4-1-2024

Beyond Technology: Social Predictors of Energy Efficiency in Industrial Facilities

Garret B. Cowdery
University of Dayton

Beyond Technology: Social Predictors of Energy Efficiency in Industrial Facilities

Honors Thesis

Garret Baer Cowdery

Department: Mechanical and Aerospace Engineering

Advisor: Jun-Ki Choi, Ph.D.

April 2024

Beyond Technology: Social Predictors of Energy Efficiency in Industrial Facilities

Honors Thesis

Garret Baer Cowdery

Department: Mechanical and Aerospace Engineering

Advisor: Jun-Ki Choi, Ph.D.

April 2024

Abstract

Energy is the lifeblood of the industrialized world with electrical energy expected by the National Renewable Energy Laboratory (NREL) to increase 25% between 2016 to 2050 in the United States. Combined with the ever-present climate crisis, energy-efficient buildings are becoming increasingly important to conserve resources and alleviate strain on aging energy systems. The Industrial Assessment Center (IAC) program through the US Department of Energy aims to reduce the consumption of large, single-site energy users, industrial and commercial buildings, through comprehensive energy audits. Such investigations find that energy-efficient structures are a technological challenge as much as social. The mentality of building occupants towards energy use strongly impacts the efficiency of the building with the energy conscientiousness of the inhabitants being a key factor in maximizing theoretical performance. Not in My Backyard (NIMBY) is a social phenomenon where communities rise in opposition to controversial facilities that serve to upset community wellbeing. These are generally energy-intensive projects that may detract from the natural beauty or environmental health of an area. The negative reaction originates from difficult-to-measure factors such as personal attitudes and trust between involved parties but can be loosely predicted by specific demographic quantities. This investigation aimed to primarily analyze the quantity, scale, and quality of community energy systems at the county level of Ohio in conjunction with collected IAC data and NIMBY demographics to identify potential external predictors for industrial energy intensity based on NIMBY sensitivity. Ultimately, only a weak correlation is found between industrial facility energy usage and the listed attributes, but the investigation paints a vivid demography of people, energy resources, and industrial agglomeration while emphasizing and supporting the need for continual research into the social functions that drive technical success.

Acknowledgements

I would like to thank the time, patience, and experience of my Advisor Dr. Jun-Ki Choi during a time in my life of exceptional distress, and for allowing me the freedom to actualize my research goals in the ways I deemed best fit. I would also like to thank the exceptional individuals of the University of Dayton Industrial Assessment Center for their record keeping and dutiful lean energy analysis that provided me with the site level data I needed to investigate facility energy usage.

University *of* Dayton

Table of Contents

Introduction

Electrification of the United States is predicted to rise in all sectors. Energy consolidation into electricity is desired for its ease of exchangeability into mechanical or thermal energy, historically low cost, and transportability [1]. Because of this, the National Renewable Energy Laboratory (NREL) estimated between the years 2016 and 2050, nationwide electric demand is expected to increase a minimum of 25% from 3,783 TWh to 4,722 TWh putting significant strain on the aging electric grid [2].

Despite expected demand, historical analysis of North American Electrical Reliability Council (NERC) blackout events discovered an increasing frequency and duration of outages in the United States [3, 4]. These events are the majority attributed to extreme weather events which will be exacerbated by climate change [5]. The balkanization of the electric grid through deregulation will further impact infrastructure reliability through market competition to keep operating costs low [6].

According to the U.S. Energy Information Administration's monthly energy review, the largest end-user of energy in the United States since 1975 is the industrial sector [7]. In 2022, industry consumed a leading 32.77% of a yearly total of 100.42 quadrillion BTU's [8]. When considering only electricity industry loses its lead but still maintains a significant 25.8% portion of 2022's sale of 3.81 trillion kWh [9]. While residential and transportation consumption is distributed, industrial and commercial applications are concentrated to consumers providing high opportunity for grid strain reduction through operational and process optimization.

Industrial processes are entirely reliant on energy to transform resources into goods. Whether its mechanical, chemical, electrical, or human, all industrial sites can be considered primary resource processing plants converting energy plus raw material into a final product. In the case of electricity or even natural gas, the further distance they must travel in a distribution network, more energy is lost to unavoidable transmission inefficiencies. These generally come in the form of a line loss charge. Therefore, locational proximity to energy sources would prove an economic advantage for heavy energy users with less expense for transmission losses and more paid energy. Furthermore, workforce proximity to energy infrastructure may affect consumption rates. Sense of place is linked to the field of environmental psychology where an individual's environment and relationship to it shapes their behavior. Affinities and dislikes of an environments traits influence the way people treat that environment [10, 11]. If the workforce of a manufacturer were to live where more energy is imported than generated, they may feel sensitized to consumption as energy is an exotic import. Local demographics can help indicate firm energy intensity based on the energy generation concentrations of a region.

It is imperative that grid strain is reduced, and U.S. Department of Energy sponsored Industrial Assessment Centers and commercial energy assessment programs provide a service to streamline facility energy consumption [12]. The groundwork of the assessment involves a lean energy analysis (LEA) generating a facility energy consumption profile. These profiles indicate energy intensive processes prior to site visit and likewise highlight areas for significant saving opportunities early on. Unfortunately, the time input of LEA less assessments reduces volume of assessments that can be completed per year and divert attention away from understanding process flow. The latter can negatively impact a team's ability to propose meaningful operational recommendations and decrease grid strain since primary process is closely related to energy intensity [13]. To increase focus on process, an approximate percentage distribution of thermal and electric energy can theoretically be modeled using proximity relations between an individual facility and its energy infrastructure, and its local and county demographics including energy infrastructure statistics.

A literature review indicated a limited body of research investigating firm energy intensity based on electric infrastructure proximity and surrounding demographics Academic focus has been primarily placed on investigating economic forces driving agglomeration, or how agglomeration impacts firm energy efficiency. A small portion of investigation has been made regarding energy resource agglomeration and its value in indicating firm energy intensity but is foundational in nature. There is also work investigating firm energy usage but requires granular detail of facility equipment. Unfortunately, such lists are rarely kept by small to medium sized manufacturers. This work hopes to make current understandings of place psychology, and economic or advantageous reasons for site selection more robust in the context of predicting firm energy usage from a majority external perspective.

The structure of this paper will proceed as follows. A literature review will be presented on relevant topics: industrial agglomeration studies with emphasis on proven predicting factors and energy efficiency effects, energy infrastructure site selection criteria, and how psychology of place impacts building energy efficiency and electric infrastructure site selection. Section three will present research methodology to create the necessary data to research. Section four will present the results of the data analysis, and section five will present relational results using the dataset discussed in section four. Section six will discuss findings and present future research opportunities.

Literature review

Industrial Agglomeration Patterns and Effects

When accounting for industry agglomeration and conglomeration, the seminal work of Ellison et al. (1997) models the tendency of plants from similar industries to group together based on 2 ,3, and 4 number industrial codes. It's found that highly specialized industries like furs, wine, or raw resource processing is found to be highly agglomerated. It is possibly explained through the idea of natural advantage or that decreased transportation cost paired with idea spillover from the raw resource industry itself drives industrial growth of these processors. Every other industry was found to have little to no concentrations with each other [14]. Ellison and Glaeser follow up their previous work with Ellison et al. (1999) where natural advantage in industry agglomeration if further explored in relation to industry geographic concentration. The results were inconclusive with the writers conjecturing that 50% of observed agglomerated industries are concentrated due to natural advantage. But, their model fails to account for local geography and industry idea spillover such as why shipbuilding isn't concentrated in Colorado or the fur industry being concentrated in New York [15].

Trailing works such as Rosental et al. (2001) expanded on the scope of Ellison and Glaeser by conducting analysis at the zip code, county, and state level within the United States. Findings indicated that natural resource access, raw input, and non-perishable output strongly effected agglomeration at the state level. Transportation modes effected agglomeration at the county level for shipping sensitive industries, and idea spillover was only a major concentrator at the zip code level. Labor share effected all levels of agglomeration and may be able to transport idea spillover when workers move. More is left to be found as only 30% of agglomeration is explained with such modeling [16].

When generating empirical based models, Todd et al. (2003) found that industry increases at a rate far faster when the majority of firms are small to medium sized. Growth rate of new businesses also scales from 1% to 9% per year with industrial concentration as it nears the U.S. National average [17]. In order to make models more robust due to the complexity of agglomeration, O'Donoghue et al. (2004) attempts to simplify the process. A localization quotient is utilized which compares the local and national ratio of employment in specific industrial sectors. This model loses granularity and interpretability but increases ease of determining agglomeration at the county level [18].

While agglomeration is better understood at a general level, Diego et al. (2010) aimed to find city-specific causes for agglomeration. Within large population centers, driving factors for agglomeration continue through labor pooling, but also increased opportunity due to that pooling. Idea spillover can occur more often, and employees can be better matched to employers. There is also an argument that cities create intense competition where only the most productive firms survive. Diversity, competition, and shared resource hubs drive agglomeration in large population centers, but further modeling is required to identify which factors are stronger [19].

Ellison and Glaeser return and apply Marshallian theories of industry agglomeration. These are goods, labor, and ideas. When applying these ideas empirically based on a dataset, all three hold true and stable, and are equal in magnitude. The variable of natural advantage is found less important. This may be due to the finite number of natural advantages samples in the dataset. This work also highlights the need to analyze agglomeration patterns with time due to how transportation costs for goods have fallen so how has idea transportation been effected [20].

Industrial agglomeration energy efficiency can only be achieved through intentional guidance. Based on data from China's industrialization between the 2000s to 2010s, Feng et al. (2018) identified that low quality diversified and specialized agglomeration has low energy efficiency. Low quality diversified agglomeration has the poor side effect of lower nearby community energy efficiency as well. Causes of low quality were attributed to little direction from government to factory owners and builders leading to haphazard poorly intentioned construction [21].

Working off the suggestion from Ellison and Glaeser to perform a longitudinal study of agglomeration, Mathieu et al. (2022) analyzed industrial agglomeration in the United States across 44 years. Results found that over time, labor market pooling and goods access became a less important factor while knowledge spillovers increased. This was attributed by the writers to shocks in trade and technology in the form of increased trade competition but independent of falling transportation cost prices [22].

When considering foreign firms, industry level agglomeration greatly impacted the site selection preference for Japanese firms opening industrial sites in the U.S., and financial incentives from state or local governments played negligible roles in attracting business. Domestic firms kept Japanese firms interested in geographic locations with a death of domestic activity leading to Japanese apathy [23]. Turning to the Japanese home islands, firms that employed energy efficient practices, saw nearby firms do the same. In a different same vein, cement agglomerated firms saw negative correlation between energy efficiency and agglomeration. The paper emphasized the importance of considering local circumstances in energy efficiency agglomeration predictions [24].

Instead of focusing on economic, political, or cultural factors, an attempt was made by Moreno-Cruz et al. (2017) to model firm agglomeration based on energy usage. Incorporating energy into the agglomeration patterns identified that productivity of energy resources correlated to population center size while prevalence of roads and rivers magnified productivity. Unfortunately, the theory can only be applied over single core applications where nearby labor activity is not accounted for in this model [25].

When observing energy agglomeration across a longer-term period, it was found that industries readily clustered around cheap available power. This came in the form of hydroelectric power in the 20s to 50s where cheap electricity was a driving factor and continual growth motivator for industry. This is opposed to industries founded after the 50s when grid energy powered by coal plants came to out compete hydroelectricity. The cheap energy drove labor pooling, idea spillover, and reduced cost of goods transportation which spurred industry development far after the heyday of hydropower [26].

Electric Infrastructure Site Selection Criteria and Hurdles

Energy infrastructure site selection is a crucial element in the construction process and final outcome. The grid operates as one large machine, and placement of contributing elements affects operations. Power generation equipment has been historically limited by natural resources with the transmission lines of the grid coming to the power versus the power being constructed where infrastructure already is.

Renewable energy is a particularly difficult sector of power generation to define as opposed to thermal generation sites, renewables are wholly dependent on natural advantage to maximize generation. For wind power stations, the predominant factor influencing site selection is wind speed and density with distance to roads and power infrastructure following up natural resources since a shorter distance results in less infrastructure needing to be built. Common restrictions are centered around protected land and species. It is important to note though that societal factors such as distance to urban areas, noise pollution, and local acceptance of the site are often vital to start construction in the first place [27]. From an economic lens, the natural resource advantage of wind speed and density as well as distance to infrastructure are vital to decreasing costs of wind installations. This severely limits opportunity but if companies are willing to take greater risks in site selection more land is suitable for economic wind power. Such decisions would have to be driven by chance or greater data [28].

Similar to wind, solar power site selection is driven by natural resource availability with total solar irradiation being the most important feature. This is followed by proximity to power infrastructure, substations, sloping of the land, and distance to transport infrastructure [29]. Only then, social considerations like distance to population centers and land use, how is the land being cultivated conserved, is considered in selection. It is important to note that public support, impact on local economy, and policy support is greater cited for solar projects as a determinant in site selection than wind power [30].

Thermal power plants are the baseload generators of any functioning electric grid. Their energy is reliable, thus so must their site. Site selection is a finalizing decision which dictates limits and operational capacities of any generating station. Thermal power plant site selection can be quite a challenging process as the weights of the different criteria are interdependent. While population centers are dependent on their energy, they are offput and ailed by emissions from combustion or safety risks from nuclear. Thermal power sites like coal or natural gas can significantly hamper tourism and natural or cultural heritage. Since these static sites require constant human interaction, security, both geologic and human, is necessary to be considered [31]. For thermal installations, the existence of the fuel supply is of primary importance. Geology is also considered to accommodate the large structures that house the generating equipment. Then, land and water availability must be considered to properly size and cool the thermal system. Transport infrastructure then ensures a consistent supply of fuel. Distance to population and load centers are also vital areas to consider. Because these plants will be consistent output sites, land use is important as it will not only effect generation capacity but also community relations [32]. Favorable sites allow for low cost of construction and generation, and location close to load source decreases transmission expenses. Power plants though don't want to cluster. Excess generation concentration can overload the grid infrastructure. Veto effects of local communities must also be considered. Local obstinance to construction to an ideal site may prove more costly in the long run than selecting a less than optimal site. The high-power density of thermal power stations and the high power consumption density of factories make combined heat and power (CHP) applications attractive. Grid strain can be reduced by basing power infrastructure on sites with a large, constant load source [33].

Like thermal plants, substations are also static installations that are integral to baseline grid operation. Likewise, their construction considers security, both to natural and human risks, economics of construction and grid connection, environmental impact, and operational impact [34]. Land acquisition costs tend to be the main determinant of economics, and geography and topology are integral to the environment. Grid connection is mainly dominated by line planning and followed by distance from load center. Closer to load center is more favorable [35]. Proximity to other substations though must be avoided as grid stability is dependent on evenly spaced stations [36].

Psychology of Place and Energy

Experiential and instructional events or a combination of the two affect an individual's sense of place understanding, and attachment. Sense of place is often measured in civic engagement reasoning that an large active voter base indicates widespread care about who governs their place. High citizen satisfaction using the citizen satisfaction index is a strong indicator of place attachment [37]. Using that sense, environmental education can be tied into location affinities to foster ecological stewardship in residents. One's care about place affects their receptiveness to caretaking. Affinity to location influences action [38].

This sense of place manifests itself through not in my back yard (NIMBY) activities by the residents. Controversial facilities or power infrastructure is resisted by certain communities as it poses some form of threat whether it poses significant health risks or ruins the image of the neighborhood [39].

A study using Italy as the resident place investigated causes of "NIMBYism's" in relation to gas-fired thermal power plants. Generating companies looking to build often avoid highly activistic communities. Population density weakly correlates to decreased probability of site selection. Developers also closely leverage existing infrastructure like gas pipeline and grid tie-in locations [40].

A study focused on energy projects in the United States analyzed how the different geographic impacts NIMBY. For communities that economically identify as a part of the energy industry, agriculture, or modernity see energy projects as opportunities at the local, state, and national level. They serve as modernization projects and help increase national independence. But at the local level, agriculture identifiers see projects as a threat due to land loss and import of transient, non-local labor. Those that a predominantly suburb, nature, home oriented at the local level see projects as a threat as they damage natural beauty, community tax revenue, and home value. Rural and industrial geographic identifiers at the local level see opportunity due to general tax increases with rate reduction. From a more general angle at the national and local level projects are seen as an opportunity to contribute to national energy independence by doing their part. The national, state and local level expand on this by seeing it as a service. The local level only sees projects as a threat as they do not address local needs. Generally NIMBY sentiment arises from local populations being or feeling disenfranchised by a high level decision [41]. Setting proper boundaries can help alleviate the issue. If the project poses only a perceived threat community dialogue erases apprehension [42].

The primary driver of energy characteristics that will be analyzed in the context of the social phenomenon known as NIMBY (Not in my Back Yard). NIMBY is a social response by communities against large, controversial infrastructure projects. These range from affordable housing blocks to hazardous waste facilities. In a case study in Catalonia Spain analyzed potential NIMBY projects, and found energy, infrastructure, and urban pressure projects most contentious. Industry was barely a factor. The upper echelons of government generally proposed & upheld plans. Local government and community platforms and associations generally oppose projects. Locals upheld the opposition. NIMBY complex phenomena that involve much of personal perception, community perception, trust between parties, and respect boundaries between parties. Complex human dynamic [43].

The result of NIMBY is commonly attributed to culture not attitude. A case study regarding nuclear power facilities, and a sample size of 734 found that public awareness and sensitivity of free market failures in nuclear power drove equality minded communities to go anti-nuclear. Acceptors were more trusting of the capitalist system and rejectors more egalitarian asking for greater government economy regulation. While public trust and social characteristics are hard to measure, demographics correlate to NIMBY opinions. For this study, Women and high home income individuals were found to be more likely to oppose construction of hazardous waste facilities [44]. In the UK, residents of a town were gauged to see opinions on a new electric transmission line. The sample was representative of longstanding residents of town, but the elderly were overrepresented. 75% of participants lived in town more than 10 years with a minimum age of 18 and maximum of 92. Of the respondents, 60% opposed all options citing a lack of trust in the developer and lots of trust in community organizations. Results were statistically significant through a Chi squared test, age, gender, education, and length of residence explained 4% of variance in objections. Sociodemographic variables, place attachment variables explained another 4%, total 8%. Educational attainment, significant in earlier steps, was no longer significant, suggesting that the influence of education on objections was actually captured by these project-related variables. Finally, variables related to the power line project itself were included. These explained an additional 31% of the variance, bringing the total to 39%. Most project-related variables had significant effects, except for trust in the local campaign group. The length of residence and place discovered remained significant predictors from the previous steps [45].

From a more social lens, the social and cultural barriers imposed by people in places contribute to a location's ability to be energy efficient. Public apathy and misinformation regarding energy efficiency flows downstream from the same poor understanding of where energy comes from. Americans believe they are entitled to cheap, abundant electricity, and utilities and politicians look to uphold this expectation through the use of fossil fuel thermal power stations. Costly and novel renewable energy is incongruent with this perspective. Despite falling costs and increasing efficiency, cultural presumptions about renewable energy sources preclude their construction in otherwise sorely needed locations [46].

This is evident in energy use in large urban areas. Carbon emissions are greater with population density. The correlation is attributed to gas heating and energy inefficient buildings in large population centers. Although when observing more detailed metrics, the individual energy user in an urban environment is less carbon intensive than non-urban. This may suggest greater energy resource respect in urban environments [47].

In the home, carbon intensity is driven by technological innovation with 42% of energy savings from energy efficiency. But behavioral plasticity is also a key factor. The most energy efficient homes had all the latest technological innovations in addition to capable residents. They were knowledgeable of building control systems, kept lower temperature setpoints in the winter and higher in the summer, limited use of the washing machine and dryer. Human action energy savings are found to be near equivalent to pure technological building retrofits [48]. When modeling human social networks, it was found that 11%-31% less energy was consumed by households when communities were in active energy saving dialogue [49].

Methodology

As this work is an exploratory analysis, a high-level county wide investigation of Ohio will be conducted to reveal any trends between established research and industrial energy consumption. County data will be acquired from public sources. Manufacturer counts will be sourced from the most recent 2020 U.S. Decennial Census, and infrastructure counts will be found through the Ohio Department of Transportation (ODOT) Transportation Information Mapping System (TIMS) database [50, 51]. Shapefiles for the counties of Ohio will also be acquired through TIMS. Electrical energy data will be acquired through the EPA eGRID database plus substation locations through the Open Street Maps Foundation. Thermal energy data of oil and natural gas wells will be sourced through the Ohio

Department of Natural Resources (ODNR) well locator database [52-54]. All additional population characteristics and employment statistics will also come from the 2020 U.S. Decennial Census [55-61]. Each of these databases will be used to create a county level profile of people, energy, and industry. This process of data processing is outlined in figure 1.

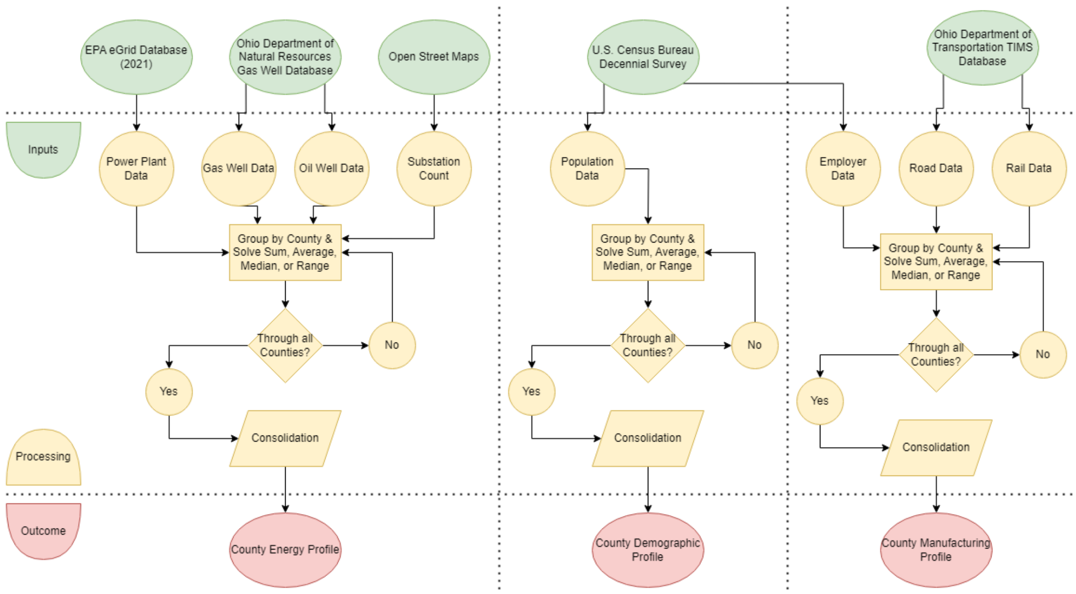


Figure 1: Data Transformation Process Flow

Based on the literary buildup, there is a loose connection between sites of industry, energy generation, and population characteristics. Therefore, the following variables will be necessary. The main points of focus are that industry tends to collect loosely based on natural advantage, idea spillover and labor availability. Since energy is a vital resource to any manufacturing process, natural advantage will be analyzed under the lens of what is the total number, types, and size of those resources. To a lesser extent, the total length of road and number of freight trains per day in a county indicate strong transportation arteries that are necessary for importing needed natural resources. Idea spillover will be interpreted as the presence of similar industries and education levels of the host county. Labor availability will be assumed analogous to total population.

Regarding natural advantage and electrical energy resources, power generators and substations tend to agglomerate based on their own form of natural advantage through existing infrastructure, distance to load, and site suitability for a particular type of generator. The total number of substations and power plants plus the size, and types of power plants illustrate greatly what energy resources a community needs, tolerates, or has capacity for. Additionally, it will be important to understand the quality of the power plants of each community. This can be easily engaged through the capacity factor of the generating station. The.capacity factor is the ratio of total energy generated through the year to the total possible energy generated if the station ran completely uninterrupted. Power stations that have low capacity factors are considered peaking plants that only come online in reaction to grid demands, whereas high capacity factor indicates baseload, continuous operation. It is important to note that while peaking plants are smaller scale than baseload facilities, the ignition process produces more emissions than steady state operation so enough ignition cycling may average out to be equal to the emissions of certain baseload facilities. Community engagement is also an important facet of power plant construction as if a community is willing to tolerate large polluting structures, they will assumedly have a low NIMBY sensitivity and tolerate polluting, energy inefficient factories. Therefore, total sum emissions from power resources will be collected by county.

Thermal energy is primarily sourced through natural gas. This resource has been a predominantly cheaper method to generate heat energy, and only recent advances have seen electric induction heating reach parity in capability and cost. Thus, the number of natural gas wells, well field size, and discovery year will be important to gauge the gas independence of a county. Note, this excludes total distance of distribution piping where counties low in gas resources may be large consumers. This will be missed in the investigation. Oil wells within Ohio will also be included. While not directly used for heating, oil is an important raw resource of petrochemical processes, and the presence of an oil well on a chemical plant site decreases operating costs and makes the plant more competitive. It may serve a role in identifying industry agglomeration.

Considering that community NIMBY sensitivity and energy relationships may lead to further insight into lens and the energy consumer producer, place attachment will have to be addressed. Based on background research and critical judgement, age, income levels, home values, number of homeowners, and years of occupancy will be considered for health of the community. Based on the case studies found, place attachment can be loosely interpreted through these statistics. Older, homeowning, high earners will be more likely to be tied to a locale than a newly moved, low earning, young professional. Additionally, the percentage of the workforce contributing to manufacturing and energy plus raw resource production will be factored into the analysis. The share of the economy invested in each industry may correlate to energy conscientiousness and cost of energy due to the scale of stake and experience local workers and officials have in each respective activity.

IAC factory data contains the location, Standard Industrial Classification (SIC) code, floor area, yearly sales, electrical energy cost in dollars per year and consumption in kWh per year, and thermal energy cost in dollars per year and consumption in MMBtu per year. Unit cost is calculated by the quotient of energy cost and consumption, and thermal electric ratios are calculated by the quotient of thermal consumption over electrical consumption, both in kWh. As it has been established that natural gas has a historical precedence for heat energy, the thermal electric ratio gauges the thermal intensity of a facility's process. All variables to be collected and analyzed are shown in the table below.

Table 1: Variables Under Consideration for the Analysis

Database	Variables
Industry:	Count, IAC Sample Size, Road Length, Number of Freight Trains
Energy:	Number of Power Plants, Substations, Oil Wells, and Gas Wells, Power Plant Size, Capacity Factor, Pollution Output, Well Size, Well Discovery Year
People:	Population, Age, Income, Education, Home Value, Number of Homeowners, Year of Occpancy, Workforce Distrubution (MFG vs ENERGY)
IAC:	Floor Area, Sales, Energy Consumption, Energy Cost (Unit Cost), Thermal Electric Ratio

The Pearson correlation coefficient (*r*) will be primarily metric used to gauge relationships between county profiles and IAC factory energy data. The coefficient primarily describes the normalized covariance or the strength of a linear relationship between two variables. It is mathematically expressed in equation 1.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (1)$$

x_i & y_i – Individual Sample Points

$\bar{x}$ & $\bar{y}$ – Sample Mean

i - index

n – sample size

r – Pearson Correlation Coefficient

The numerator is the covariance or statistical measure of the linear relationship between two variables. It is computed by summing the difference between each sample point and its mean value. The denominator is a normalization factor to ensure the value of r is between -1 and 1. A value of -1 or 1 indicates a perfect correlation, and anything near 0 as no relationship with the sign indicating a proportional or inverse proportional relationship. In this case it will be IAC data against county industry, energy, and people profiles to highlight any linear relationships that exist.

Data Exploration

Industrial Agglomeration Data

Analyzing manufacturing site counts from the 2020 Decennial Survey, it reveals the manufacturing sites or businesses classified with SIC codes of 2000-3999. Observing figure 2a, major manufacturing bases exist within the Cuyahoga, Franklin, Montgomery, Butler, and Hamilton counties of Ohio. From those counties, manufacturing appears to spread out and distribute into neighboring counties. Every county further away from the sources of industry sees less and lesser populations of manufacturers. A small base also exists in Lucas County, most likely associated with industry in Detroit and the automobile sector. It is important to note that if one were to draw a line through Hamilton County and Clark County, there is a slightly stronger manufacturing presence to the northwest than to the southeast.

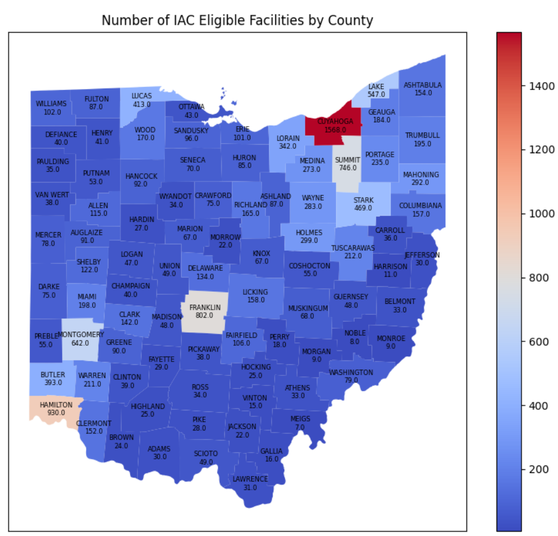


Figure 2a: Manufacturer Count by County

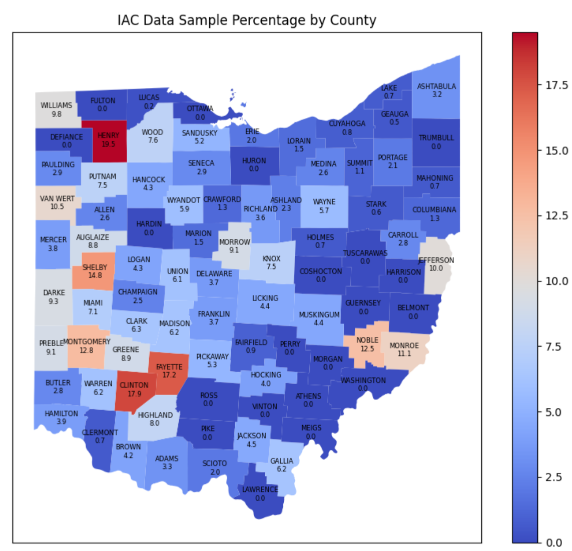
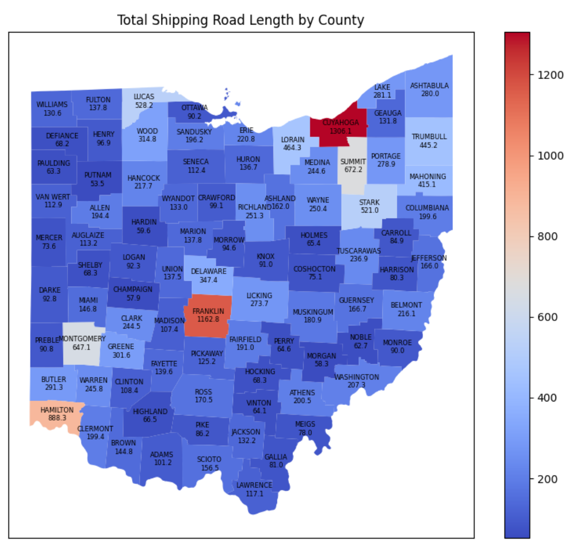


Figure 2b: Sample Size of Industrial Data

Based on the sum of manufacturers in each county, the IAC dataset accounts for on average 4% of each county's manufacturing base. The distribution is illustrated in figure 2b. As the IAC database originates from the University of Dayton, the distribution aligns with the university's location in Montgomery County with outreach extending more likely into neighboring counties and falling off further outward. Additonally, the dataset is not randomly selected so results must be taken with caution.

Considering other industial properties, the total road length was tallied in each county. This road length is measured in unknown units and accounts for all types of roads that are traversable by tractor trailor. Roads not traverable by truck can indicate high density of people, but don't indicate much about business operation types since the type of traffic using the roads is not differentiated. Roadways in figure 3a seem to match the number of manufacturers as higher lengths of road are seen in counties with higher levels of manufacturing. Similarly, the number of trains per day match. The figure of 3b depicts the number of freight trains through each county only on the mainlines of rail. Similar to roadways, higher number of trains are seen in areas with higher number of manufacturing. Although, it is important to note that branch lines are important drivers of industry and their exclusions may be detracting from data detail. Just because the southeastern portion of the state sees less manufacturing there are still noticeable numbers of trains traveling through those areas. As trains most often support heavy industry, this implies there is another connection occuring that could be addressed through other data visualizations.



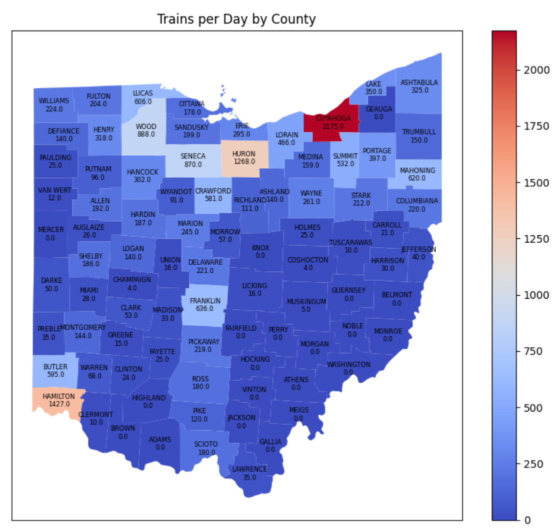
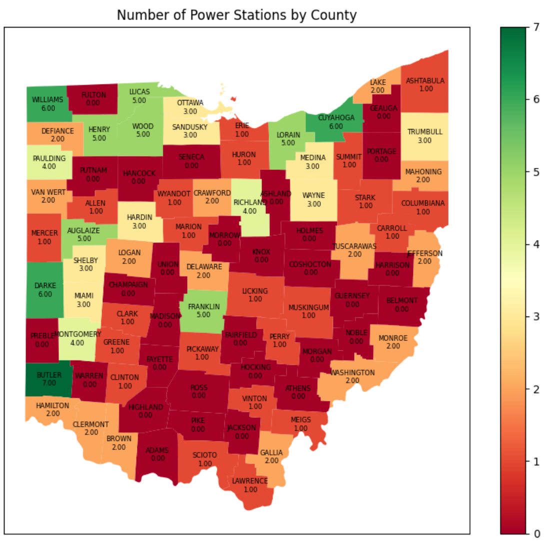


Figure 3a: Total Truck Traversable Road   Figure 3b: Number of Freight Trains Each Day

<u>County Energy Resources Data</u>

Considering energy resources, it is observed in figures 4a and 4b that counties high in manufacturing have high numbers of power stations and substations. Larger counts of both generators and transmission infrastructure are found in the northwestern slice of the state. There are also large collections along the eastern and southern border of the state.

This may likely be due to the natural advantage of these areas. The Ohio river runs along this border providing a large source of cooling to large thermal power stations. Lake Erie in the north also performs a similar role. Explanations for the quantity of power stations in the northwest section is not easily explained by natural advantage through these graphs alone, more investigation further on is required.



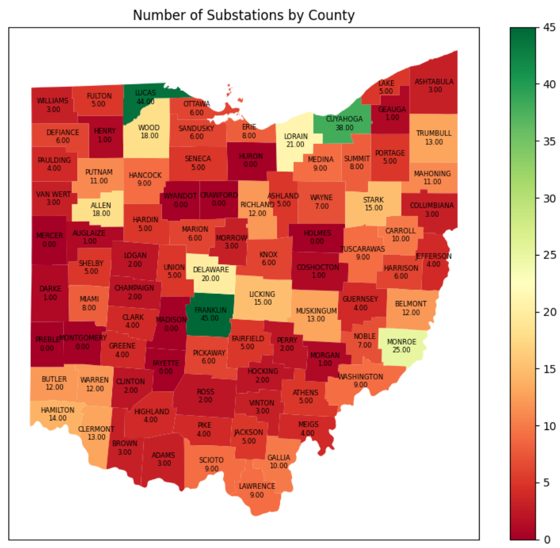
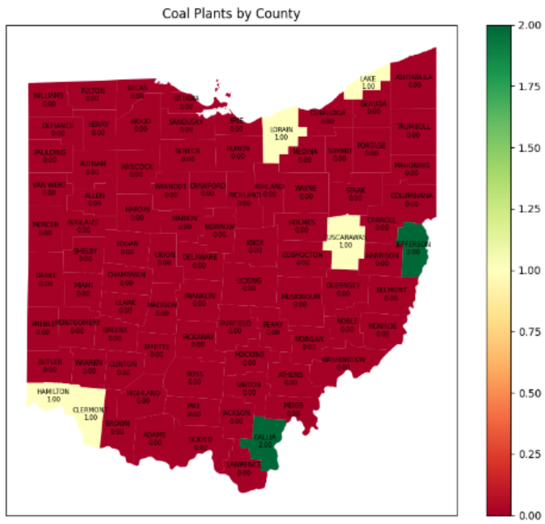


Figure 4a: Count of Power Plants

Figure 4b: Count of Substations

Observing counts of each type of power plant reveals a more enlighting picture. The traditional, Rankine cycle operated, baseload power plants are idenfified in coal and nuclear installations. The only two nuclear power plants of Ohio in figure 5b are located on the large thermal resivoir of Lake Erie. This body of water serves as an excellent cooling resource that would pose little risk of safety for nuclear power. The Couties of Lake and Ottowa border manufacturing centers indiciating closeness to load source and less need of infrastructure. The power they provide is in demand.



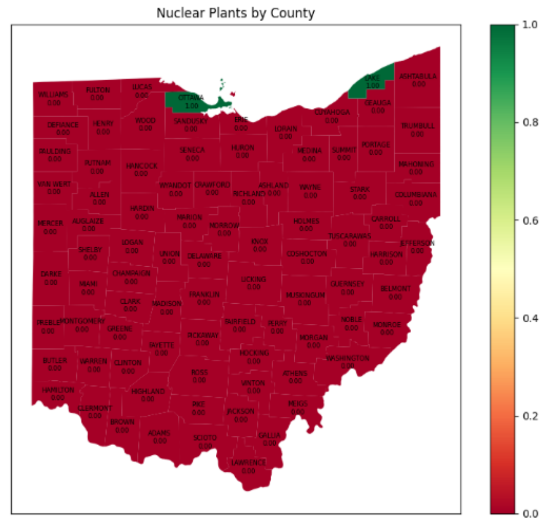
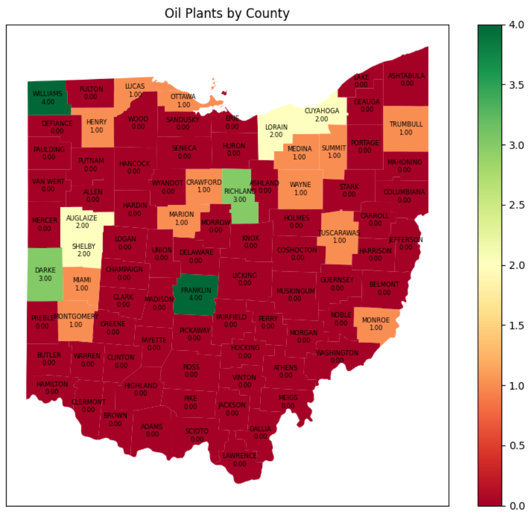


Figure 5a: Coal Plant Tally Figure 5b: Nuclear Plant Tally

Coal plants in figure 5a similarly exisit in Lorain, Lake, and Hamilton county providing much needed electricity to the manufacturing bases located nearby. But, large concentrations of power stations exist in Gallia and Jefferson County. These counties are the aforementioned sparsely populated by manufacturing areas of southeast Ohio. More information is needed to explain why.

Biomass and hydropower are also baseload factors, but they are of more limited quantites and smaller scale. The technology is far less potent and widespread than coal or nuclear to have a significant impact on grid performance or pollution output. The biomass and hydro powerplant distribution can be observed in Appendix A.

Gas and Oil power stations can be considered peaking power plants. Their fast startup time and reactive controls enable them to better respond to transient grid demand rather than coal or nuclear stations. Fast startups and shutdowns are hard on the equipment of coal and nuclear power stations, but Oil and Gas handle the erratic behavior well. Thus, it would make sense to see higher quantities in the northeast for these stations as there is greater presence of industry. That industry may also be pulling varaible demands on the grid justifying then need for peaking power plants. Despite this, there are still significant gas concentrations in the southeast. These may be combined cycle gas plants that utilize a Rankine cycle that recycles heat loast from the gas turbine’s Brayton cycle. Rankine cycles require an active cooling source such as the Ohio River in that region.



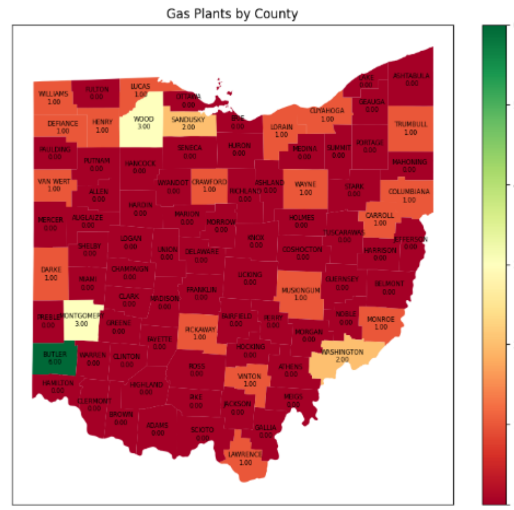
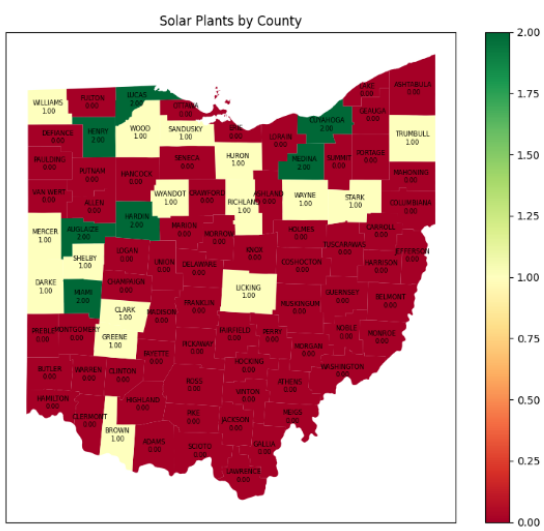


Figure 6a: Oil Plant Count Figure 6b: Gas Plant Count

Renewable energy sites in figure 7a and 7b are more difficult to rationalize based on the presence of industry. Natural advantage may be the primary driving factor for these power stations. The sites selected provide the most energy at the least cost to the installer. The communities where these types of power plants exist also lack baseload generation so the presence of renewables provides a degree of grid resilience. This allows these communities to be less dependent on long distance transmission lines.



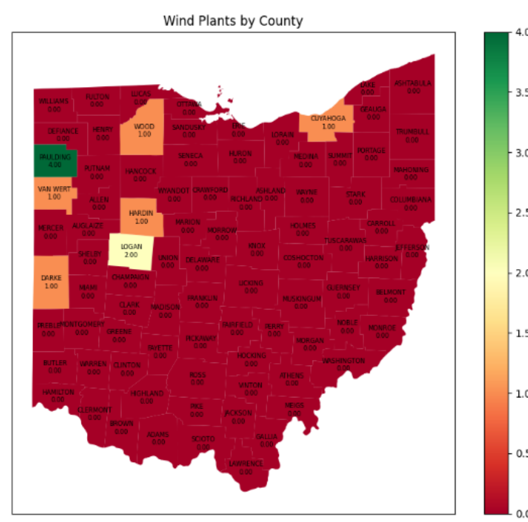
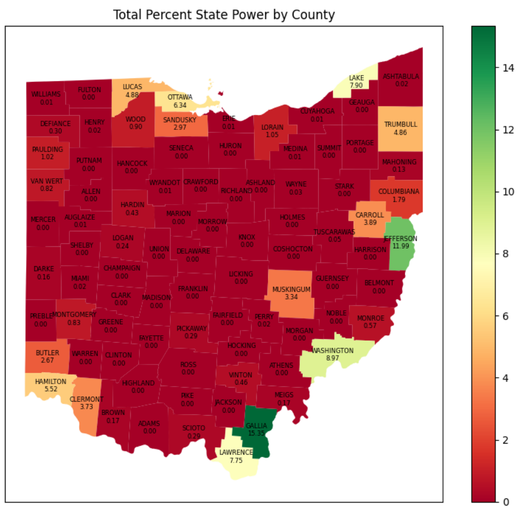


Figure 7a: Solar Plant Count Figure 7b: Wind Plant Count

Expectedly, the total percentage of the state of Ohio's electric contributors in figure 8a and 8b primarily comes from counties with the large baseload generators of coal and nuclear. Counties with high levels of gas, oil, hydro, biomass, and renewable also contribute significant portions. High power output occurs in counties that have high natural advantages for power generation or near industry.



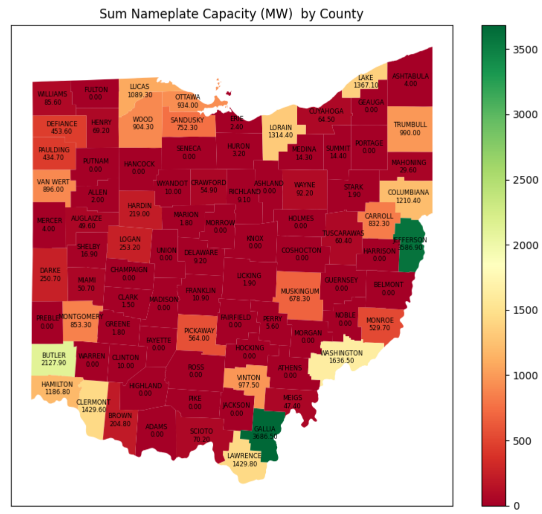


Figure 8a: Percent Share of State Grid Source Figure 8b: Total Power Generation Capacity

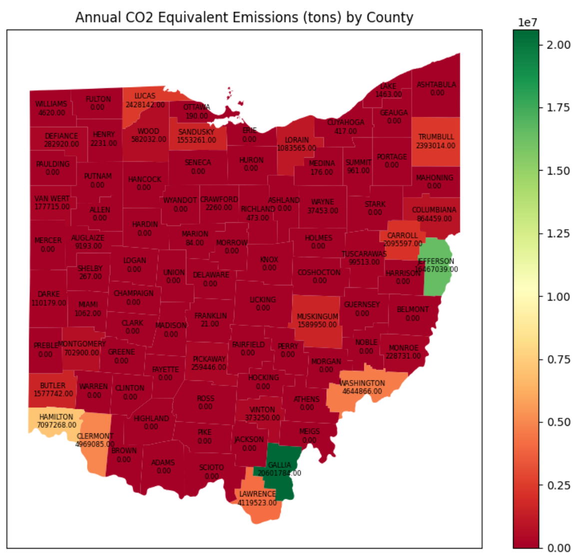


Figure 8c: CO2 Emissions from Power Generation

While figures 8a and 8b highlight power generation to the state, figure 8c shows where the majority of the pollution is being emitted. the majority of pollution emissions are concentrated in counties with large coal, oil, and gas power stations. The coaling stations contribute the most to CO2 emissions as can be seen by the counties of Jefferson and Galia. Lesser concentrations can be observed around Lucas, Ottowa, and Lorrain.

Taking capacity factor into account, these numbers are further justified. Counties high in pollution output, and grid contribution see the highest capacity factors. This, once more, indicates that power generation within these communities is constant, and electricity is their resource of export. This can be rationalzied as the predominant philosophy of power plant consutrction has been based on economy of scale. Large power stations supported by natural advantage could provide power to the load sources far away over high voltage transmission wire. Such an approach is good for margins by maximizing output, but bad for grid resiliency. This is due to centralization, and the presence of renewable energy plus emissions resctricions has been degrading the output of these stations in the electric grid makeup. Another name for locations low in market interaction, but high in natural electricy generation advantage is an energy community. Just as how some towns in West Virginia survive off of the revenue and export of coal, some counties of Ohio survive by transforming those raw resources into another form of raw resource, electricity.

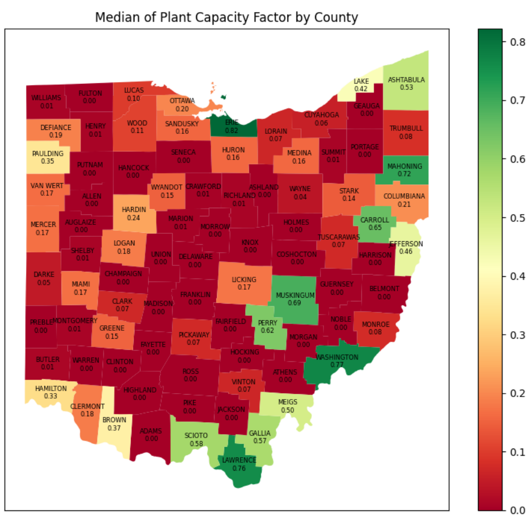


Figure 9a: Capacity Factor Median

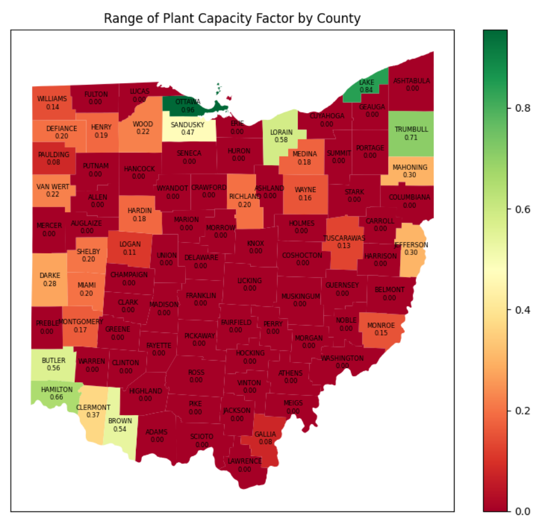


Figure 9b: Capacity Factor Range

Seeing that figure 9b highlights the capacity factor range, there are greater capacity factor ranges in counties close to manufacturing. The increased range implies the existence of more peaking power plants. Some serve baseload while others respond. There is greater diversity in generation technologies due to the greater diversity in electrical load.

Observing natural gas well locations and size, they are primarily clustered in the southeast of the state. Being that this region is near appachia, fossil reseverves would be expected. The appalachain mountains are known as large coal reserves within the United

States. Where there is coal or oil, the fossil fuel creation process has the byproduct of natural gas. This region may also be less developed. Rural houses often have their own natural gas wells for heating and other domestic purposes. The reason being that a gas supplier would need to lay the necessary infrastructure, and the cost of such an endeavour would outstrip the cost of installing a well. The average well size throughout those regions is small compared to the number of wells supporting this theory. Allen county in figure 9b may be a net exporter of natural gas due ot the low number of wells and high well size.

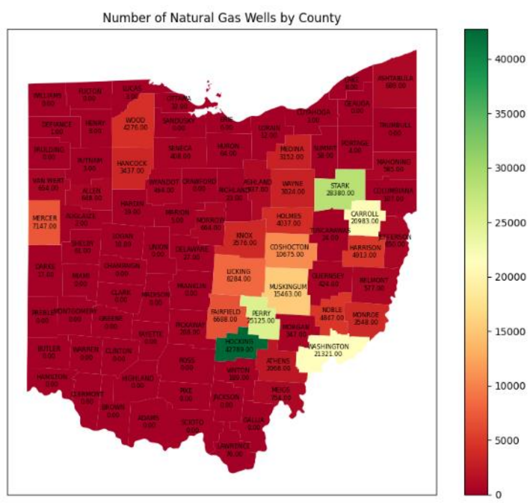


Figure 10a: Gas Well Count

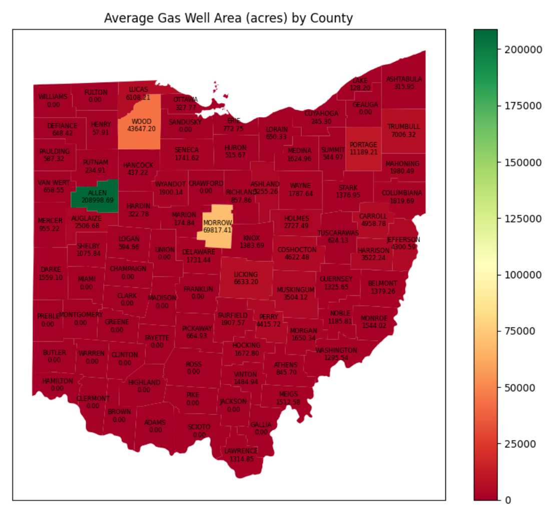


Figure 10b: Mean Gas Well Area

A similar story to the Gas wells is observed in the oil wells of this region. Most wells in figure 10a are clustered along the eastern border with some extending into the west across the state. The average well size in figure 10b is quite small indicating individual and isolated operation. Augalize county may have a commercial operation capitalizing on the county's natural resources as there is a large resivour compared to a small number of wells. Little insight was revealed through mean discovery date for either type of well. The figures are attached in Appendix B for viewing.

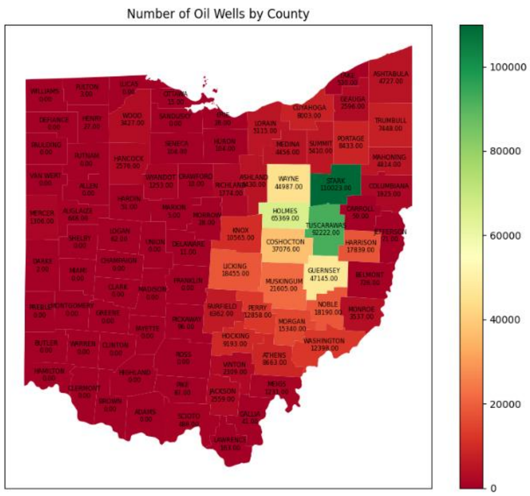


Figure 10a: Oil Well Count

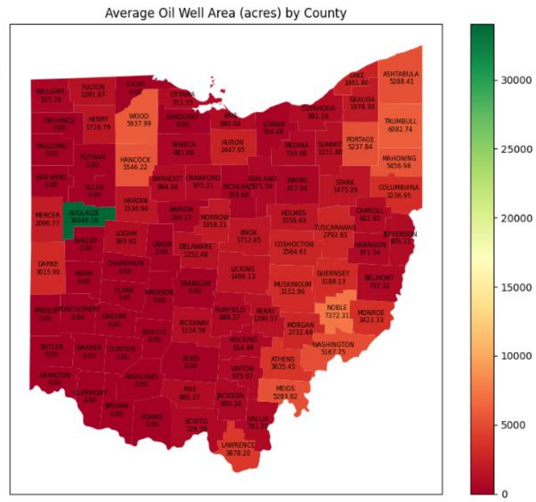
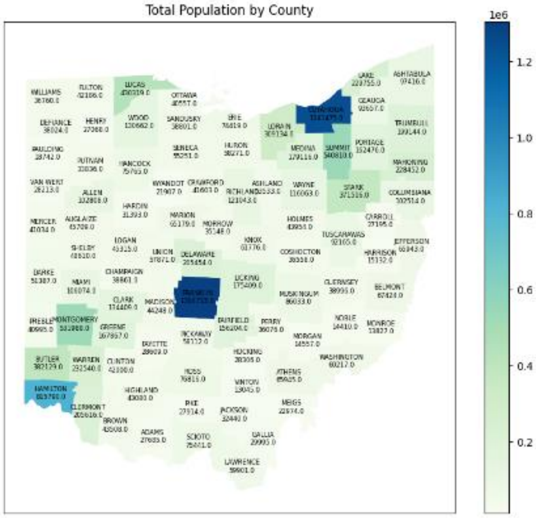


Figure 10b: Mean Oil Well Area

County Demographics and NIMBY Data

Addressing demographics data, it is observed in figures 11a, 11b, and 11c that counties high in manufacturing and electric power infrastructure have high population numbers, higher median incomes and lower median age. It is important to note the outliers to this correlation. Take for instance Athens and Ottawa county. Athens has low levels of manufacturing but a low median age. This is likely due to the presence of Ohio University and the high student population. Ottawa is high in manufacturing but has a high median age. This occurrence is less readily explainable. The population statistics also explain the energy resource distribution. The increased number of peaking plants are also reacting to residential or commercial demand in addition to manufacturing. There is simply more activity justifying greater necessity of spontaneity in the system.



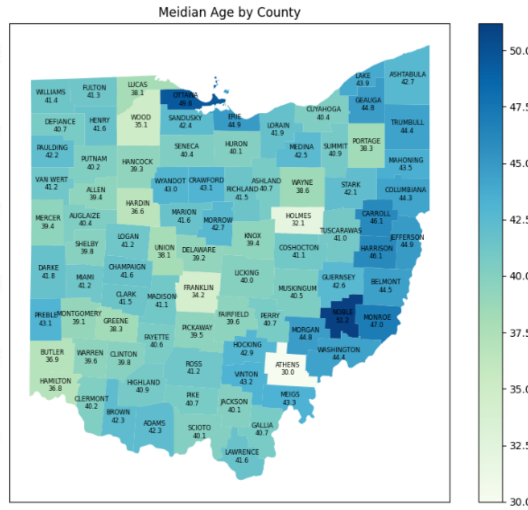


Figure 11a: Total Population Counts Figure 11b: Median Age Values

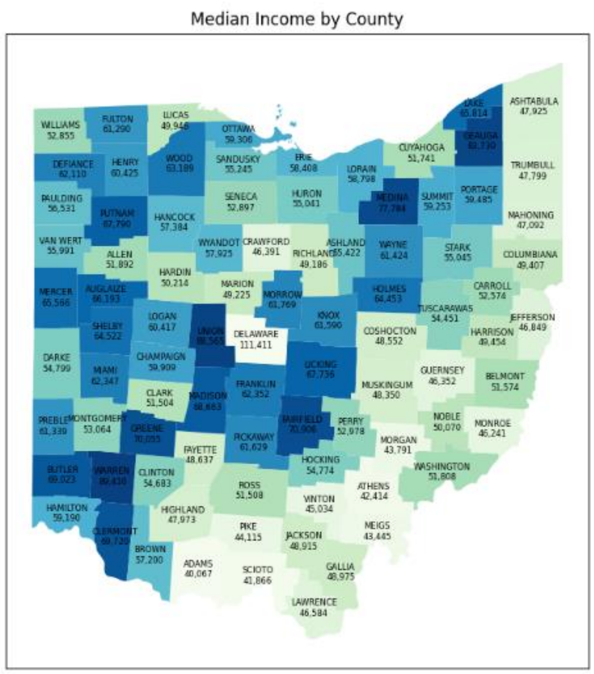


Figure 11c: Median Income Values

The tendency of the state to split between northeast and southwest is accentuated by the median age and income graphics in figure 11b and 11c. Those northwest with higher manufacturing counts have demographics with a central tendency of younger age and higher incomes. The southeast is the opposite. Energy communities reliant upon raw resource or energy export appear to earn less and have longer staying residents than do the places that process and transform those raw inputs.

This sentiment is echoed by figure 12a with the median home value higher in regions near manufacturing, but not in centers of manufacturing. This is likely the surrounding suburbs of the centers of undustry. Despite Cuyahoga and Franklin county being high in manufacturing counts, their neighboring counties of Geauga, Medina, and Delaware have comparatively higher home values. People may not want to live where manufacturing is. Likewise, figure 12b highlights areas higher in manufacturing seeing renters and homeowners having a central tendency of more recent year of residence. In the southeast, there are more longstanding residents. As shown in figure 12c these people are more likely to be home owners. Manufacturing centers see less home ownership. This is foreseeable due to the presence of large citities necessitating high density housing arrangements to accommodate not only manufacturing workers but the complex economy of the region.

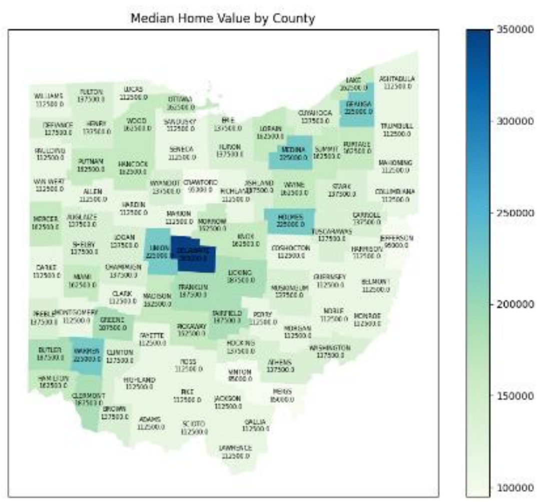


Figure 12a: Median Home Values

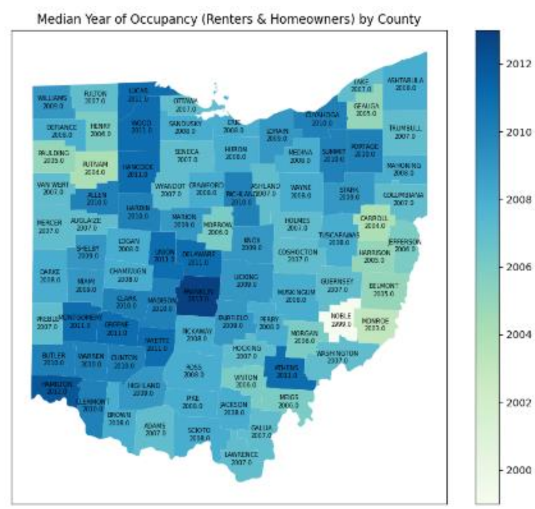


Figure 12b: Median Year of First Occupancy

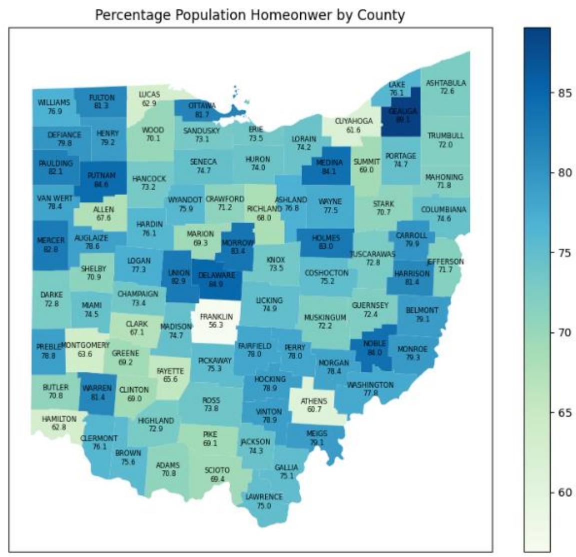


Figure 12c: Percentage of County as Homeowners

Education levels seen in figures 13a, 13b, and 13c demonstrate that manufacturing based economies attract higher educated people. This is seen by the quantity of bachelors and graduate degree educated citizens located in large manufacturing bases of Cuyahoga, Delaware, and Hamilton county. But, the higher number of manufacturing sites increase the likelihood of highly specialized processes requiring highly skilled professionals. The northwest is high in manufacturing, but contains low numbers of bachelors and graduate educated individuals. The presence of the large cities and diverse economies of Cleveland, Columbus, and Cincinnati in Cuyahoga, Hamilton, and Delaware county respectively may be a plausible reason for the presence of elevated education.

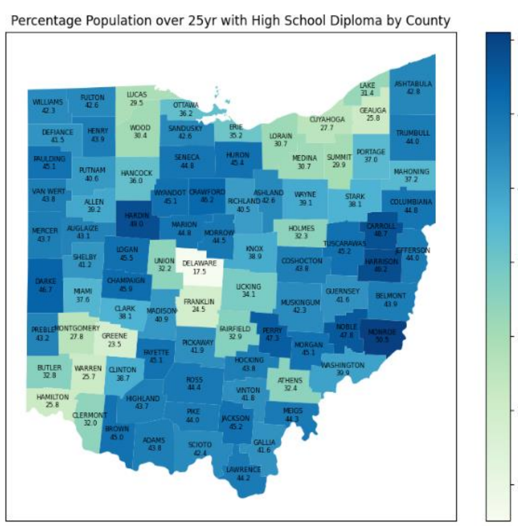


Figure 13a: Max Education High School

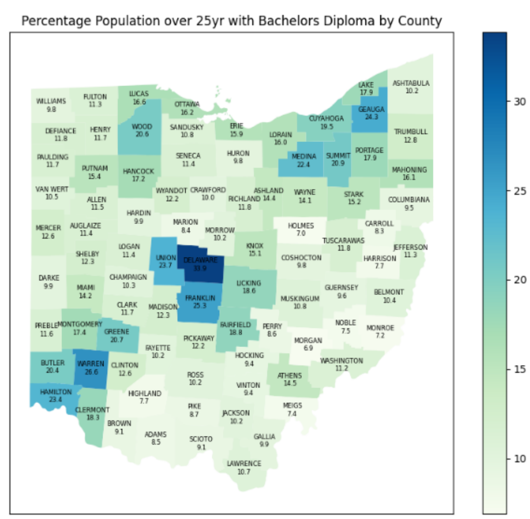


Figure 13b: Max Education Bachelors

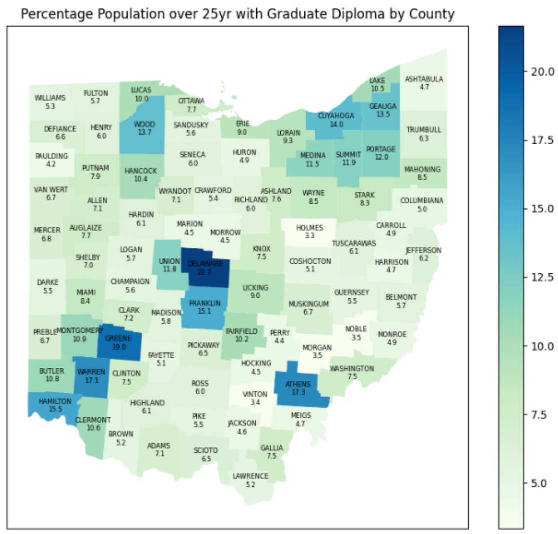


Figure 13c: Max Education Graduate Studies

Investigating the workforce allocation to manufacturing versus energy resources solidifies the state split between energy and manufacturing discussed in previous sections. The northwest portion of Ohio in figure 14a is high in reliance on manufacturing for the local economy while the southeast in figure 14b is reliant on raw resource extraction and energy generation. The line through the middle two sections are where the most people and diverse commerce is likely found. There is less singular dependence on these industries.

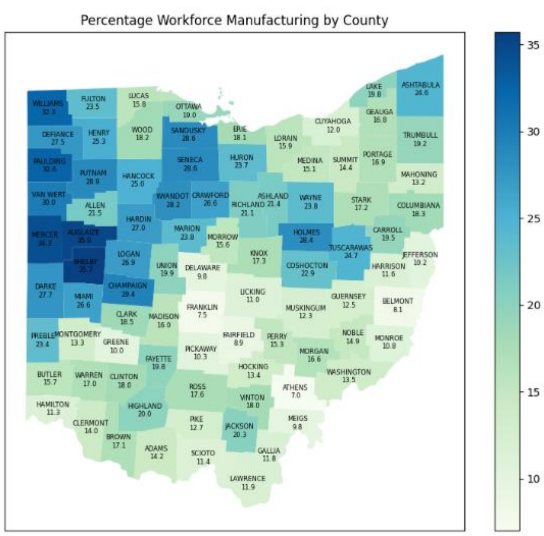


Figure 14a: Manufacturing Workforce

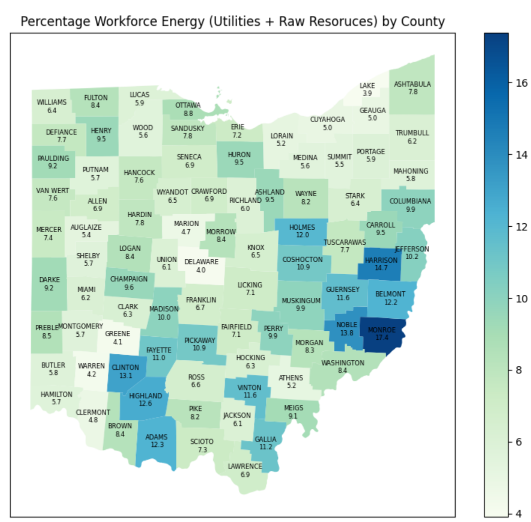


Figure 14b: Energy Workforce

Note that the percentage of dependence is different between the two. Manufacturing dependent counties exceed 35% of a county's workforce while energy counties only exceed 16%. This may indicate that there is less economic gain to be had with energy resources, and there is a finite capacity on how many energy extractors and transmitters can but established in one locale. Manufacturing on the other hand has greater capacity for expansion and engulfment of the local workforce.

Relational Analysis

The correlation matrices generated include the data set variable names. Some of which may be difficult to discern meaning on their own. Thus, Appendix C contains a crosswalk between variable name and generalized meaning to increase readability and interpretability of results.

The first correlation matrix in table 15 establishes relationships between high level manufacturing data and the IAC database. The first most notable aspect is the relationship between variables in the IAC database. Sales and floor area have moderate correlations with energy consumption both thermal and electrical. They also correlate to the thermal electric ratio. This internal validation indicates that energy usage is highly individualized. Even when lumped into categories, facilities manufacturing the same product can differ greatly in energy use based on unique attributes. This could include construction year and associated standards, the types of upgrades and changes experienced by the plant, the quality of maintenance, and much more.

Considering then the industrial agglomeration variables, there is a weak inverse correlation between facility size, road length, and the number of manufacturers in the area. This denies the idea of agglomeration wherein like businesses attract. Larger manufacturers are less likely to exist where there are more manufacturers, but only weakly. Electric consumption and sales also weakly, inversely correlate with the number of facilities, but electricity costs corelate positively with facility quantity. Thermal energy usage is left unexplained by the results.

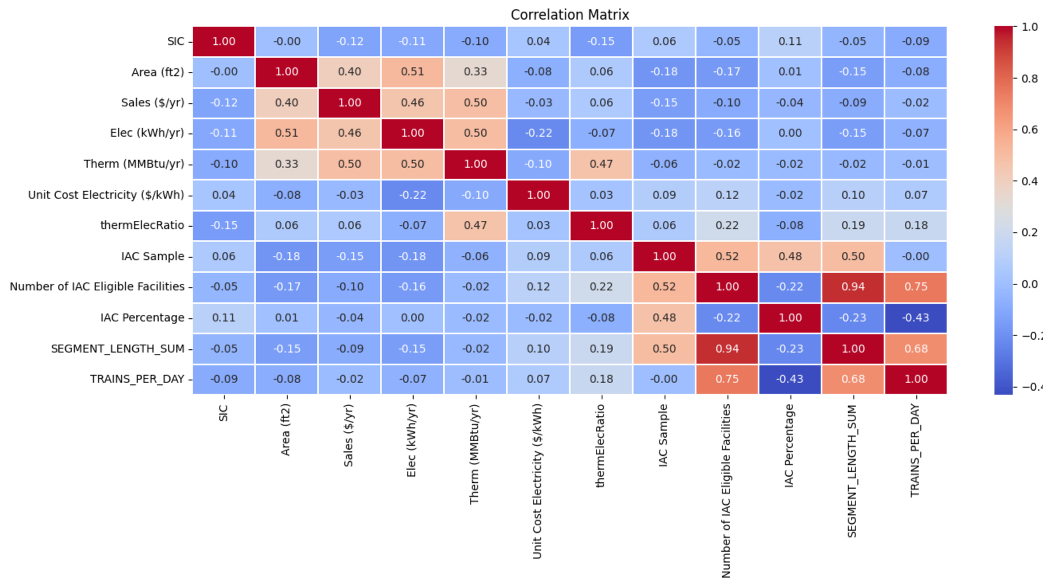


Figure 15: Manufacturing v. IAC Data Correlation Matrix

Analyzing the energy resource datapoints in comparison to collected IAC data on industrial energy consumption, the trend of weak correlations continues. In figure 16, floor area weakly and inversely correlates to average power plant nameplate capacity. There is also a peculiar weak, inverse correlation between the number of gas power plants and the floor area, sales, electricity consumption, and thermal energy consumption. A place that is high in gas power may see less presence of manufacturing sites due to the economic benefit of the gas plants. Further investigation is required. It is also important to note the weak inverse correlation to SIC code and the size of gas wells and the number of coal plus gas plants. Certain facilities may make best use of a local gas well, and lower SIC codes could be factories that benefit or are more likely to have their own gas well. Additionally, some manufacturers may act in a supporting role to these power plants. Parts fabrication, repair, and outage support are large industries that power plants need to operate. The more time spent offline the less money the utility makes. Therefore, outages become spectacles as hundreds if not thousands of people depending on site size to hasten the repair and maintenance process. There is also a small $r = 0.15$ positive correlation between thermal energy consumption and the presence of nuclear power. An explanation is unknown but can be disregarded due to the small sample size of nuclear power plants.

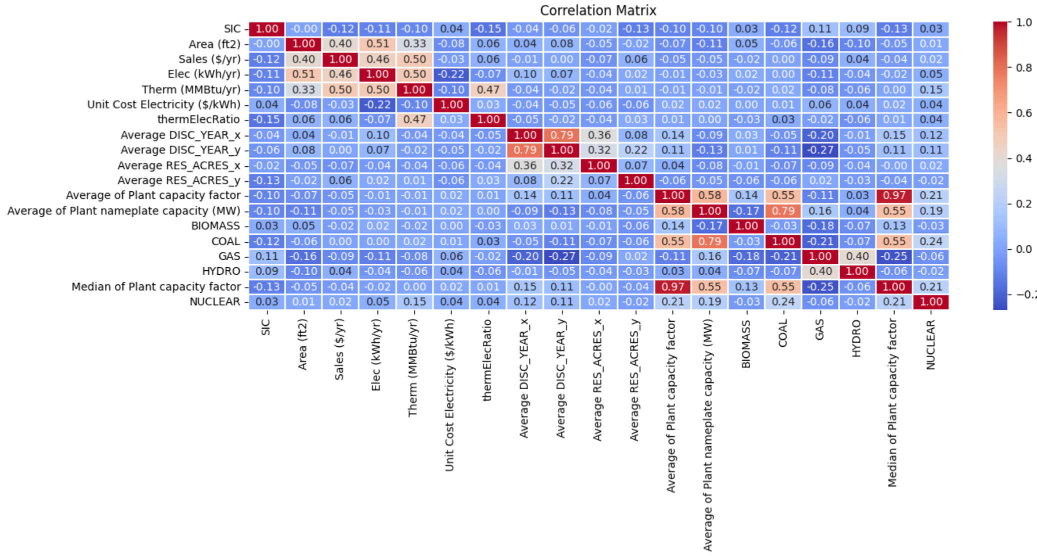


Figure 16: Energy First Half v. IAC Data Correlation Matrix

Further considering energy data in figure 17, the area of a facility weakly and inversely correlates to the number of power stations and sum of nameplate capacity. The number of substations in a county weakly and inversely correlates to the size, sales, electrical, and thermal energy consumption of a facility. This may imply that high manufacturing density leads to more diverse but decreased firm size. Larger facilities benefit from removal of urban areas much like larger scale power plants. Further investigation is required to verify. The thermal electric ratio has an unexplainable weak correlation with the number of oil wells.

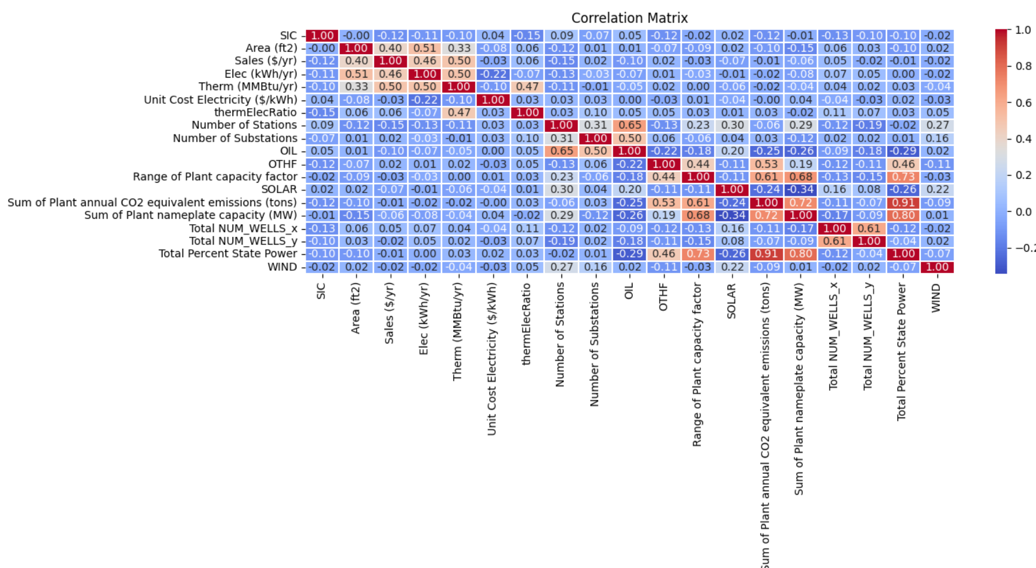


Figure 17: Energy Second Half v. IAC Data Correlation Matrix

Consideration of population demographics and IAC factory energy consumption in figure 18 reveals far more promising and intriguing results. Areas with higher percentages of workers in the energy and raw resource industry weakly correlates to increased facility electrical and thermal energy consumption. This may be due to the type of industry in support of the energy and raw resource industries, or there is greater energy use desensitization. Due to the prevalence of energy in the economy, populations are less averse to energy waste since it is so plentifully collected and traded from the locale. Populations with higher percentages of only high school workers see a weak positive correlation with electrical energy consumption, and the trend goes inverse for bachelor and graduate education levels.

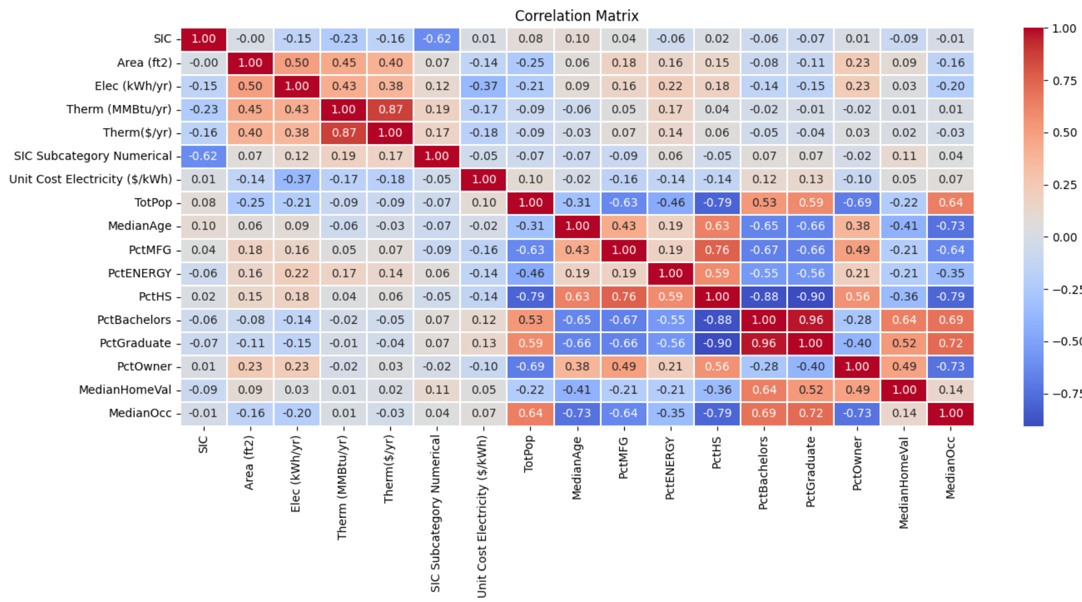


Figure 18: Population v. IAC Data Correlation Matrix

Higher total population and median years of occupancy see an inverse relationship with electrical energy consumption, but the number of homeowners and percentage workforce of manufacturing in a county see a weak positive correlation. The cost of both thermal and electrical energy is left mostly unexplained in the assembled correlation matrixes. So too is the thermal electric ratio untouched. Ultimately, electrical energy usage seems better explained by such a high-level approach than does thermal. Thermal energy may be more process-oriented implying its existence at a facility is purely technical, well managed, and requires dedicated skilled labor to operate. In contrast, electricity is a commodity and resource to be used and processed making a more social challenge.

Discussion and Conclusion

The research here raises more questions of why and how than answers. The energy connection established in the initial investigation proved to be weaker than expected. But demographic data showcased far more potential in predictive power. The research conducted within this scope of this body revealed that energy consumption is a complex byproduct between many different and difficult to identify interactions between people and their environment. In constructing county level profiles of the state of Ohio for industrial populations and resources, energy resources, and demographics, the weak agglomerative and social aspect of facility energy consumption were brought to light. Small relationships between energy use and the collected data were identified and possible explanations were proposed. Ultimately, there are still unanswered questions regarding the sources variables and their correlations warranting further investigation.

Identified weaknesses of the analysis are detailed below and justify further investigation plus correction through any iterative works. Limited statistical analysis was performed on the collected data. Where data was not summed, median values were the primary metric of measure to identify data centrality. Where the sample size was sufficiently small or large enough mean values are used due to the assumption of a normal tendency. Outliers were not filtered but included in the data analysis. This may skew the relations and correlations. The Pearson correlation coefficient is limited in scope and only identifies linear relationships. Cluster analysis, machine learning decision trees, random forests, or neural networks may reveal more insightful or practical results.

Areas for future research would include addressing the identified weaknesses. Additional granularization of the data may yield further intrigue. One such case is the SIC codes used. North American Industry Classification System (NAICS) codes are far more detailed than SIC which could help differentiate different types of establishments further instead of lumping every manufacturer and their energy data under an umbrella term. Additionally, breaking down the analysis into an intra-county investigation may yield greater findings. Correlation matrix results indicated that energy use is still highly facility specific, and observing more local demographics and characteristics could yield more poignant insight. Data transformation is required to truly draw out the relationships at play.

It is the hope that continued exploration into the human-energy relationship dynamic is continued to be researched. Agglomeration of human productivity centers is weakly understood. Even more unfortunately, the variables to predict reaction and interaction between communities and new projects both manufacturing and energy related are ill defined. The energy crisis is both a technical and human challenge. Continuing to understand how both interoperate will lead to a brighter future.

References

1. Tsao, J.Y., et al., *The electrification of energy: Long-term trends and opportunities.* MRS Energy & Sustainability, 2018. **5**.
2. Mai, T.T., et al., *Electrification futures study: scenarios of electric technology adoption and power consumption for the United States*. 2018, National Renewable Energy Lab.(NREL), Golden, CO (United States).
3. Ewart, D., *Whys and wherefores of power system blackouts.* IEEE Spectrum;(United States), 1978. **15**(4).
4. Hines, P., J. Apt, and S. Talukdar, *Large blackouts in North America: Historical trends and policy implications.* Energy Policy, 2009. **37**(12): p. 5249-5259.
5. Stott, P., *How climate change affects extreme weather events.* Science, 2016. **352**(6293): p. 1517-1518.
6. Lerner, E.J., *What's wrong with the Electric Grid?* Industrial physicist, 2003. **9**(5): p. 8-10.
7. Administration), E.U.S.E.I., *Total Energy Monthly Data*. 2022, Energy Information Administration: Washington, D.C.
8. Administration), E.U.S.E.I. *Total Energy Consumption in the United States from 1975 to 2022, by Sector (in Quadrillion British Thermal Units)*. 2023 [cited 2023 11/12/2023]; Available from: https://www.statista.com/statistics/239790/total-energy-consumption-in-the-united-states-by-sector/.
9. Administration), E.U.S.E.I., *Electric Power Annual*. 2023, U.S. Energy Information Administration: Washington, D.C.
10. Russell, J.A. and L.M. Ward, *Environmental psychology.* Annual review of psychology, 1982. **33**(1): p. 651-689.
11. Bott, S., J.G. Cantrill, and O.E. Myers Jr, *Place and the promise of conservation psychology.* Human ecology review, 2003: p. 100-112.
12. Energy), D.U.S.D.o. *Industrial Assessment Centers*. 11/12/2023]; Available from: https://iac.university/.
13. Beyene, A. and A. Moman, *Process oriented industrial classification based on energy intensity.* Applied thermal engineering, 2006. **26**(17-18): p. 2079-2086.
14. Ellison, G. and E.L. Glaeser, *Geographic concentration in US manufacturing industries: a dartboard approach.* Journal of political economy, 1997. **105**(5): p. 889-927.
15. Ellison, G. and E.L. Glaeser, *The geographic concentration of industry: does natural advantage explain agglomeration?* American Economic Review, 1999. **89**(2): p. 311-316.
16. Rosenthal, S.S. and W.C. Strange, *The determinants of agglomeration.* Journal of urban economics, 2001. **50**(2): p. 191-229.
17. Gabe, T., *Local industry agglomeration and new business activity.* Growth and Change, 2003. **34**(1): p. 17-39.
18. O'Donoghue, D. and B. Gleave, *A note on methods for measuring industrial agglomeration.* Regional studies, 2004. **38**(4): p. 419-427.
19. Puga, D., *The magnitude and causes of agglomeration economies.* Journal of regional science, 2010. **50**(1): p. 203-219.

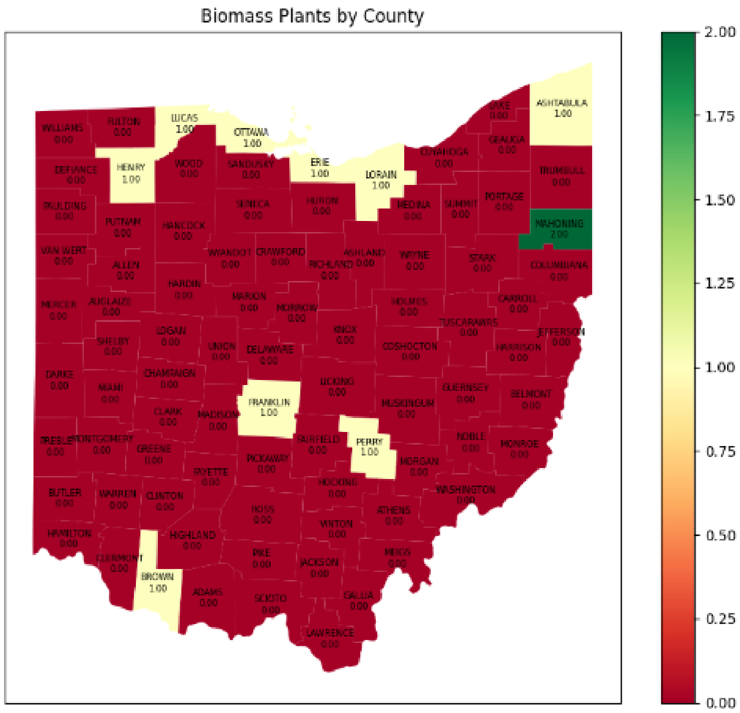
20. Ellison, G., E.L. Glaeser, and W.R. Kerr, *What causes industry agglomeration? Evidence from coagglomeration patterns.* American Economic Review, 2010. **100**(3): p. 1195-1213.
21. Han, F., R. Xie, and J. Fang, *Urban agglomeration economies and industrial energy efficiency.* Energy, 2018. **162**: p. 45-59.
22. Steijn, M.P., H.R. Koster, and F.G. Van Oort, *The dynamics of industry agglomeration: Evidence from 44 years of coagglomeration patterns.* Journal of Urban Economics, 2022. **130**: p. 103456.
23. Head, K., J. Ries, and D. Swenson, *Agglomeration benefits and location choice: Evidence from Japanese manufacturing investments in the United States.* Journal of international economics, 1995. **38**(3-4): p. 223-247.
24. Tanaka, K. and S. Managi, *Industrial agglomeration effect for energy efficiency in Japanese production plants.* Energy Policy, 2021. **156**: p. 112442.
25. Moreno-Cruz, J. and M.S. Taylor, *An energy-centric theory of agglomeration.* Journal of Environmental Economics and Management, 2017. **84**: p. 153-172.
26. Severnini, E., *The power of hydroelectric dams: Agglomeration spillovers.* 2014.
27. Rediske, G., et al., *Wind power plant site selection: A systematic review.* Renewable and Sustainable Energy Reviews, 2021. **148**: p. 111293.
28. Shorabeh, S.N., et al., *The site selection of wind energy power plant using GIS-multi-criteria evaluation from economic perspectives.* Renewable and Sustainable Energy Reviews, 2022. **168**: p. 112778.
29. Rediske, G., et al., *Determinant factors in site selection for photovoltaic projects: A systematic review.* International Journal of Energy Research, 2019. **43**(5): p. 1689-1701.
30. Shao, M., et al., *A review of multi-criteria decision making applications for renewable energy site selection.* Renewable Energy, 2020. **157**: p. 377-403.
31. Milovanović, Z., et al., *Modeling of the optimization procedure for selecting the location of new thermal power plants (TPP).* International Journal of Mathematical, Engineering and Management Sciences, 2021. **6**(1): p. 118.
32. Sambasivarao, K., D.K. Raj, and D. Dua, *An expert system for site selection of thermal power plants.* Journal of Basic and Applied Engineering Research, 2014. **1**: p. 36-40.
33. Barda, O.H., J. Dupuis, and P. Lencioni, *Multicriteria location of thermal power plants.* European Journal of Operational Research, 1990. **45**(2-3): p. 332-346.
34. Um, S., et al. *Comprehensive Evaluation Indexes Framework and Evaluation Method for Substation Site Selection*. in *Journal of Physics: Conference Series*. 2021. IOP Publishing.
35. Qin, C., et al., *Location of substation in similar candidates using comprehensive evaluation method base on DHGF.* Measurement, 2019. **146**: p. 152-158.
36. Wang, L., et al. *Site selection and capacity determination of substation based on power-weighted K-means*. in *2021 IEEE 4th International Conference on Automation, Electronics and Electrical Engineering (AUTEEE)*. 2021. IEEE.
37. Zenker, S. and N. Rütter, *Is satisfaction the key? The role of citizen satisfaction, place attachment and place brand attitude on positive citizenship behavior.* Cities, 2014. **38**: p. 11-17.

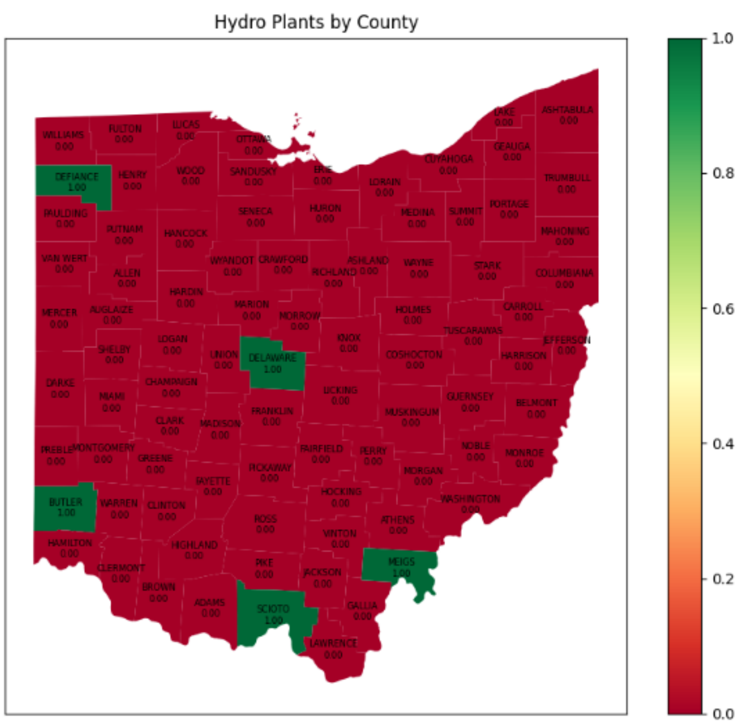
38. Kudryavtsev, A., R.C. Stedman, and M.E. Krasny, *Sense of place in environmental education.* Environmental education research, 2012. **18**(2): p. 229-250.
39. Vaske, J.J. and K.C. Kobrin, *Place attachment and environmentally responsible behavior.* The Journal of environmental education, 2001. **32**(4): p. 16-21.
40. Garrone, P. and A. Groppi, *Siting locally-unwanted facilities: What can be learnt from the location of Italian power plants.* Energy policy, 2012. **45**: p. 176-186.
41. Bergquist, P., et al., *Backyard voices: how sense of place shapes views of large-scale energy transmission infrastructure.* Energy research & social science, 2020. **63**: p. 101396.
42. Abraham, M. and G.M. Maney, *Transforming place and belonging through action research, community practice, and public policy: Comparing responses to NIMBYism.* Current sociology, 2012. **60**(2): p. 178-201.
43. Pol, E., et al., *Psychological parameters to understand and manage the NIMBY effect.* European review of applied psychology, 2006. **56**(1): p. 43-51.
44. Vittes, M.E., P. Pollock III, and S.A. Lilie, *Factors contributing to NIMBY attitudes.* Waste Management, 1993. **13**(2): p. 125-129.
45. Devine-Wright, P., *Explaining "NIMBY" objections to a power line: The role of personal, place attachment and project-related factors.* Environment and behavior, 2013. **45**(6): p. 761-781.
46. Sovacool, B.K., *The cultural barriers to renewable energy and energy efficiency in the United States.* Technology in Society, 2009. **31**(4): p. 365-373.
47. Timmons, D., N. Zirogiannis, and M. Lutz, *Location matters: Population density and carbon emissions from residential building energy use in the United States.* Energy research & social science, 2016. **22**: p. 137-146.
48. Zhao, D., et al., *Interaction effects of building technology and resident behavior on energy consumption in residential buildings.* Energy and Buildings, 2017. **134**: p. 223-233.
49. Xu, X., et al., *The impact of place-based affiliation networks on energy conservation: An holistic model that integrates the influence of buildings, residents and the neighborhood context.* Energy and buildings, 2012. **55**: p. 637-646.
50. Bureau, U.S.C., *County Business Patterns: CBP2020*. 2021, U.S. Census Bureau.
51. Transportation, O.D.o., *ODOT TIMS: Ohio Rail Lines, Road Inventory, County Shapefiles*. 2024, Ohio Department of Transportation - Transportation Information Mapping System.
52. Agency, U.S.E.P., *eGRID2020 Data*. 2021, U.S. Environmental Protection Agency.
53. Contributors, O., *GeoJSON export of Substations in the Ohio area*. 2024, OpenStreetMap.
54. Resources, O.D.o.N., *ODNR Well Finder - Gas and Oil Well Database and Location Shapefiles*. 2024, Ohio Department of Natural Resources.
55. Bureau, U.S.C., *ACS 5-Year Estimates - Demographic and Housing Estimates: S0101*. 2021, U.S. Census Bureau.
56. Bureau, U.S.C., *ACS 5-Year Estimates - Industry, Occupation, and Class of Worker: S2405*. 2021, U.S. Census Bureau.
57. Bureau, U.S.C., *ACS 5-Year Estimates - Educational Attainment: S1501*. 2021, U.S. Census Bureau.

58. Bureau, U.S.C., *ACS 5-Year Estimates - Income in the Past 12 Months: S1901*. 2021, U.S. Census Bureau.
59. Bureau, U.S.C., *ACS 5-Year Estimates - Detailed Housing Characteristics: B25026*. 2021, U.S. Census Bureau.
60. Bureau, U.S.C., *ACS 5-Year Estimates - Financial Characteristics: B25075*. 2021, U.S. Census Bureau.
61. Bureau, U.S.C., *ACS 5-Year Estimates - Plumbing Characteristics: B25039*. 2021, U.S. Census Bureau.

Appendixes

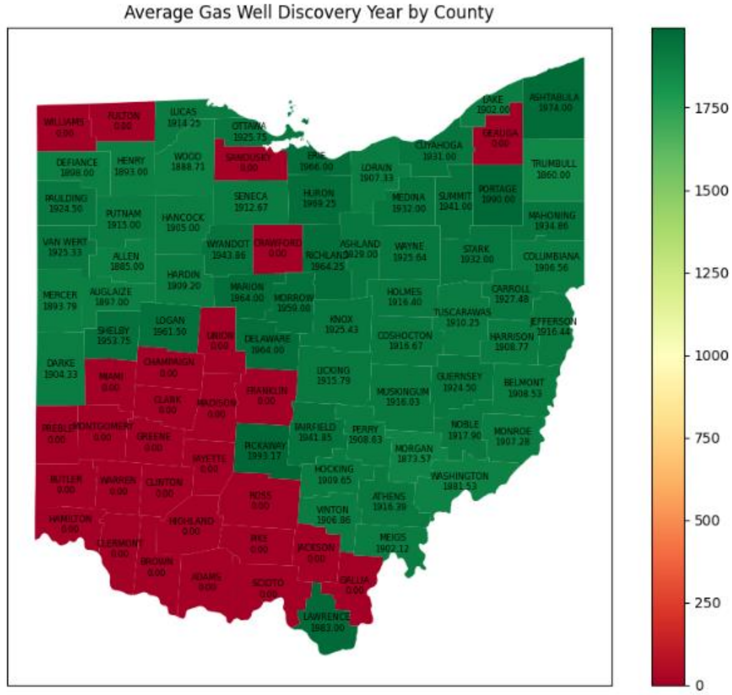
Appendix A: Biomass and Hydro Power Plants of Ohio



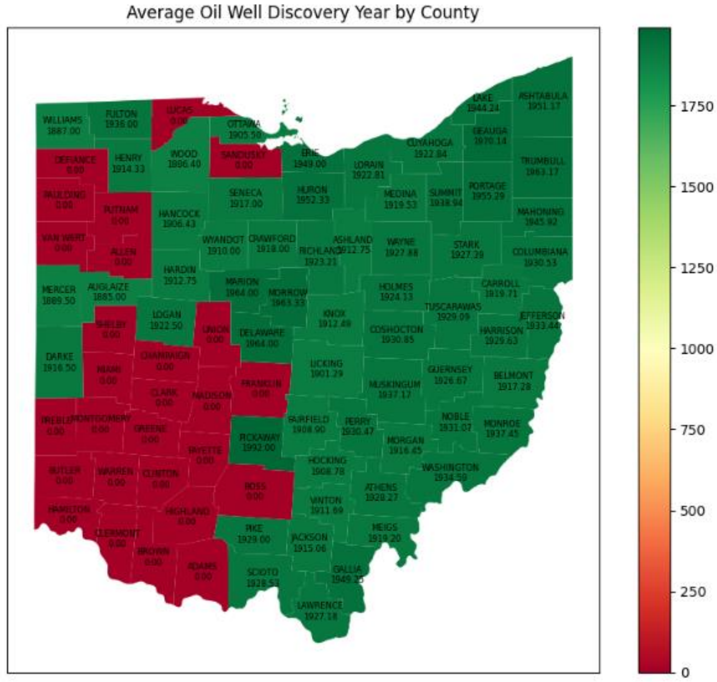


Appendix B: Gas/Oil Well Average Discovery Year:

Average Gas Well Discovery Year by County



Average Oil Well Discovery Year by County



Appendix C: Variable Name Crosswalks

Manufacturing Data Crosswalk

Variable Name	Description
IAC Sample	IAC Sample Size
Number of IAC Eligible Facilities	Number of IAC Eligible Facilities
IAC Percentage	IAC Data Sample Percentage
SEGMENT_LENGTH_SUM	Total Shipping Road Length
TRAINS_PER_DAY	Trains per Day

Energy Data Crosswalk

Variable Name	Description
Number of Stations	Number of Power Stations
Sum of Plant nameplate capacity (MW)	Sum Nameplate Capacity (MW)
Average of Plant nameplate capacity (MW)	Average Nameplate Capacity (MW)
Sum of Plant annual CO2 equivalent emissions (tons)	Annual CO2 Equivalent Emissions (tons)
Total Percent State Power	Total Percent State Power
Average of Plant capacity factor	Average of Plant Capacity Factor
Median of Plant capacity factor	Median of Plant Capacity Factor
Range of Plant capacity factor	Range of Plant Capacity Factor
BIOMASS	Biomass Plants
COAL	Coal Plants
GAS	Gas Plants
HYDRO	Hydro Plants
NUCLEAR	Nuclear Plants
OIL	Oil Plants
OTHF	Other Plants
SOLAR	Solar Plants
WIND	Wind Plants
Number of Substations	Number of Substations
Total NUM_WELLS_x	Number of Oil Wells
Average DISC_YEAR_x	Average Oil Well Discovery Year
Average RES_ACRES_x	Average Oil Well Area (acres)
Total NUM_WELLS_y	Number of Natural Gas Wells
Average DISC_YEAR_y	Average Gas Well Discovery Year
Average RES_ACRES_y	Average Gas Well Area (acres)

Demographic Data Crosswalk

Variable Name	Description
TotPop	Total Population
MedianAge	Median Age
PctMFG	Percentage Workforce Manufacturing
PctENERGY	Percentage Workforce Energy (Utilities + Raw Resources)
PctHS	Percentage Population over 25yr with High School Diploma
PctBachelors	Percentage Population over 25yr with Bachelors Diploma
PctGraduate	Percentage Population over 25yr with Graduate Diploma
MeanIncome	Mean Income
MedianIncome	Median Income
PctOwner	Percentage Population Homeowner
MedianHomeVal	Median Home Value
MedianOcc	Median Year of Occupancy (Renters & Homeowners)

IAC Data Crosswalk

Variable Name	Description
SIC	Site SIC Code
Area (ft2)	Floor Area
Sales ($/yr)	Facility Yearly Sales
Elec (kWh/yr)	Electricity Consumption
Therm (MMBtu/yr)	Gas Consumption
Unit Cost Electricity ($/kWh)	Cost of Electricity
Unit Cost Gas ($/MMBtu)	Cost of Gas
thermElecRatio	Thermal Electric Ratio