	Source
1	Population	2019 population estimate	Large populations may justify enhanced attention	US Census
2	Economic status	Index from 1 to 4 (4=distressed) based on 3-year average unemployment rates, per capita market income, and poverty rates	Higher economic distress increases vulnerability	ARC
3	Share bachelor's degree or higher	Share of population with at least bachelor's degree, 2019	Lower education levels increase vulnerability	USDA
4	Rurality	USDA's rural-urban continuum codes from 1 to 9 (1=most urban, 9=most rural)	Higher rurality increases vulnerability	USDA
5	Share minority population	Share of population that is nonwhite; includes Hispanic or Latino population	Racial minorities may face discrimination, increasing vulnerability	Census
6	Share linguistic isolation	Share of households that are linguistically isolated	Linguistic isolation may increase vulnerability	EPA EJScreen
7	Share pre-1960 housing	Share of households living in homes constructed before 1960 (lead paint indicator)	Older housing stock increases vulnerability	EPA EJScreen
8	Air toxics cancer risk	Nationwide percentile for lifetime cancer risk from inhalation of air toxics	Higher cancer risk increases vulnerability	EPA EJScreen
9	Toxic water discharges	Nationwide percentile for risk-screening environmental indicators modeled toxic concentrations at stream segments	More toxic water discharges increases vulnerability	EPA EJScreen
10	Superfund sites	Nationwide percentile for count of proposed or listed Superfund sites within 5 kilometers (or nearest one beyond 5 kilometers)	Proximity to Superfund sites increases vulnerability	EPA EJScreen
11	Ambient ozone	Nationwide percentile for ozone summer seasonal average of daily maximum 8-hour concentration in air, in parts per billion	Higher ozone levels increase vulnerability	EPA EJScreen
12	Ambient PM2.5	Nationwide percentile for PM2.5 levels in air, g/m3 annual average	Higher PM2.5 levels increase vulnerability	EPA EJScreen

Notes: For EPA EJScreen, data are aggregated from census block groups to the county level, with each block group weighted by population. ARC=Appalachian Regional Commission; USDA=US Department of Agriculture; BLS=Bureau of Labor Statistics; EPA=Environmental Protection Agency; EJ=Environmental Justice. PM2.5=particulate matter smaller than 2.5 microns.

Data sources: ARC 2020; EPA 2020; USDA Economic Research Service 2020, 2021; BLS 2021; US Census 2021.

As noted above, most of the metrics presented in the above table are poorly correlated with one another, suggesting that they provide independent, complementary information. However, three variables do show moderately high correlation, warranting further discussion. Table 2 reports the correlation scores between each metric.

Table 2. Correlation between Vulnerability Metrics

		1	2	3	4	5	6	7	8	9	10	11	12
1	Population		-0.13	0.32	-0.34	0.23	0.28	-0.04	0.20	0.23	0.26	0.05	0.16
2	Economic status	-0.13		-0.55	0.18	0.26	-0.04	-0.25	0.37	0.02	-0.07	-0.22	0.30
3	Bachelor's degree	0.32	-0.55		-0.40	-0.02	0.07	-0.04	-0.09	0.16	0.28	0.11	-0.09
4	Rurality	-0.34	0.18	-0.40		-0.15	-0.11	0.27	-0.38	-0.40	-0.51	-0.01	-0.34
5	Share minority	0.23	0.26	-0.02	-0.15		0.56	-0.30	0.37	0.02	0.00	-0.15	0.21
6	Share linguistic isolation	0.28	-0.04	0.07	-0.11	0.56		-0.05	0.05	0.01	0.00	0.09	0.03
7	Share pre-1960 housing	-0.04	-0.25	-0.04	0.27	-0.30	-0.05		-0.51	-0.08	-0.06	0.23	-0.27
8	Air toxics cancer risk	0.20	0.37	-0.09	-0.38	0.37	0.05	-0.51		0.28	0.24	-0.27	0.75
9	Toxic water discharges	0.23	0.02	0.16	-0.40	0.02	0.01	-0.08	0.28		0.34	0.09	0.32
10	Superfund sites	0.26	-0.07	0.28	-0.51	0.00	0.00	-0.06	0.24	0.34		-0.02	0.25
11	Ambient ozone	0.05	-0.22	0.11	-0.01	-0.15	0.09	0.23	-0.27	0.09	-0.02		-0.06
12	Ambient PM2.5	0.16	0.30	-0.09	-0.34	0.21	0.03	-0.27	0.75	0.32	0.25	-0.06	

Two pairs of metrics show moderate correlation, and one pair shows high correlation. Not surprisingly, metrics 2 (ARC's index of economic status) and 3 (share of population with a bachelor's degree or higher) are negatively correlated (r^2=-0.55), since counties with higher education levels can reasonably be expected to not to be in economic distress. I nonetheless include both metrics because the policy interventions needed to support a county in economic distress and low levels of educational attainment will likely look very different from those targeting communities that are not in economic distress and which have high levels of educational attainment. For example, a county heavily reliant on fossil fuel extraction may be economically prosperous even though its workers have relatively low levels of education because average wages in coal, oil, and natural gas extraction are well above economy-wide averages. However, if the extraction sector declined, that county's workforce would likely face challenges in transitioning to new sectors.

Also unsurprising is that metrics 5 (minority population) and 6 (linguistic isolation) are positively correlated (r^2=0.56), in part because the metric for minority population includes Hispanics and Latinos, who speak predominantly Spanish. Again, I choose to nonetheless include both metrics in this analysis because their policy implications differ considerably. For example, minority populations may face discrimination based on their physical appearance, whereas linguistically isolated populations would face other challenges, such as the need for language education to access the local labor market.

Finally, metrics 8 (air toxics cancer risk) and 12 (ambient fine particulate matter, PM2.5) are highly correlated (r^2=0.75). I choose to include both here because although they are often copollutants from facilities such as coal-fired power plants, and even from wildfires, they pose different health risks that may require different types of public health intervention (Woodruff et al. 1998; Tschofen et al. 2019).

3. Results and Analysis

This section provides a visual representation of which US counties are vulnerable to economic risks associated with a downturn in fossil fuels, and which additional metrics increase vulnerability. As noted in the previous section, these results represent an initial effort to characterize and categorize communities to inform policymakers' decisions on where to focus attention and resources as the country shifts away from coal, oil, and natural gas. The results do not indicate which communities may be vulnerable to other effects of the energy transition, particularly the potential for higher energy costs (see, e.g., Drehobl and Ross 2016; Ross et al. 2018; Carley et al. 2018; Bednar and Reames 2020).

How to interpret this section

This section is divided into six parts. The first three address extraction, the next two, power plants, and the last, oil refining. In each section, I begin with a US map that highlights the counties with the highest absolute level of the relevant activity. For extraction, this is the volume of resources extracted in a recent year. For power plants and refineries, this is the nameplate capacity of each plant in the county.

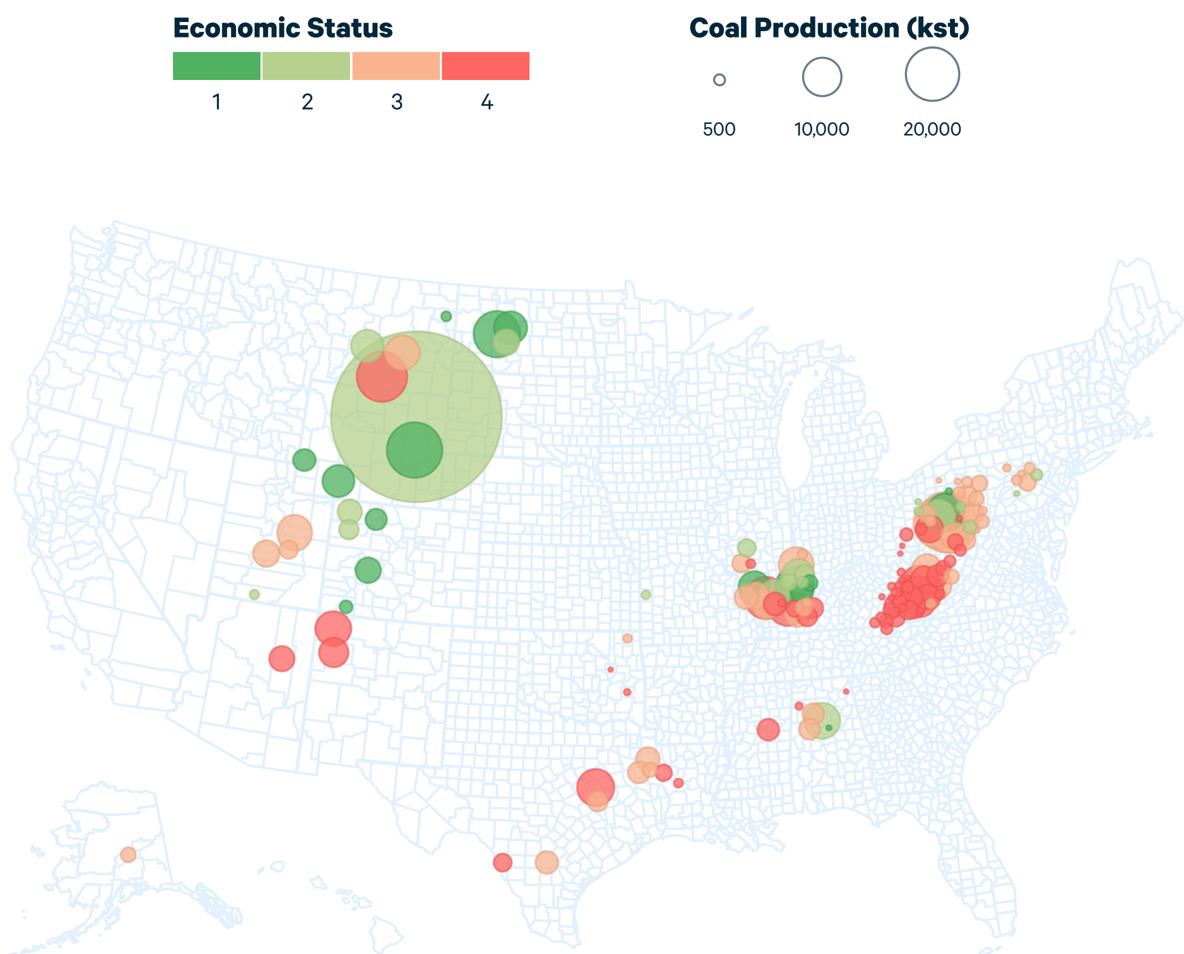
Each map displays county-level energy activity alongside the ARC's measure of economic status. Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates. Circle sizes represent the scale of energy activity in each county, while the color of the circle indicates the county's economic status. If you are interested in mapping the other metrics of socioeconomic or environmental vulnerability, please visit our interactive data tool available online at **https://www.rff.org/publications/data-tools/mapping-vulnerable-communities/**.

Following each map, I rank the top 25 counties for each energy activity on an absolute basis. Alongside that ranking, I provide recent population estimates and, for coal-fired power plants, the share of plant capacity that has been retired in recent years. Using those two metrics, I calculate the level of energy activity per capita in each county, which can serve as a useful proxy for the importance of the energy activity in the local economy.

3.1. Coal Production

Because it is the most carbon-intensive fuel, coal will almost certainly be the energy source that declines most rapidly under any ambitious set of climate policies. Indeed, US coal production has declined dramatically in recent years, though most of this decline has been due to market factors led by low-cost natural gas (Coglianese et al. 2020). Coal is produced mainly in Wyoming, Appalachia, and the Midwest, with limited production in other locations.

Figure 1. County-Level Coal Production in 2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

In 2019, more than one-third of all US coal was produced in Campbell County, Wyoming. This fact alone may make it the most vulnerable county in the nation to the energy transition. The county is near average nationally for most socioeconomic indicators, having relatively low environmental risk indicators with the exception of high ambient ozone levels. Among the remaining top 25 coal-producing counties, socioeconomic risk indicators are high for a substantial number of counties in Appalachia, the rural Southwest, and the rural Intermountain West. The most prominent environmental risk indicators are for toxic water discharges, which are well above average for most counties in the top 25, and ambient ozone concentrations.

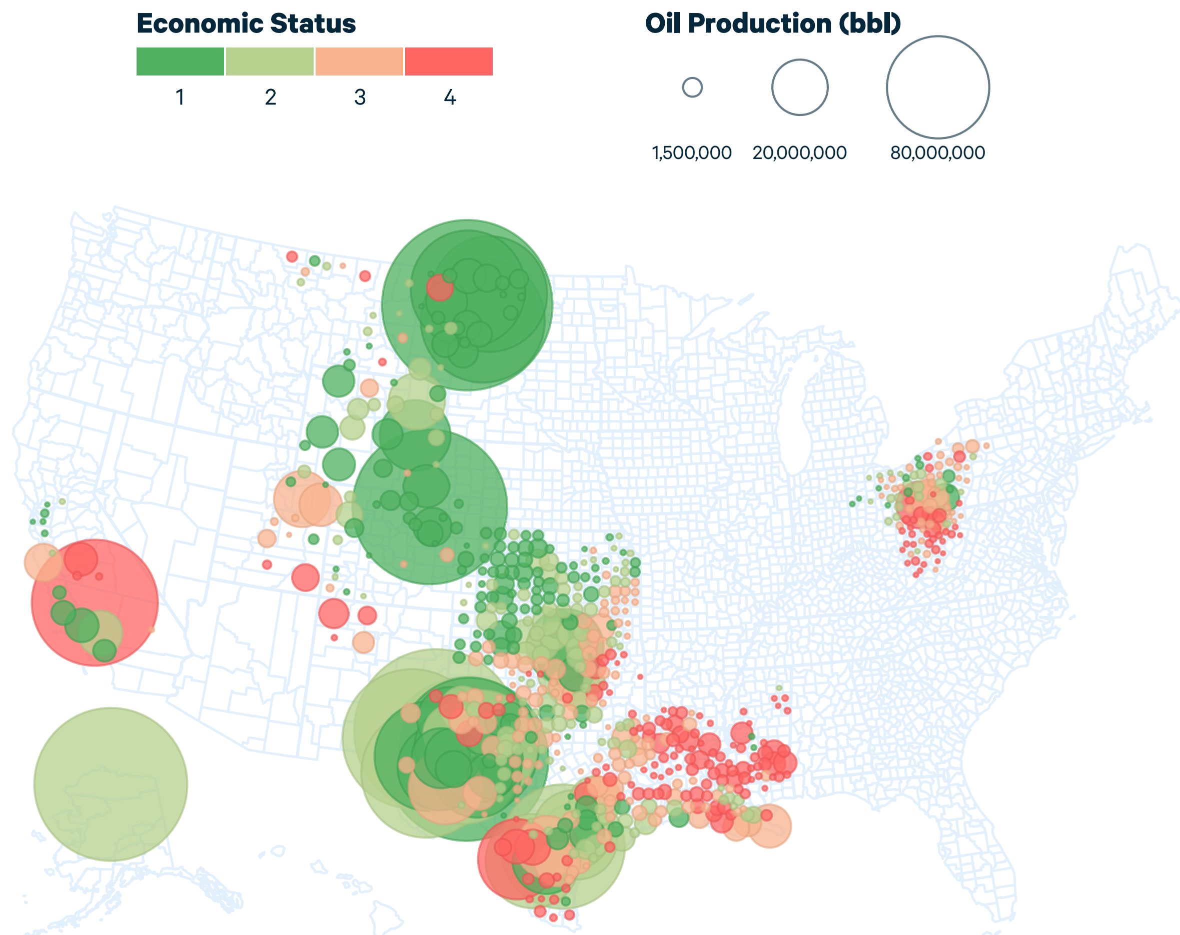
Table 3. Top 25 Coal-Producing Counties and Vulnerability Indicators

				Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	Population	Coal production (kst)	Coal production per capita	Economic status	Bachelor's degree	Rurality	Share minority population	Share linguistic isolation	Share pre-1960 housing	Air toxics cancer risk	Toxic water discharges	Superfund sites	Ambient ozone	Ambient PM2.5
Campbell County, WY	46,140	243,773	5.28	2	19%	5	12%	0%	4%	9%	61%	8%	95%	20%
Greene County, PA	36,506	28,306	0.78	3	18%	6	6%	0%	47%	51%	67%	53%	59%	65%
Converse County, WY	13,640	23,243	1.70	1	17%	6	11%	0%	18%	10%	63%	5%	96%	4%
Big Horn County, MT	13,338	18,700	1.40	4	18%	6	73%	0%	21%	14%	58%	26%	86%	23%
Marshall County, WV	30,785	18,319	0.60	3	18%	3	3%	0%	50%	49%	80%	87%	63%	64%
Mercer County, ND	8,267	15,617	1.89	1	22%	7	7%	3%	21%	6%	98%	1%	53%	8%
Marion County, WV	56,097	13,006	0.23	3	23%	4	7%	0%	50%	46%	87%	99%	45%	54%
Franklin County, IL	38,701	12,794	0.33	4	17%	4	4%	0%	46%	59%	94%	65%	88%	93%
Logan County, WV	32,607	11,473	0.35	4	10%	6	4%	0%	33%	67%	99%	35%	33%	49%
Union County, KY	14,505	11,342	0.78	4	11%	6	18%	0%	31%	59%	76%	47%	79%	81%
Gibson County, IN	33,452	10,150	0.30	1	18%	6	6%	0%	39%	53%	64%	60%	84%	84%
Washington County, PA	206,865	10,076	0.05	1	30%	1	8%	0%	46%	68%	74%	61%	79%	95%
Limestone County, TX	23,519	9,594	0.41	4	15%	6	41%	5%	18%	70%	34%	15%	56%	86%
San Juan County, NM	123,958	9,040	0.07	4	15%	3	61%	4%	12%	37%	92%	83%	98%	15%
Jefferson County, AL	659,300	8,900	0.01	2	33%	1	50%	1%	29%	99%	83%	87%	26%	99%
Rosebud County, MT	9,063	8,456	0.93	3	18%	9	45%	0%	17%	15%	79%	8%	85%	26%
Sullivan County, IN	20,690	8,302	0.40	3	12%	3	8%	0%	39%	43%	67%	59%	85%	77%
Carbon County, UT	20,269	8,047	0.40	3	17%	7	17%	1%	41%	15%	66%	9%	99%	9%
McLean County, ND	9,541	7,421	0.78	1	21%	8	11%	0%	35%	6%	71%	1%	42%	9%
Ohio County, WV	41,755	7,330	0.18	2	32%	3	8%	0%	57%	55%	83%	73%	71%	72%
Musselshell County, MT	4,651	7,019	1.51	2	16%	8	4%	1%	42%	6%	98%	31%	83%	18%
Sweetwater County, WY	43,051	6,828	0.16	1	22%	5	20%	3%	17%	11%	33%	4%	97%	12%
Raleigh County, WV	74,254	6,627	0.09	3	18%	3	13%	1%	31%	41%	87%	71%	41%	37%
Buchanan County, VA	21,221	6,606	0.31	4	12%	9	5%	0%	25%	66%	17%	46%	38%	39%
Knox County, IN	36,895	6,464	0.18	2	17%	5	7%	0%	49%	49%	69%	97%	86%	82%

3.2. Oil Production

US oil production has grown dramatically over roughly the past decade, led by parts of Texas, New Mexico, North Dakota, Colorado, and Oklahoma. However, substantial quantities of oil are produced in more than a dozen other states. In some states, production is highly concentrated in a small number of counties. In some states, such as California and Colorado, a downturn in oil production would have limited effects on the economy statewide but significant effects for the communities where energy activities are concentrated.

Figure 2. County-Level Crude Oil Production in 2018–2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

Largely because of the recent growth in oil production, economic status is relatively strong in most producing counties. However, common socioeconomic risk factors include relatively low education levels, along with high rurality and linguistic isolation, which could pose risks to future economic growth. The most prominent environmental risk indicators in these counties are high levels of air toxics and ambient ozone. Kern County, California, stands out as particularly at risk for three main reasons: (1) its high socioeconomic and environmental risk levels, (2) a lack of access to “tight oil” formations that have driven most of the recent US oil production growth, and (3) the high carbon intensity of most of its oil (Masnadi et al. 2018). Loving County, in the Permian Basin region of Texas, is the least populous county in the United States, which explains its very high per capita figures.

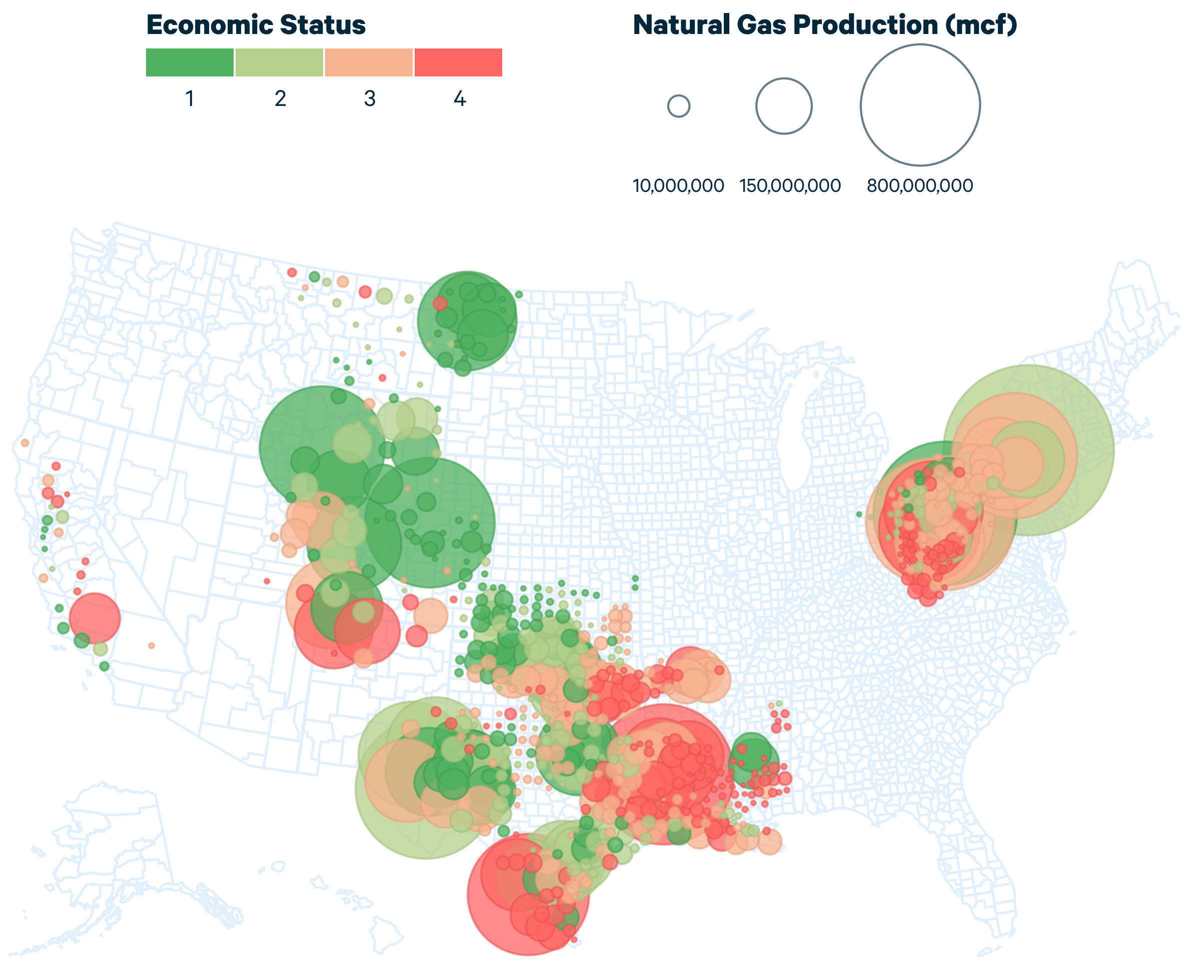
Table 4. Top 25 Crude Oil–Producing Counties and Vulnerability Indicators

				Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	Population	Oil production (bbl)	Oil production per capita	Economic status	Bachelor's degree	Rurality	Share minority population	Share linguistic isolation	Share pre-1960 housing	Air toxics cancer risk	Toxic water discharges	Superfund sites	Ambient ozone	Ambient PM2.5
McKenzie County, ND	13,632	206,231,512	15,128.49	1	26%	9	22%	4%	21%	43%	94%	1%	68%	8%
Midland County, TX	172,578	189,503,922	1,098.08	1	27%	3	54%	6%	21%	66%	13%	93%	91%	44%
Lea County, NM	71,070	188,631,200	2,654.16	2	14%	5	64%	6%	30%	45%	0%	19%	97%	39%
Weld County, CO	324,492	168,635,292	519.69	1	28%	2	34%	3%	15%	76%	87%	50%	99%	53%
North Slope Borough, AK	9,872	164,615,000	16,674.94	2	17%	7	69%	4%	7%	1%	0%	0%	0%	0%
Eddy County, NM	58,460	136,156,027	2,329.05	2	16%	5	52%	3%	33%	59%	16%	21%	98%	26%
Martin County, TX	5,753	134,016,957	23,295.14	1	18%	3	47%	4%	30%	52%	20%	59%	89%	41%
Reeves County, TX	15,695	116,180,451	7,402.39	2	12%	7	79%	11%	35%	69%	10%	32%	91%	25%
Kern County, CA	896,764	110,851,741	123.61	4	16%	2	65%	10%	20%	87%	40%	76%	100%	100%
Karnes County, TX	15,650	107,666,119	6,879.62	2	15%	6	63%	7%	32%	71%	89%	22%	16%	79%
Dunn County, ND	4,332	107,010,409	24,702.31	1	21%	9	16%	2%	35%	17%	70%	1%	56%	7%
Mountrail County, ND	10,218	92,549,430	9,057.49	1	20%	9	38%	1%	30%	36%	17%	0%	49%	6%
Williams County, ND	35,350	90,408,944	2,557.54	1	24%	7	19%	1%	23%	31%	94%	1%	63%	9%
Howard County, TX	36,459	87,623,802	2,403.35	2	13%	4	51%	2%	45%	53%	17%	32%	82%	38%
Loving County, TX	152	83,047,027	546,362.00	1	-	9	19%	9%	23%	69%	9%	44%	96%	28%
Upton County, TX	3,671	74,270,073	20,231.56	2	10%	8	58%	8%	42%	53%	0%	24%	73%	34%
La Salle County, TX	7,531	60,521,023	8,036.25	2	7%	6	85%	18%	23%	68%	70%	10%	14%	79%
Reagan County, TX	3,741	52,531,529	14,042.11	1	10%	6	72%	13%	30%	50%	0%	16%	64%	35%
Glasscock County, TX	1,388	51,106,016	36,819.90	1	27%	8	44%	11%	12%	51%	15%	39%	77%	38%
Ward County, TX	11,720	49,180,683	4,196.30	1	12%	6	59%	7%	32%	63%	9%	57%	90%	32%
DeWitt County, TX	20,187	41,828,686	2,072.06	2	13%	6	45%	4%	37%	67%	64%	20%	14%	78%
Gonzales County, TX	20,826	41,688,233	2,001.74	2	13%	6	58%	8%	27%	60%	72%	23%	19%	82%
Dimmit County, TX	10,308	41,036,494	3,981.03	4	14%	6	91%	11%	28%	78%	25%	8%	28%	77%
Andrews County, TX	18,705	39,498,552	2,111.66	1	12%	6	60%	11%	32%	54%	9%	48%	95%	37%
Kingfisher County, OK	15,765	38,781,744	2,459.99	1	22%	6	23%	4%	25%	61%	35%	29%	94%	52%

3.3. Natural Gas Production

Like oil, natural gas is produced at scale in hundreds of US counties, with top producers found in Pennsylvania, Louisiana, Texas, Colorado, Ohio, Wyoming, and New Mexico. Although it is less carbon intensive than coal or oil on an energy-equivalent basis (assuming methane emissions are kept to low levels), US natural gas production will need to decline in the coming decades to achieve ambitious climate targets.

Figure 3. County-Level Natural Gas Production in 2018–2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

Socioeconomic indicators are mixed across the top 25 producing counties, with relatively strong indicators for most Pennsylvania counties (with the exception of older housing stock), and more worrisome indicators for several counties scattered in Appalachian Ohio, West Virginia, Louisiana, and Texas. Environmental risk indicators vary widely but are generally highest for exposure to air toxics, toxic water discharges, and ambient ozone. Tarrant County, home of Fort Worth, has by far the largest population among these counties, and although its socioeconomic indicators are relatively strong, environmental risk indicators are in the 80th percentile or higher across all measures.

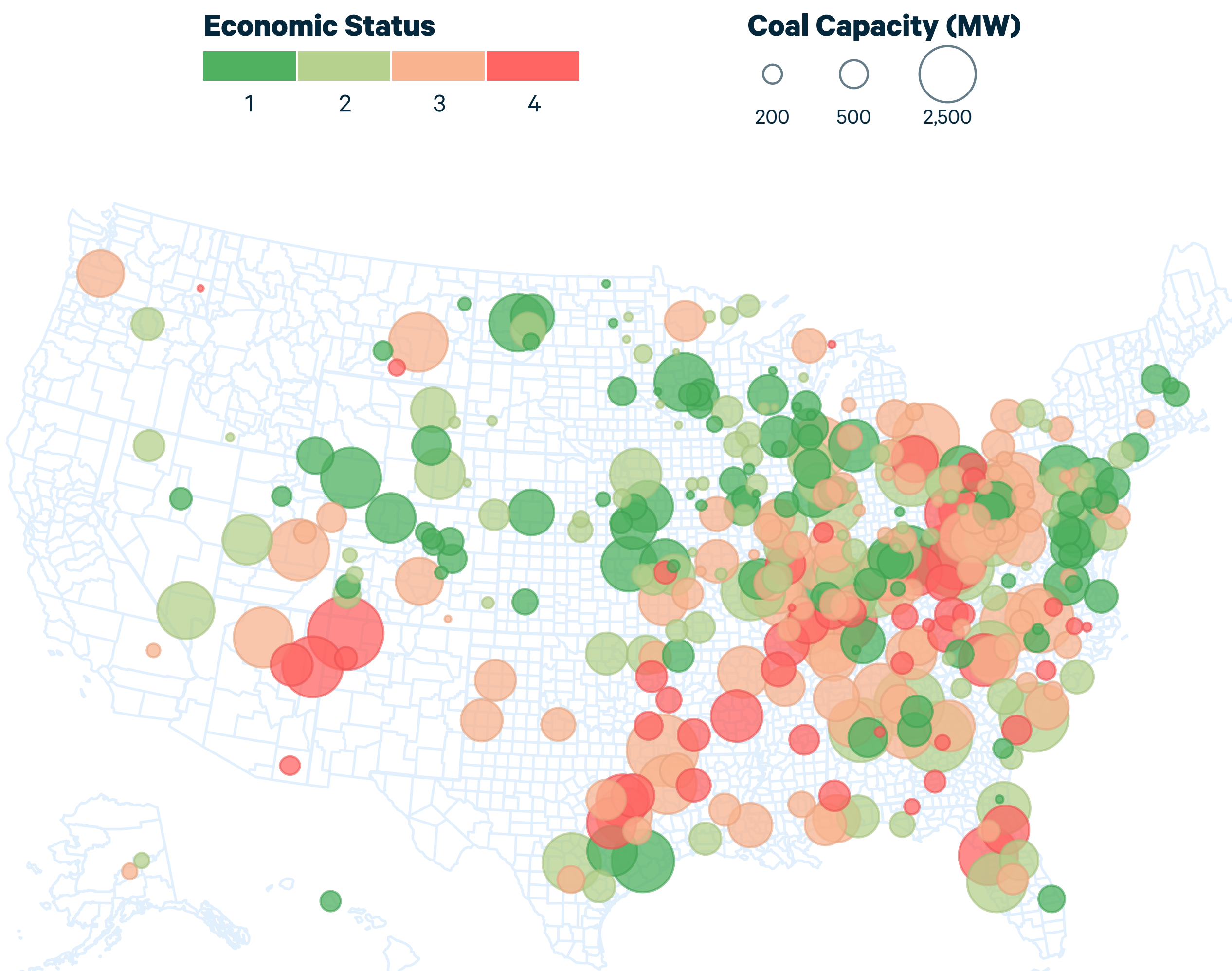
Table 5. Top 25 Natural Gas–Producing Counties and Vulnerability Indicators

				Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	Population	Natural gas production (mcf)	Natural gas production per capita	Economic status	Bachelor's degree	Rurality	Share minority population	Share linguistic isolation	Share pre-1960 housing	Air toxics cancer risk	Toxic water discharges	Superfund sites	Ambient ozone	Ambient PM2.5
Susquehanna County, PA	40,589	1,668,056,109	41,096.26	2	19%	6	4%	0%	40%	44%	47%	82%	19%	32%
Washington County, PA	206,865	1,183,968,938	5,723.39	1	30%	1	8%	0%	46%	68%	74%	61%	79%	95%
Reeves County, TX	15,695	1,122,347,608	71,188.58	2	12%	7	79%	11%	35%	69%	10%	32%	91%	25%
De Soto Parish, LA	26,812	1,117,304,841	41,859.90	4	15%	2	42%	1%	18%	96%	55%	53%	22%	95%
Greene County, PA	36,506	1,019,005,117	27,913.36	3	18%	6	6%	0%	47%	51%	67%	53%	59%	65%
Weld County, CO	324,492	956,923,449	2,948.99	1	28%	2	34%	3%	15%	76%	87%	50%	99%	53%
Belmont County, OH	67,006	932,978,408	13,923.80	3	17%	3	7%	0%	51%	48%	87%	78%	65%	67%
Sublette County, WY	9,813	889,098,117	90,604.11	1	23%	9	11%	0%	18%	2%	0%	9%	96%	5%
Bradford County, PA	60,833	886,195,777	14,567.68	3	19%	6	4%	0%	44%	25%	75%	75%	20%	30%
Webb County, TX	275,910	827,815,898	3,000.31	4	19%	2	97%	23%	10%	99%	70%	4%	13%	91%
Eddy County, NM	58,460	648,449,798	11,092.20	2	16%	5	52%	3%	33%	59%	16%	21%	98%	26%
Monroe County, OH	13,654	565,221,544	41,396.04	4	13%	8	3%	0%	44%	47%	99%	78%	53%	60%
McKenzie County, ND	13,632	541,428,319	39,717.45	1	26%	9	22%	4%	21%	43%	94%	1%	68%	8%
Lea County, NM	71,070	540,085,508	7,599.35	2	14%	5	64%	6%	30%	45%	0%	19%	97%	39%
Jefferson County, OH	65325	533,624,686	8,168.77	4	16%	3	10%	1%	51%	62%	95%	52%	65%	81%
Garfield County, CO	60,061	488,311,722	8,130.26	1	31%	5	32%	4%	14%	21%	85%	24%	96%	2%
Panola County, TX	23,148	445,420,026	19,242.27	3	16%	6	27%	1%	18%	96%	37%	50%	26%	93%
Midland County, TX	172,578	440,643,742	2,553.30	1	27%	3	54%	6%	21%	66%	13%	93%	91%	44%
Doddridge County, WV	8,406	439,199,421	52,248.33	3	17%	9	5%	0%	36%	75%	34%	65%	31%	53%
Loving County, TX	152	424,924,466	2,795,556.00	1	-	9	19%	9%	23%	69%	9%	44%	96%	28%
Montezuma County, CO	26,183	420,374,880	16,055.26	3	30%	6	27%	1%	20%	6%	37%	24%	96%	4%
Tarrant County, TX	2,084,931	390,831,194	187.46	1	32%	1	53%	7%	16%	80%	82%	80%	87%	92%
Lycoming County, PA	113,299	375,086,444	3,310.59	3	23%	3	9%	0%	49%	48%	79%	96%	36%	65%
Karnes County, TX	15,650	373,681,488	23,877.41	2	15%	6	63%	7%	32%	71%	89%	22%	16%	79%
Culberson County, TX	2,204	372,587,203	169,050.50	3	10%	9	76%	28%	30%	36%	0%	5%	89%	15%

3.4. Coal-Fired Power Plants

Dozens of coal-fired power plants have been retired in recent decades, and absent widespread deployment of carbon capture, utilization, and storage (CCUS), coal-fired generation will need to approach zero in the coming decades to achieve ambitious climate goals. The map below indicates operating and retired coal power capacity, with plants scattered across the country. Concentrations are found in part of Appalachia, the industrial Midwest, and the Southeast. However, as with fossil fuel extraction, effects are likely to be most acute in rural regions, where these plants play an outsized role in supporting local jobs and tax revenue.

Figure 4. County-Level Coal-Fired Power Plant Capacity in 2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

The top five counties with the highest aggregate capacity of coal-fired power are also classified as having economic distress. A substantial number of counties in the top 25 also have relatively low education rates, highlighting the potential need for workforce retraining. Environmental indicators vary widely across the group but generally show high levels of toxic water discharges, which may be associated with ponds that store toxic coal ash, and PM concentrations, which may be associated with the high levels of PM generated from coal combustion. In some locations (e.g., San Juan County, New Mexico, and Titus County, Texas), a large amount of capacity has been retired in recent years. What's more, additional unit and plant retirements have occurred since these data were published, meaning that for several counties, the share of retired capacity today is higher than shown in the table.

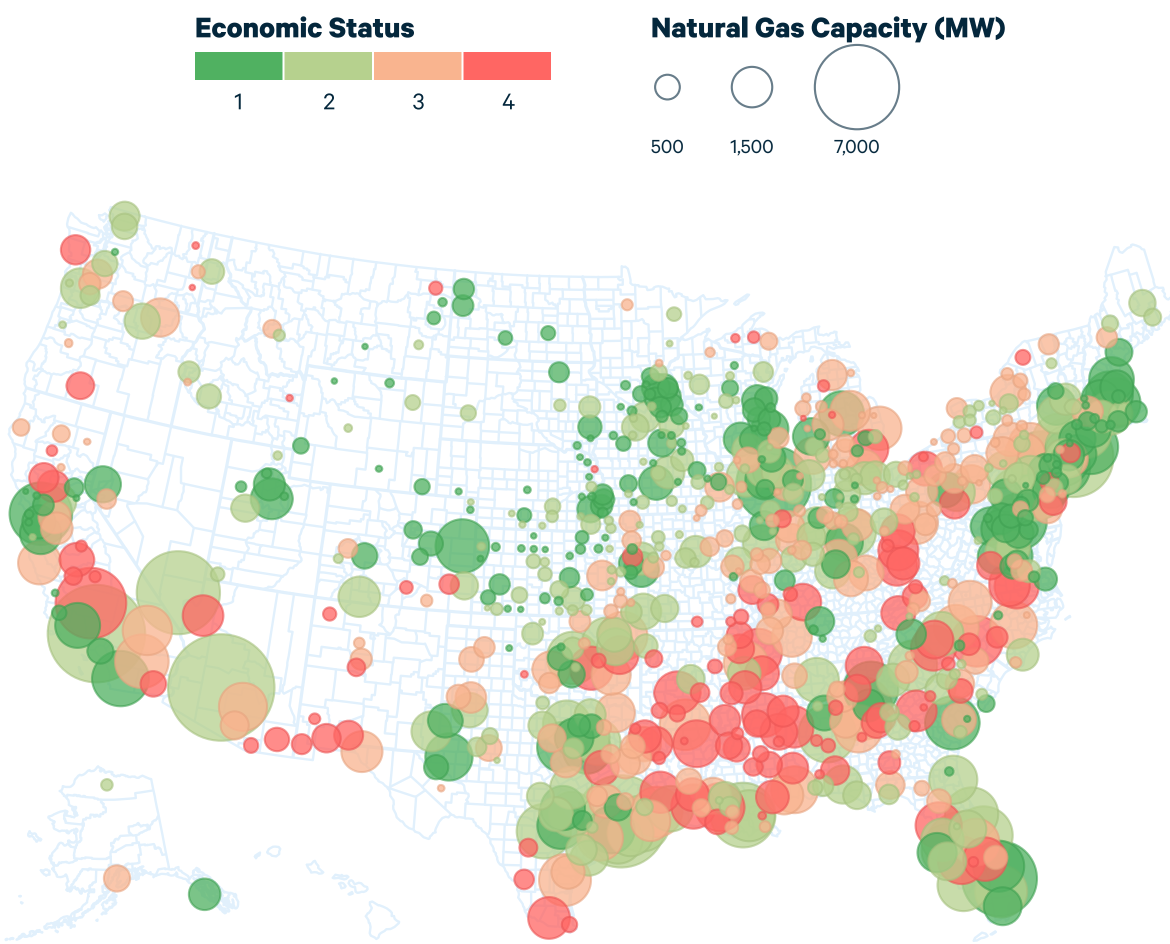
Table 6. Top 25 Coal-Fired Power Plant Counties and Vulnerability Indicators

					Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	**Population**	**Coal capacity (MW)**	**Share retired**	**Coal capacity per 100 capita**	**Economic status**	**Bachelor's degree**	**Rurality**	**Share minority population**	**Share linguistic isolation**	**Share pre-1960 housing**	**Air toxics cancer risk**	**Toxic water discharges**	**Superfund sites**	**Ambient ozone**	**Ambient PM2.5**
Indiana County, PA	84,501	4,766	5%	5.64	3	23%	4	6%	1%	40%	35%	76%	49%	72%	97%
Jefferson County, OH	65,325	4,509	4%	6.90	4	16%	3	10%	1%	51%	62%	95%	52%	65%	81%
San Juan County, NM	123,958	4,118	38%	3.32	4	15%	3	61%	4%	12%	37%	92%	83%	98%	15%
Gallia County, OH	29,898	3,687	0%	12.33	4	16%	6	7%	1%	22%	63%	88%	75%	43%	63%
Titus County, TX	33,033	3,654	69%	11.06	3	16%	7	55%	7%	16%	87%	72%	28%	39%	90%
Monroe County, MI	150,500	3,625	10%	2.41	2	21%	3	9%	0%	36%	37%	69%	67%	73%	66%
Monroe County, GA	27,520	3,564	0%	12.95	2	27%	3	28%	1%	13%	98%	93%	60%	27%	95%
Bartow County, GA	107,738	3,499	0%	3.25	2	19%	1	22%	2%	10%	93%	41%	49%	41%	96%
Berkeley County, SC	221,091	3,395	10%	1.54	2	25%	2	36%	2%	5%	93%	87%	76%	13%	56%
Gibson County, IN	33,452	3,340	0%	9.98	1	18%	6	6%	0%	39%	53%	64%	60%	84%	84%
Person County, NC	39,507	3,321	0%	8.41	3	16%	2	34%	1%	21%	73%	89%	90%	57%	58%
St. Clair County, MI	159,128	3,144	17%	1.98	3	19%	1	9%	0%	35%	36%	39%	56%	60%	64%
Putnam County, WV	56,682	2,933	0%	5.17	2	26%	2	4%	0%	15%	87%	94%	86%	44%	73%
Jefferson County, AL	659,300	2,822	0%	0.43	2	33%	1	50%	1%	29%	99%	83%	87%	26%	99%
Muhlenberg County, KY	30,774	2,822	59%	9.17	4	13%	6	8%	0%	23%	69%	90%	74%	56%	72%
Beaver County, PA	163,929	2,741	100%	1.67	2	25%	1	10%	1%	54%	62%	89%	74%	81%	98%
Fort Bend County, TX	787,858	2,737	0%	0.35	1	46%	1	66%	6%	2%	80%	89%	77%	17%	96%
Milwaukee County, WI	948,201	2,654	0%	0.28	3	31%	1	48%	4%	62%	45%	98%	85%	68%	38%
Clermont County, OH	206,428	2,647	46%	1.28	1	29%	1	6%	0%	20%	56%	78%	87%	87%	87%
Emery County, UT	10,014	2,615	0%	26.11	3	16%	7	9%	1%	26%	8%	61%	6%	99%	7%
Spencer County, IN	20,327	2,600	0%	12.79	1	15%	8	5%	0%	28%	62%	90%	79%	79%	83%
Stewart County, TN	13,561	2,600	0%	19.17	3	16%	8	8%	0%	14%	71%	58%	29%	49%	55%
Apache County, AZ	71,818	2,588	0%	3.60	4	12%	6	82%	17%	6%	9%	72%	17%	96%	2%
Sweetwater County, WY	43,051	2,513	0%	5.84	1	22%	5	20%	3%	17%	11%	33%	4%	97%	12%
Stokes County, NC	45,467	2,491	0%	5.48	3	14%	2	9%	1%	15%	67%	82%	54%	68%	46%

3.5. Natural Gas-Fired Power Plants

Like natural gas production, gas-fired power plants will tend to outlast coal because of their lower emissions intensity (so long as methane emissions are minimal). However, ambitious climate scenarios over next several decades will require most gas-fired power to adopt CCUS technologies, incorporate net-zero fuels such as biogas or hydrogen, or be retired. Existing capacity is concentrated in and around urban centers, allowing generators to respond quickly to increased demand during peak periods (e.g., hot summer days).

Figure 5. County-Level Natural Gas-Fired Power Plant Capacity in 2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

Because they are some of the nation's most populous counties, leading natural gas power plant counties show relatively strong socioeconomic indicators but also high levels of environmental and public health risks. Los Angeles County is a prime example. It is a thriving metropolis with high levels of income and education, but it is also home to a large population that suffers from environmental justice concerns. Two counties stand out as having particularly worrisome socioeconomic indicators: Kern County, California, which is also highly vulnerable to a downturn in oil production; and Heard County, Georgia, which has very high levels of capacity per capita coupled with relatively high economic stress and low education levels.

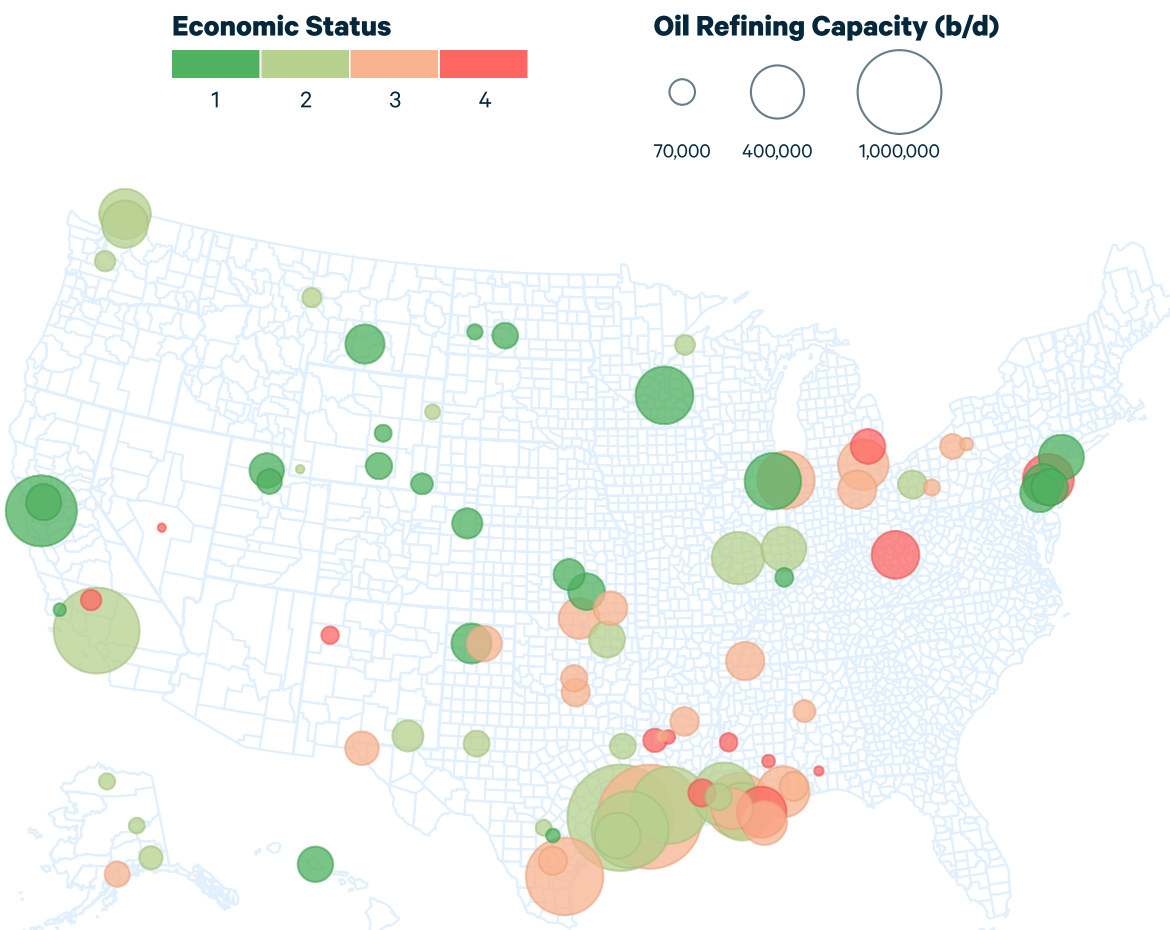
Table 7. Top 25 Natural Gas-Fired Power Plant Counties and Vulnerability Indicators

				Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	Population	Natural gas capacity (MW)	Natural gas capacity per 1,000 capita	Economic status	Bachelor's degree	Rurality	Share minority population	Share linguistic isolation	Share pre-1960 housing	Air toxics cancer risk	Toxic water discharges	Superfund sites	Ambient ozone	Ambient PM2.5
Maricopa County, AZ	4,410,824	11,691	2.65	2	33%	1	44%	5%	8%	97%	95%	83%	99%	51%
Los Angeles County, CA	10,014,009	9,709	0.97	2	33%	1	74%	13%	48%	94%	99%	95%	98%	99%
Harris County, TX	4,698,619	8,290	1.76	2	31%	1	70%	13%	14%	98%	93%	92%	23%	98%
Clark County, NV	2,231,647	6,984	3.13	2	24%	1	57%	7%	3%	85%	99%	3%	99%	27%
Queens County, NY	2,405,464	6,449	2.68	2	32%	1	75%	19%	68%	94%	98%	95%	41%	52%
Palm Beach County, FL	1,496,770	5,616	3.75	1	37%	1	45%	8%	9%	61%	43%	82%	1%	41%
Will County, IL	692,310	5,576	8.05	1	34%	1	36%	3%	16%	62%	94%	80%	88%	92%
Polk County, FL	724,777	5,259	7.26	3	20%	2	40%	4%	12%	85%	84%	83%	4%	65%
Kern County, CA	896,764	4,925	5.49	4	16%	2	65%	10%	20%	87%	40%	76%	100%	100%
St. Charles Parish, LA	52,879	4,112	77.76	2	25%	1	35%	1%	14%	100%	91%	61%	16%	77%
Heard County, GA	11,879	3,967	333.95	3	9%	1	15%	1%	15%	93%	67%	25%	22%	93%
Contra Costa County, CA	1,150,215	3,793	3.30	1	42%	1	56%	7%	23%	63%	95%	85%	17%	99%
Northampton County, PA	304,807	3,599	11.81	1	30%	2	23%	3%	45%	99%	75%	94%	40%	91%
Brevard County, FL	606,392	3,241	5.35	2	30%	2	25%	2%	7%	64%	44%	82%	3%	35%
Autauga County, AL	55,601	3,171	57.02	2	27%	2	25%	1%	7%	99%	70%	78%	17%	96%
San Diego County, CA	3,343,364	3,116	0.93	1	39%	1	54%	7%	18%	85%	98%	59%	79%	93%
Chambers County, TX	42,454	3,034	71.47	2	23%	1	33%	6%	8%	81%	69%	76%	13%	77%
Prince George County, MD	909,308	3,015	3.32	1	33%	1	87%	6%	24%	82%	62%	89%	70%	77%
Middlesex County, NJ	829,685	2,996	3.61	1	44%	1	56%	9%	34%	75%	87%	99%	47%	65%
Cobb County, GA	790,588	2,848	3.60	1	47%	1	48%	4%	6%	98%	43%	32%	60%	98%
Bexar County, TX	1,986,049	2,835	1.43	2	28%	1	72%	7%	18%	73%	87%	92%	43%	93%
Effingham County, GA	64,296	2,834	44.08	1	20%	2	21%	1%	8%	86%	51%	40%	8%	71%
Suffolk County, NY	1,481,093	2,824	1.91	1	36%	1	32%	4%	33%	45%	35%	96%	66%	22%
Union County, NJ	558,067	2,765	4.96	1	36%	1	60%	13%	60%	79%	78%	97%	35%	78%
Kit Carson County, CO	7,097	2,751	387.67	1	19%	7	23%	4%	33%	9%	32%	12%	80%	7%

3.6. Oil Refining

Oil refineries are essential components of today's energy system, but they are also major polluters—of both greenhouse gases and air emissions that pose considerable health risks to nearby populations. The United States is home to the largest fleet of oil refineries in the world, centered along the Gulf Coast, with most other refineries located close to major population centers. Little public information is currently available on the outlook for domestic refining under ambitious climate scenarios.

Figure 6. County-Level Oil-Refining Capacity in 2019



Note: Economic status levels are determined by the ARC based on 3-year averages of county-level unemployment rates, per capita market income, and poverty rates.

Most of the nation’s top refining counties have a large share of minority population and high levels of environmental risk, highlighting the fact that environmental injustice continues to disproportionately affect communities of color. Environmental risks from air toxics, water discharges, proximity to Superfund sites, and PM2.5 are extremely high—some of these counties place in the top 1 percent of all US counties. Some also show economic distress and low levels of education, particularly along the Gulf Coast.

Table 8. Top 25 Oil-Refining Counties and Vulnerability Indicators

				Socioeconomic indicators						Environmental risk indicators (National percentiles)				
Location	**Population**	**Oil refining capacity (b/d)**	**Oil refining capacity per capita**	**Economic status**	**Bachelor's degree**	**Rurality**	**Share minority population**	**Share linguistic isolation**	**Share pre-1960 housing**	**Air toxics cancer risk**	**Toxic water discharges**	**Superfund sites**	**Ambient ozone**	**Ambient PM2.5**
Harris County, TX	4,698,619	1,603,505	0.34	2	31%	1	70%	13%	14%	98%	93%	92%	23%	98%
Jefferson County, TX	251,565	1,536,524	6.11	3	20%	2	59%	5%	25%	100%	88%	83%	9%	89%
Los Angeles County, CA	10,014,009	1,030,800	0.10	2	33%	1	74%	13%	48%	94%	99%	95%	98%	99%
Nueces County, TX	362,265	825,000	2.28	3	22%	2	70%	4%	26%	28%	60%	80%	2%	82%
Calcasieu Parish, LA	203,112	813,500	4.01	2	22%	3	32%	2%	21%	100%	90%	89%	10%	80%
Galveston County, TX	342,139	810,000	2.37	2	31%	1	42%	3%	14%	80%	92%	85%	14%	73%
Contra Costa County, CA	1,150,215	682,871	0.59	1	42%	1	56%	7%	23%	63%	95%	85%	17%	99%
St. John the Baptist Parish, LA	43,184	578,000	13.38	3	16%	1	65%	2%	12%	100%	57%	48%	16%	80%
East Baton Rouge Parish, LA	456,781	517,700	1.13	2	35%	2	55%	2%	15%	100%	91%	80%	15%	97%
St. Charles Parish, LA	52,879	442,400	8.37	2	25%	1	35%	1%	14%	100%	91%	61%	16%	77%
Dakota County, MN	425,423	438,000	1.03	1	42%	1	21%	2%	11%	50%	75%	84%	27%	35%
Lake County, IN	498,700	435,000	0.87	3	23%	1	46%	2%	43%	54%	93%	99%	85%	81%
Will County, IL	692,310	417,865	0.60	1	34%	1	36%	3%	16%	62%	94%	80%	88%	92%
Jackson County, MS	143,277	356,440	2.49	3	21%	2	32%	1%	11%	83%	47%	82%	22%	79%
Madison County, IL	264,461	356,000	1.35	2	27%	1	15%	1%	36%	82%	98%	93%	95%	90%
Whatcom County, WA	225,685	347,000	1.54	2	34%	3	21%	2%	22%	69%	69%	91%	3%	22%
Philadelphia County, PA	1,584,064	335,000	0.21	4	30%	1	65%	7%	71%	86%	100%	96%	74%	94%
Lucas County, OH	428,348	327,800	0.77	3	26%	2	31%	1%	49%	44%	63%	36%	70%	74%
St. Bernard Parish, LA	46,721	315,000	6.74	4	12%	1	37%	2%	15%	87%	62%	84%	16%	63%
Boyd County, KY	47,240	291,000	6.16	4	19%	2	7%	0%	33%	76%	79%	94%	37%	63%
Brazoria County, TX	374,264	265,000	0.71	2	30%	1	52%	4%	10%	83%	88%	77%	11%	87%
Skagit County, WA	128,206	264,000	2.06	2	26%	3	25%	3%	25%	48%	33%	70%	3%	17%
Union County, NJ	558,067	258,500	0.46	1	36%	1	60%	13%	60%	79%	78%	97%	35%	78%
Plaquemines Parish, LA	23,410	255,600	10.92	3	19%	1	36%	2%	8%	71%	67%	73%	16%	49%
Crawford County, IL	18,807	253,000	13.45	2	17%	7	12%	1%	47%	58%	98%	63%	87%	85%

4. Conclusion

Transitioning away from carbon-intensive energy sources is an urgent priority to limit the damages to society from climate change. However, the transition will also have concentrated costs for communities where fossil fuels are a current lynchpin of local economic activity, employment, and public revenues. This analysis provides an initial effort to identify which US counties are most vulnerable to the energy transition because of high levels of fossil fuel activities plus socioeconomic and environmental risk factors that may exacerbate local challenges. While the analysis does not address the specific benefits of a transition to clean energy for each county, I note that counties will benefit in different ways from an energy transition. Policymakers, businesses, and other stakeholders can use this analysis and refine it to better understand how to allocate resources to reduce or prevent the local economic, social, and public health challenges associated with the energy transition.

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