# COMMUNITY ARCHETYPES IN THE PERMIAN BASIN AND THEIR RELATIONSHIP TO ENERGY RESOURCES

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## EXECUTIVE SUMMARY

The Permian Energy Development Lab (PEDL) is a new research coalition in West Texas and Southeastern New Mexico, managed by a consortium of higher education, public sector, civic, community, and philanthropic organizations[1]. PEDL's mission is to catalyze advanced energy research, prepare new energy professionals and entrepreneurs, and create value for energy communities.

To meet the three parts of this mission, a comprehensive facts-based understanding of the diverse communities within the large Permian region, not relying on impressions or preconceptions, is essential. Therefore, this report is intended to serve as a foundational data-focused description of Permian Basin communities at the county-level, illustrating the differences and commonalities between the communities. This report focuses on the region's strengths and needs, especially regarding its relationship (past, present, and future) with the energy industry. The report provides a framework to simplify the study a large and diverse geographic area grounded by aligning counties based on shared properties rather than just physical location. The framework of archetypes presented can also be used to help design and implement future energy technology research, educational, and outreach programs to equitably develop and deploy advanced energy technologies that benefit the communities in the Permian Basin.

The core Permian Basin is a region that covers more than 51,000 square miles and includes 50 counties in Southeastern New Mexico and Western Texas PEDL also includes counties adjacent to the Permian Basin in outreach and research efforts; thus, the analysis in this paper includes 66 counties. Through cluster and socioeconomic analyses, we identified seven distinct community archetypes in the Permian region at the county-level; values in parentheses indicate the number of counties within each archetype:

- Archetype 1: High oil and gas (O&G) production (4)
- Archetype 2: High renewable energy capacity (8)
- Archetype 3: Very small populations and population loss (17)
- Archetype 4: High percent of residents with less than high school education (9)
- Archetype 5: High unemployment and high percent of residents with less than high school education (26)
- Archetype 6: Exceptionally small population with high gross domestic product (GDP) and very high O&G production (1)
- Archetype 7: Very high population gain (1)

[1] More information about PEDL and its founding partners can be found at https://pedl.tech.

One goal of the clustering effort was to characterize the profile of the Permian Basin and facilitate deeper community engagement. Indeed, starting with a set 66 counties, 64 counties could be accurately described in just five archetypes with remaining two counties parsing into unique archetypes, based on population and economic dynamics. In addition to facilitating community engagement, these archetypes highlight the diversity and commonalities within the Permian, with some archetypes containing a substantial number of Permian basins (e.g., Archetypes 3 and 5) while others highlight unique nature of individual counties (e.g., Archetypes 6 and 7).

The main utility of the archetypes is to allow for more informed sampling across the expanse and diversity of Permian counties for future research activities in the region. After describing the archetypes, this report suggests future research and engagement activities. By leveraging the patterns illuminated by the archetypes, PEDL can produce community-engaged research, workforce development, and in-community activities that are more tailored to the diverse community landscape of the Permian.

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# PERMIAN BASIN

The Permian Basin is a region that covers more than 51,000 square miles and includes 50 counties[2] in Southeastern New Mexico and Western Texas (Fairhurst et al., 2021). Whereas subsistence farming and ranching supported early settlement of the region, the oil and gas (O&G) industry has dominated the region economically since the early twentieth century, producing more than 28 billion barrels (BBL) of oil and 203 trillion cubic feet (CF) of natural gas between 1920 and 2019 (Ko et al., 2023). Carbon-based energy production has continued to grow in the Permian, with oil production reaching more than 5.5 million BBL per day and natural gas approaching 24 billion CF per day in mid-2023. Future reserves continue to be significant as well, with Fairhurst et al. (2021) reporting that the Permian will be able to produce for decades, with 120 to 137 billion barrels of oil equivalent (BOE) remaining—"twice the volume produced during the first 100 years of hydrocarbon production" (p. 1099). Direct O&G jobs doubled between 2009 and 2019 to toal >87,600.However, O&G jobs in the Permian are declining. Between September 2019 and September 2020, Texas saw more than 76,000 O&G jobs lost (Chase, 2022). Beyond market forces, innovation in the O&G sector is leading to fewer jobs required to support production. Indeed, new O&G jobs created post pandemic still lag 2019 levels, reaching less than half of jobs lost during 2019-2020 (Chase, 2022).

Concurrently, new energy production has been growing in the region. Approximately 13% of power generation capacity in Texas[3] comes from renewable energy (RE) sources provided by the Permian (Ko et al., 2023), and between 2020 and 2022, 13,000 jobs were created supporting RE production, storage, and use (Chase, 2022). Additionally, new advanced energy strategies for low-carbon industries appear to be well-suited for development in the Permian, including hydrogen generation and storage, geothermal energy, and carbon capture, use, and storage (Abramson et al., 2022; Foxhall, 2024; Lin et al., 2024). Thus, renewable and advanced energy technologies are a reality in the Permian, but regional and state government perceptions are predominantly focused on traditional energy sources (Foxhall et al., 2023).

## Energy Transitions

Energy transitions are not new and have been ongoing at least since the early 1800s (Bhutada, 2022; EIA, 2013), influenced by innovations and technological progress. Hydraulic fracturing, driven in part by innovations developed and proven in the Permian

[2] PEDL also includes counties adjacent to the Permian Basin in outreach and research efforts; thus, the analysis in this paper includes 66 counties.

[3] Renewable energy (RE) sources in Texas contributed one fourth of electricity in 2022, and Texas leads the U.S. in wind power generation and is among the leading states for solar generation (U.S. Energy Information Administration [EIA], 2023a).

Basin, significantly lowered production costs for natural gas and enabled the transition in power production away from coal (Kolstad, 2017). The transition to renewable and advanced energy technologies (e.g., wind power, solar photovoltaics, green hydrogen, geothermal, carbon capture and sequestration) is associated with improvements in air quality (Gharbi et al., 2023) and greater decentralization of energy production, storage, and supply. New ways to store and distribute energy will require new technology and business models that could enhance local economic activity.

To contextualize the potential economic, human health, and environmental impacts associated with transitions to advanced energy, community input and support in the transition process is vital. Efforts toward new types of energy production and use, from hydraulic fracturing to wind farms, can face resistance if the benefits from their development are not locally and equitably distributed and if local citizenry are excluded from the decision-making process (Susskind et al., 2022). Further, decision-making that includes community members produce better outcomes (Bidwell, 2016).

Developing an understanding of communities' identities and values can aid in collaborative transition processes. Pursuing energy transitions with communities as active participants in a process of change encourages residents to guide the transition in a manner that benefits its members rather than actively or passively rejecting it (O'Faircheallaigh, 2010). Therefore, leaders advocating for energy transition and technological change must engage participatory and inclusive processes to build trust, explore costs and benefits for the community, and jointly plan future activities (Hoppe et al., 2016). Encouraging citizen engagement throughout the policy, planning, and implementation phases offers improved pathways to achieve energy, economic, and environmental benefit for communities.

However, given the geographic vastness and diversity of Permian communities, direct engagement with all communities is challenging. Thus, this report presents an initial, data-focused approach to aid in PEDL's future engagement activities.

## Diverse Communities of the Permian

The process of engaging communities on energy transitions is challenging, even when conducted in a single community. The Permian Basin is a vast region of diverse communities ranging from mid-size cities (e.g., Midland and Odessa with populations of more than 131,000 and 112,000, respectively) to many towns and entire counties of a thousand or fewer residents. Adjacent to the Permian Basin is the metropolitan area of El Paso that is a major economic force in the greater region. Each community has its own peculiar industrial, economic, and cultural relationship with the O&G industry. The heterogeneous nature of Permian communities in size, economic basis, geographic features, and other qualities makes an "every community" analysis challenging due to resource restraints, such as time and distance. An initial understanding of the region can instead be built by aggregating communities based on similar criteria and features. This approach offers the benefit of developing a profile of the region more rapidly and revealing unexpected similarities and differences between communities therein.

Characterizations of regional similarities and differences have often followed the urban-rural typology, whereby population and its density are the primary criteria for classification (Dijkstra et al., 2021 and references therein). Other researchers have developed typologies based on unique geographical criteria such as city, rural, coastal, mountain, and other locational features (Batista e Silva et al., 2021). While some issues are held in common based on geographic and population criteria, other social and economic opportunities are not well captured using these approaches. Many socioeconomic challenges and opportunities surrounding poverty, community safety, affordable housing, and public-school quality cut across traditional typologies (Parker et al., 2018). Therefore, local context must be considered when developing an understanding of differences and similarities between communities. To achieve this understanding, we followed an approach used in previous research (e.g., Alejandre et al., 2022) wherein regional archetypes are developed to aggregate similar characteristics of various types to identify commonalities for community engagement.

## REGIONAL ARCHETYPES

### Rationale

Archetypes offer a strategic approach for addressing common concerns and opportunities across communities that share important features. Thus, before tackling the complicated process of accessing and comparing shared social values and business attitudes between Permian counties, we sought to define regional archetypes to broaden our understanding of the Permian region and better understand similarities in challenges and opportunities associated with energy transitions. The Permian Basin includes 50 counties in Southeastern New Mexico and Western Texas. PEDL also includes counties adjacent to the Permian Basin in outreach and research efforts; thus, the analysis in this paper includes 66 counties.

### Method

We first compiled data[4] from disparate sources at the county-level and identified Permian-wide trends using that data. We then performed a cluster analysis to create regional archetypes of Permian counties. Regional archetypes can be based on many

[4] The full dataset and report can be found at <insert link to data & slide deck published on PEDL website>.

factors, including key community characteristics, social contexts, as well as site-based scenarios (Carroll & Pavelglio, 2016; Thorn et al., 2021). We sought to create Permian archetypes using key community data, including those characterizing population dynamics, community well-being, employment, and economic performance, as well as role in energy production. For this initial analysis, we consider the following data: O&G production; RE capacity; population size and change rate; high school (HS) educational achievement; poverty rate; unemployment rate; employment in natural resources, construction, and maintenance; and gross domestic product (GDP) per capita.

In our description of the archetypes, we employed within-region comparisons based on standard deviation separation. Therefore, "very low" values are defined as those falling two standard deviation below the mean, "low" values are one standard deviation below the mean, "average" values fall within one standard deviation above or below the mean, "high" values are one standard deviation above the mean, and "very high" values exceed the mean by two standard deviations or more (relative/ to other counties in the Permian).

Using these criteria, we hope that Permian archetypes can assist engagement processes in the region by bundling disparate communities into simplified groups based on important criteria related to energy transitions.

## DATA SOURCES

### *O&G Production*

This report uses 2022 data from the Railroad Commission of Texas (2023) and the New Mexico Oil Conservation District (2023) to estimate oil and gas production at the county-level. The Railroad Commission of Texas provides oil and oil condensate production in barrels (BBL) and gas and gas casinghead production in thousand cubic feet (MCF). The New Mexico Oil Conservation District provides composite oil production in BBL and composite gas production in MCF. To combine these values into one O&G production amount by county, we multiplied the gas MCF values by six to convert to BOE, based on the conversion factor used by the U.S. Geologidfcal Survey (USGS, 2005), and summed the gas BOE estimates with oil BBL.

### *RE Nameplate Capacity*

The EIA tracks county-level nameplate capacity by technology across all electric power plant generators with one MW or greater combined capacity (EIA, 2023b). To estimate the capacity of mature, commercially deployed renewable technologies for each Permian county, we summed the capacities for wind, solar, batteries, and hydropower for 2022. Other more nascent RE technologies, such as green hydrogen, geothermal, carbon capture and sequestration,were not including in this initial modeling.

*Population, HS Education, Poverty Rate, and Unemployment Rate*

County-level population estimates, percent of the adult population without a HS diploma, poverty rates, and unemployment rates for 2021 are provided by the USDA's Atlas of Rural and Small-Town America (USDA, 2023). We also used USDA's population change rate estimates from 2010–2020.

*Employment in Natural Resources, Construction, & Maintenance*

Using the American Community Survey (ACS) five-year estimates (U.S. Census Bureau, 2021), we examined percent workforce employed in natural resources, construction, and maintenance in the Permian for years 2017–2021.

*GDP Per Capita*

County-level GDP is assessed by the Bureau of Economic Analysis (BEA, 2023a). To calculate GDP per capita, we divided current dollar estimates for 2022 by county population estimates.

## ANALYSIS

To assign Permian counties to regional archetypes, we performed a K-means cluster analysis using centered values for each key metric (Hartigan and Wong, 1979; Likas et al., 2003; UC Business Analytics R Programming Guide). In brief, we define $\chi_i$ as a data point assigned to the cluster $C_k$ and $\mu_k$ as the average or mean value of all points ascribed to cluster $C_k$. Each observation ($\chi_i$) is assigned to a given cluster such that the sum of squares (SS) distance of the observation to their assigned cluster centers ($\mu_k$) is minimized. The variation within a cluster (W) is determined as the SS Euclidean distances between data points and a centroid:

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

To measure total variation within a cluster (tot.withiness), the SS are summed to measure the compactness of a cluster.

$$tot.withiness = \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Thus, we identified the optimal number of groups for our clustering solution by plotting the "within-group sum of squares" against the number of clusters, noting that lower values signify higher similarity within the groups. Further, we also plotted average silhouette width by number of cluster groups, which is another assessment of group fit—higher silhouette width indicates better group fit. Based on the curves in both plots, we found that clustering solutions with six or seven groups created the best-fitting group assignments. In K-means cluster analysis, selection of the number of clusters and interpretation of the clusters is ultimately driven by the analyst, who lends subjective meaning to the findings. After examining both solutions, we found that the seven-cluster solution provided the most meaningful and useful archetype model[5].

## Features of Permian Communities

Below we summarize the findings from the archetypes analysis. But first, we describe general patterns observed re: the Permian from the datasets used in this study.

### PERMIAN OVERVIEW

We first identified trends across counties in the Permian region (see Table 1) and found that the region has strengths that should be maintained and leveraged. The region has very high potential for clean and next-generation energy technologies. The technical potential[6] for utility-scale wind and solar power generation, for instance, is among the highest in the country (National Renewable Energy Laboratory [NREL], 2021a, 2021b). Many counties are leveraging a portion of this potential already; for example, most counties on the eastern side of the Permian have developed nameplate capacity (i.e., energy generation capacity at electric power plants) for wind energy, and most counties on the western side of the Permian have developed nameplate capacity for solar energy (EIA, 2023b). Additionally, 12 counties have nameplate capacity for batteries, and one county has nameplate capacity for hydropower. Some parts of the Permian—including El Paso and parts of New Mexico—also have favorable geothermal resources (NREL, 2018).

[5] The seven-cluster solution explained 60% of the variance between groups; thus, there are explanatory metrics missing from this analysis. However, the seven-cluster solution provided meaningful results that can guide work in the Permian region.
[6] Technical potential is the amount of energy that can be produced by a technology if all suitable land is used for development. It does not consider market or economic conditions.

Table 1. Descriptive Statistics Across Permian Counties

| Metric | Minimum | Median | Maximum |
|---|---|---|---|
| O&G production in 2022 | 0.0 BOE | 15.2 million BOE | 7.4 billion BOE |
| RE capacity in 2022 | 0.0 MW | 155 MW | 2,762 MW |
| Population in 2021 | 57 | 6,002 | 867,947 |
| Population change rate from 2010–2020 | -29% | -5.4% | 26% |
| Population without a high school education | 5.8% | 20% | 50% |
| Poverty rate in 2021 | 1.2% | 14% | 34% |
| Unemployment rate in 2021 | 0.9% | 5.6% | 11% |
| Natural resource, construction, & maintenance jobs | 0.0% | 18% | 35% |
| GDP per capita | $30 thousand | $82 thousand | $227 million |

Most counties in the Permian produce O&G; however, county-level O&G production varies widely—eight counties produced none in 2022, while a dozen produced over one billion BOE (Railroad Commission of Texas, 2023; New Mexico Oil Conservation District, 2023). Unsurprisingly, the region has many counties with high employment in natural resources, construction, and maintenance (U.S. Census Bureau, 2021).

We also found that most counties in the Permian experience social or economic challenges and that intersecting challenges exist in many counties. Most Permian counties have relatively high unemployment rates (mean of 5.6% with a standard deviation of 1.8%), higher than national average poverty rates (mean of 15.4% with standard deviation of 6.4%), and smaller, declining populations (mean decline of 3.7% with standard deviation of 13%; U.S. Department of Agriculture [USDA], 2023). Many counties also have health-related concerns and are highly uninsured, and many households in the Permian have limited English speaking and writing abilities and lack access to the internet (U.S. Department of Education, 2022; DOE, 2022; University of Wisconsin, 2023). It comes as no surprise that  most Permian counties have a least one Census tract designated as disadvantaged by the Climate and Economic Justice Screening Tool (Council on Environmental Quality [CEQ], 2022; see Figure 1). Additionally, given that many counties are highly reliant on the O&G industry and have high employment in extraction, many community members are exposed to changes in the industry.

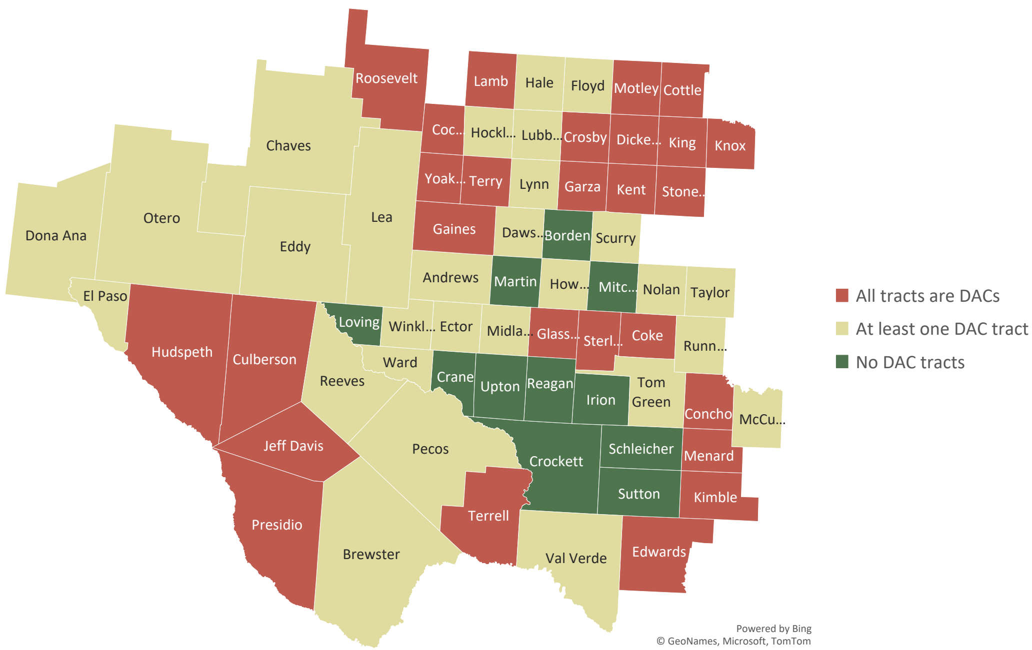


Figure 1. Disadvantaged Community Status Among Permian Counties (tracts here are equivalent to census tracts; CEQ, 2022)

## PERMIAN ARCHETYPES

Through the execution of the K-means clustering approach, we created seven archetypes using the key metrics captured in Table 1. In the next several sections and in Table 2, we describe the archetypes in detail, and in Figure 2, we provide a map that situates the archetypes within the region.

Table 2. Permian Archetype Descriptions

| Archetype Name | No. of Counties | Key Trends: Description | Key Trends: Value Range |
|---|---|---|---|
| 1 **High O&G Production** | 4 | • **Exceptionally high** O&G production | 4.5 – 7.4 billion BOE/year |
| | | • **Very low to average** installed RE capacity | 0.0 – 159 MW |
| | | • **Average to high** employment in natural resources, construction, and maintenance | 14 – 27% |
| | | • **Average to high** percent of residents without a HS diploma | 15 – 30% |
| | | • **Average to very high** unemployment rates | 5.7 – 9.6% |
| | | • **Average to high** GDP per capita | $142 thousand – $1.3 million |
| 2 **High RE Capacity** | 8 | • **Exceptionally high** installed RE capacity | 970 – 2,800 MW/year |
| | | • **Low to average** unemployment rates | 2.4 – 7.1% |
| 3 **Very Small, Decreasing Populations** | 17 | • **Very small** populations that **decreased** from 2010–2020 | 720 – 9,900 residents<br>5 – 29% loss |
| | | • **Average to high** employment in natural resources, construction, and maintenance | 15 – 29% |
| | | • **Average to high** percent of residents without a HS diploma | 11 – 26% |
| | | • **Low to average** unemployment rates | 2.9 – 6.7% |
| 4 **High Percent Less Than HS Education** | 9 | • **Exceptionally high** percent of residents without a HS diploma | 23 – 50% |
| | | • **Very small** populations | 260 – 22,000 residents |
| | | • **Average to very high** poverty rates | 14 – 34% |
| | | • **Very low to average** installed RE capacity | 0.0 – 450 MW/year |
| 5 **High Unemployment and High Percent Less HS Education** | 26 | • **Average to very high** percent of residents without a HS diploma | 11 – 34% |
| | | • **Average to very high** unemployment rates | 4.5 – 9.6% |
| 6 **Small Population, high GDP and O&G Production** | 1 | • **Exceptionally high** GDP per capita | $227 million |
| | | • **Exceptionally small** population that **decreased** from 2010–2020 | 57 residents<br>22% loss |
| | | • **Very high** O&G production | 3.5 billion BOE/year |
| 7 **High Population Gain** | 1 | • **Very large** population that **increased** from 2010–2020 | 868,000 residents<br>8% gain |

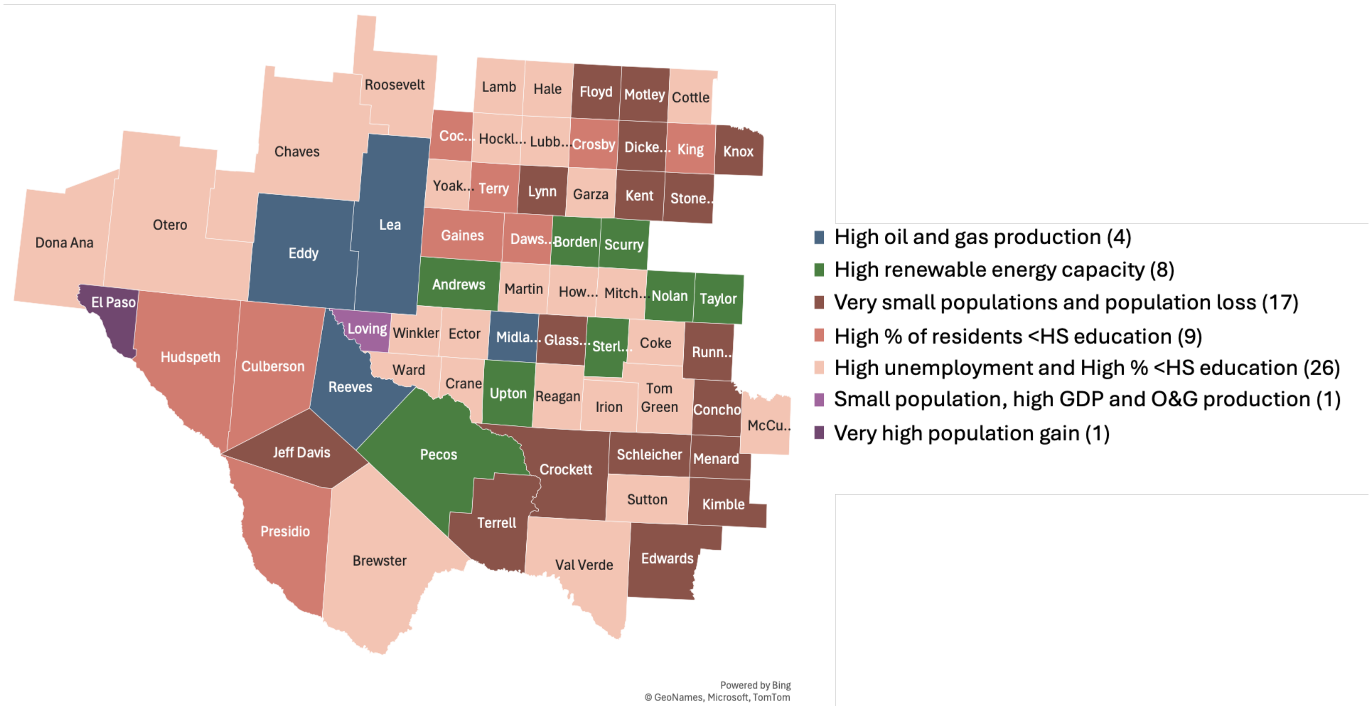


Figure 2. Archetypes' Locations in the Permian with county numbers included in each archetype in parenthesis.

## Archetype 1: High O&G Production

This archetype is characterized by exceptionally high levels of O&G production and includes four counties: Eddy and Lea counties in New Mexico, and Midland and Reeves counties in Texas.

Each county produced at least 4.5 billion BOE in 2022. Most notably, Reeves County produced the most O&G in 2022 (7.4 billion BOE) and, unsurprisingly, has high employment in natural resources, construction, and maintenance—nearly one third of the workforce in Reeves is employed in those job types. Reeves is also unique in that it has some nameplate capacity for battery storage (173 MW), in addition to some solar power (100 MW). Lea County also has some renewable nameplate capacity (352 MW of wind power).

Socioeconomically, this archetype ranks variably relative to other counties in the Permian. Counties in this archetype have average to high GDP per capita (up to $1.3 million per capita in Reeves County). However, these counties also have average to high percentages of residents without a HS diploma (up to 30% of the adult population in Reeves County) and average to very high unemployment rates (up to 9.6% of the labor force in Lea County). The poverty rates in this archetype are average for the region—as low as 11% in Midland County and as high as 17% in Reeves County.

### Archetype 2: High RE Capacity

This archetype is characterized by exceptionally high RE capacity and includes eight counties, all in Texas: Andrews, Borden, Nolan, Pecos, Scurry, Sterling, Taylor, and Upton counties.

Each county has at least 970 MW of renewable nameplate capacity installed as of the end of 2022. Most notably, Nolan and Pecos counties each have over 2,000 MW—Nolan County has nearly 2,800 MW (comprised mostly of wind), and Pecos County has over 2,100 MW (comprised mostly of solar). These counties have variable levels of O&G production—as low as 974,000 BOE in Taylor County and as high as 2.3 billion BOE in Upton County. Similarly, these counties have variable levels of employment in natural resources, construction, and maintenance—as low as 11% of the workforce in Taylor County and as high as 28% of the workforce in Borden County.

This archetype varies socioeconomically as well, with few trends common across the counties. One exception is unemployment rate, which is low to average for all counties—as low as 2.4% in Borden County and as high as 7.1% in Pecos County. Although not archetype-wide trends, a few counties score notably on poverty and education metrics. Borden and Sterling counties have very low poverty rates (2.4% and 4.5%, respectively) and very low percentages of adults without a HS diploma (each under 8%). Pecos County, on the other hand, has a high poverty rate (22%). Pecos, Upton, and Andrews counties have a high percentage of adults without a HS diploma (each just under or at 25%).

### Archetype 3: Very Small, Decreasing Populations

This archetype includes 17 counties, all in Texas: Concho, Crockett, Dickens, Edwards, Floyd, Glasscock, Jeff Davis, Kent, Kimble, Knox, Lynn, Menard, Motley, Runnels, Schleicher, Stonewall, and Terrell counties.

These counties are characterized by very small populations—each with less than 10,000 people—that decreased between 2010 and 2020. Notably, four counties lost over 20% of their populations in the 2010s: Schleicher, Edwards, Dickens, and Terrell. Although unemployment rates in this archetype are low to average (up to 6.7% in Crockett County), the percentage of adults without a HS diploma is average to high (up to 26% in Floyd County).

Additionally, although some counties in this archetype produced no O&G and had no renewable nameplate capacity in 2022, all counties have average to high employment in natural resources, construction, and maintenance, with nearly 30% of the workforce employed in those job types in Motley and Edwards counties.

### Archetype 4: High Percent Less than HS Education

This archetype is characterized by exceptionally high percentages of residents without a HS diploma (each over 20% of the adult population) and includes nine counties, all in Texas: Cochran, Crosby, Culberson, Dawson, Gaines, Hudspeth, King, Presidio, and Terry counties.

Hudspeth County is especially notable for this Archetype, since half of the adult population in this county are without a HS diploma. This archetype also has small populations (up to 22,000 people in Gaines County), and most counties in this archetype lost population in the 2010s (with the exception of Gaines County, which gained 23%). Most counties also have high poverty rates over 20% (again, with the exception of Gaines County, which is 14%).

Renewable nameplate capacity is very low to average in this archetype—although four counties (Culberson, Crosby, Dawson, and Cochran) have between 150 and 450 MW, the rest have little to no renewable capacity. Additionally, O&G production varies widely. Presidio and Hudspeth counties produced none, while Culberson produced 2.8 billion BOE. Employment in natural resources, construction, and maintenance, unemployment rates, and GDP per capita also vary widely in this archetype.

### Archetype 5: High Unemployment, High Percent Less than HS Education Permian Counties

This archetype includes the 26 counties: Chaves, Doña Ana, Otero, and Roosevelt counties in New Mexico, and Brewster, Coke, Cottle, Crane, Ector, Garza, Hale, Hockley, Howard, Irion, Lamb, Lubbock, Martin, McCulloch, Mitchell, Reagan, Sutton, Tom Green, Val Verde, Ward, Winkler, and Yoakum counties in Texas.

For most metrics, these counties have a range of scores (from very low to very high). There are, however, two archetype-wide trends—all counties have average to high percentages of adults without a HS diploma and average to high unemployment rates. Most notably, 34% of the adult population in Garza County is without a HS diploma, and unemployment is nearly 10% in Crane County.

### Archetype 6: Small Population, High GDP and O&G Production

This archetype only has one county: Loving County, TX.

This county was grouped into its own archetype because of its exceptionally small population size (57 people) and high GDP per capita ($227 million). O&G production in Loving County is very high (3.5 billion BOE), and the county has no renewable nameplate capacity. Surprisingly, the U.S. Census ACS estimates report no employment in natural resources, construction, and maintenance among residents. Loving County also has low poverty (1.2%) and unemployment rates (0.9%) and a low percentage of residents without a HS diploma (5.8%). Lastly, Loving County lost a significant proportion of their small population in the 2010s (22%).

### Archetype 7: El Very High Population Gain

This archetype only has one county: El Paso County, TX.

This county was grouped into its own archetype because of its exceptionally large population size for the region (868,000 people), which grew 8% between 2010 and 2020. El Paso has low renewable nameplate capacity (16 MW) and produced no O&G in 2022. The county also has low employment in natural resources, construction, and maintenance (9.9%), and scores in the average range for poverty rate (19%), unemployment rate (6.2%), and percentage of residents without a HS diploma (20%).

## Implications and Next Steps

### ADVANCED ENERGY DEVELOPMENT

Traditional and renewable energy activities were particularly strong uniting criteria in the clustering solution and informed the creation of Archetypes 1 and 2. Although high energy output might sometimes be associated with greater community economic well-being, this was not the case for many Permian counties. Some of the biggest O&G producers, for instance, had large GDPs per capita but also high unemployment and poverty rates. Similarly, some counties with the highest renewable nameplate capacity also had high poverty rates. Future work can examine mechanisms for leveraging energy-related economic activity to improve community economic well-being among the 12 counties in Archetypes 1 and 2 and beyond. For instance, research could explore options for and the potential benefits of community ownership structures for future advanced energy development activities. Additionally, many counties in the Permian are not involved in traditional nor renewable energy production (particularly in Archetypes 3, 4, and 5). Advanced energy development might be particularly beneficial for improving community conditions in these counties.

## WORKFORCE DEVELOPMENT

Population and HS educational attainment were also particularly impactful criteria for the clustering solution. Many counties in the Permian have small populations and high percentages of adults without HS diplomas, but these rates were particularly high in Archetypes 3, 4, and 5. Many of the smallest populations declined in the 2010s but surprisingly had lower unemployment rates. Future research can examine the 17 counties in Archetype 3 to investigate causes for population decline beyond lack of employment opportunities. Additionally, because Archetypes 4 and 5 had high proportions of adults without HS diplomas and higher poverty rates, early educational and high school interventions might be most impactful among these 35 counties.

Loving and El Paso counties are unique in the region with respect to the metrics used in the cluster analysis. Loving County has a very small population that declined in the 2010s but maintains high O&G production and an exceptionally large GDP per capita. El Paso County, on the other hand, has a large population that grew in the 2010s but limited RE capacity and no O&G production. PEDL and others working in the region should consider ways in which these unique communities can inform and support advanced energy and workforce development. For instance, given the high levels of economic and energy-related activity in Loving County, despite its small population, the county could serve as a model for recruiting workforce for advanced energy activities in rural areas.

## ENGAGEMENT AND OUTREACH

The archetypes and associated dataset should not be used in lieu of direct engagement with community members. Rather, engagement with community members is a crucial, early-stage step in energy development for increasing community buy-in and improving outcomes (Bidwell, 2016), and the social dimensions of energy transitions are of equal importance to the environmental need and technological opportunity (Goedkoop & Devine-Wright, 2016; Lehmann et al., 2012; Rogers et al., 2008; Cass & Walker, 2009). Using data-focused information in conjunction with direct engagement is key and can help to mitigate potential preconceptions within or about a region. Thus, PEDL aims to leverage community expertise and anchor its goals and research activities with community interests and values. To this end, PEDL has begun and plans to continue community engagement activities among the 66 counties included in the archetypes.

The archetypes can serve as comparative locations for research into community perceptions and explanatory factors for those perceptions. For instance, exploring community sentiments toward advanced energy technologies, local economics, environmental issues, and energy transitions will deepen our understanding of community values in the region and how they vary. Results from this type of work might vary by archetype—they could be different for high O&G producers (e.g., Archetype 1) compared to those with high RE capacity (e.g., Archetype 2) and to those with low levels of energy development (e.g., many counties in Archetypes 3, 4, and 5). Additionally, studies of Permian communities have identified community values supportive of energy transitions, whereas other values might lead to friction and resistance to change. For instance, the rural cultural trait of independence could make the concerted and collaborative work necessary for regional change more difficult due to the inability to consolidate critical mass of agreed communities (Guiso et al., 2006). The pursuit of economic growth can also be a source of friction as some community members object to population shifts and changes, whereas others welcome more opportunities for commerce. Actual responses to economic growth are more complicated than this example construes, but nevertheless, public sentiment must be probed such that mediation of meaning proceeds goal setting (Digmayer & Pogue, 2024).

By taking community values and conditions into account, advanced energy development can be co-developed and communicated using language that clearly sets out benefits to community members. Discussing future-oriented aspects of advanced energy development, in addition to more immediate concerns (e.g., impacts on personal energy costs), can help PEDL understand the broad hopes and concerns among community members for advanced energy development. For instance, communities that view advanced energies not as obstacles, but as pathways for greater autonomy, regional value creation, and increased economic resilience might be more open to hosting advanced energy research or development activities. In this way, community well-being can be achieved through mechanisms that are co-created with community members and tailored to community conditions. Thus, future research should engage community members to better understand how values vary across Permian counties.

Outreach and engagement strategies and goals might need to vary by archetype. For instance, high energy producers (e.g., Archetypes 1 and 2) might have different interests and expertise than low energy producers (e.g., many counties in Archetypes 3, 4, and 5)—the former might be more engaged in energy development strategies, and the latter might be more engaged in workforce and community development. Additionally, the full socioeconomic dataset, which can be found on the PEDL website, includes metrics that can also inform outreach activities, including internet access and English language speaking abilities by county.

## LIMITATIONS

Any attempt to assign similarities among heterogeneous data sets will leave room for discussion. Indeed, clustering methods, a county can be assigned to one or more archetype using different analysis criteria. The selection of the seven-archetype model detailed here comes from two observations: 1) it best explained the variance between the data in the study among models developed; and 2) the model showed strong coherence following review of cluster data and distribution of standard deviations among key data values among counties assigned to each archetype. Based on this review, we deemed the clustering solution yielding the seven regional archetypes as the best representation of the data.

The archetypal structure in this report uses a subset of available data, which can be revisited depending on the region's priorities. Furthermore, the analysis is based on secondary data, the inclusion of which was not chosen by community members. For example, we gathered data from wind, solar, batteries, and hydropower installed as representative of RE capacity potential. Other advanced RE technologies are more nascent and were not included in this study, including green hydrogen, geothermal, carbon capture and sequestration. Further, technologies associated with produced water and abandoned O&G wells were also not included. These currently less-developed technologies can be considered in future work as data becomes available. Thus, although the archetypes provide a starting point for advanced energy research in the region, they might not resonate with all community members. This underscores the need for community engagement that allows for the archetypes and included metrics used to be verified or corrected by community members. Survey and interview strategies can be designed to test the cohesion between counties in a given cluster, as well as to allow model counties of a cluster to be the focus of initial community engagement activities.

## CONCLUSION

Using several metrics related to energy development and community well-being, we identified seven county archetypes in the Permian region by performing a k-means cluster analysis. The main utility of the archetypes is to allow for simplified sampling across the expanse and diversity of Permian counties for future research activities in the region. Indeed, starting with a set 66 counties, 64 could be accurately described in five archetypes with remaining two counties parsing into unique archetypes, based on population and economic dynamics. By leveraging the patterns illuminated by the archetypes, PEDL can produce community-engaged research, workforce development, and in-community activities that are more tailored to the diverse community landscape of the Permian.

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