

Spatial and economic prioritization for distributed wind

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Abstract. This study investigates how distributed wind energy could be strategically deployed in areas with elevated energy burdens by analyzing spatial, economic, and demographic factors. We use a set of metrics that incorporate residential and macroeconomic variables to better capture affordability across different income levels. These metrics are correlated with demand-adjusted annual energy production, which reflects DW potential across residential, commercial, and industrial sectors.

5 Using mixed-effects modeling and state-level fixed-effects regressions, we identify key covariates associated with high energy burden. Our results reveal significant geographic variability both across and within states, with stronger correlations between DW potential and residential energy burden in regions where it is closely tied to poverty rates and agricultural activities. While noting that these associations do not imply causal effects, we group states based on correlation strength and DW potential. This highlights potential opportunities to improve energy affordability through targeted siting of distributed wind projects whose
10 low relative cost, ability to be sized to match demand, and potential to create local employment may be leveraged to alleviate energy burdens and drive local economic gains.

1 Introduction

Wind energy accounted for nearly 11% of U.S. electricity generation in 2024, primarily driven by utility-scale installations (International Energy Agency, 2024). While utility-scale deployments continue to grow in the U.S. and worldwide, an important
15 emerging market segment is distributed wind (DW), which refers to wind turbines installed at or near the site of demand such as residences, farms, campuses, or industrial facilities (Sheridan et al., 2024). DW systems typically consist of a single wind turbine or several turbines at hub heights generally between 30 and 80 m (Sheridan et al., 2024; NLR, 2024) and can operate either behind the meter (BTM), where the electricity primarily serves on-site loads, or in front of the meter (FOM), where electricity is fed directly into the local distribution grid. The former configuration is typically associated with customer-owned systems
20 while the latter is more typical of electrical cooperatives and utility-owned systems. This study focuses exclusively on BTM applications, which offer valuable opportunities to enhance energy independence, potentially lower household or consumer energy costs by offsetting retail electricity purchases, avoid some utility charges, reduce the need for extensive transmission

*NLR was formerly known as the National Renewable Energy Laboratory

upgrades, and stimulate local economic development through opportunities for workforce development and income generation when appropriately sited (U.S. Department of Energy, n.d.).

25 Previous research examined energy burden (EB) – the percentage of household income spent on energy costs – and identified it as a critical barrier to energy affordability, particularly in rural and low-income areas (Ross et al., 2018). For example, in 2018, rural households – especially low-income and elderly populations – faced EB nearly three times higher than their high-income peers. While EB is generally inversely correlated with income, this relationship is skewed by households with extremely low or outlier income values, leading to distorted or infinite values (Scheier and Kittner, 2022). To address this, Scheier and
30 Kittner (2022) propose an alternative metric, net energy return (NER), which is an algebraic transformation of EB and remains interpretable across the full income range. Their analysis also shows that around 16% of U.S. households experience energy poverty, with higher prevalence observed among Black, Hispanic, and Native American communities. Studies by Meng and Kozybay (2024) and Ross et al. (2022) suggest that renewable energy development – particularly wind – could be a potential solution to deliver economic benefits to local populations through job creation and increased tax revenues. However, according
35 to those studies, benefits may often fail to reach those most affected by high EB. Access to renewable energy technologies or other energy solutions could be further explored as a potential avenue for relief (Kerby et al., 2024; Forrester et al., 2024).

This research builds on these prior efforts while utilizing the Distributed Wind Energy Futures Study (DWEFS), a multi-year research effort with numerous data products and publications led by the National Laboratory of the Rockies (formerly National Renewable Energy Laboratory - NREL), which provides parcel-level techno-economic assessments for DW. The latest data
40 covers recent (2025) and projected future (2035) scenarios based on methodological improvements (Lockshin et al., 2025). The DWEFS model incorporates land use, siting constraints, electricity demand, wind resource availability, and policy context to size systems and simulate energy generation potential. Economic feasibility is evaluated using key financial indicators, including net present value, payback period, and threshold capital expenditure, which is the maximum viable system cost. While DWEFS is not a deployment forecast, it offers a spatially consistent framework for evaluating DW potential across both
45 BTM and FOM applications. We analyze DWEFS output (U.S. Department of Energy, Wind Energy Technologies Office, 2024) and publicly available socioeconomic data for BTM applications to construct an energy-economy framework that evaluates the deployment potential of DW in areas with energy-related financial stress. Specifically, we examine where DW could be deployed to potentially alleviate EB and increase NER, and how these are associated with high-poverty, rural, and agricultural contexts. We identify rural and agricultural areas as important factors in this study due to the elevated DW potential identified in
50 Crook et al. (2025) particularly across croplands throughout CONUS. While our analysis does not imply causality, it identifies meaningful spatial and statistical associations between DW potential and EB as well as between EB and adverse economic conditions. Our results highlight that counties that simultaneously experience high EB (or low NER) often have substantial DW potential, providing insights into where targeted investments might yield the greatest community benefit.

2 Methods

55 This work makes two primary methodological contributions. First, we develop a multiscale framework that incorporates both residential and county-level metrics. At the residential level, we analyze EB and NER. At the county level, we evaluate EB and NER relative to gross domestic product (GDP). These metrics are then used as response variables in linear mixed-effects models, with demographic and economic factors – such as poverty rate, agricultural employment share, unemployment, and ethnicity composition – serving as predictors. This approach allows us to analyze how energy expenditure relates to demographic and economic factors and how easing this burden might potentially help populations already facing associated economic hardship. Second, we conduct a spatial correlation analysis to assess the relationship between DW annual energy production (AEP) for BTM systems, energy demand, EB, and NER. While we incorporate data from three scenarios (2022, 2025, 2035), we focus primarily on 2025 and 2035. The 2022 scenario is included initially for comparative purposes and alignment with prior published work but is not the focus of the analysis. In the following subsections, we describe the data, metrics, and modeling regime developed to support these analyses.

2.1 Data sources

Table 1 summarizes the key data sources used in this study. These sources include information on cost-viable DW energy generation potential, economic indicators, and demographic characteristics, all of which are essential for our analysis. This study focuses on data for the contiguous United States, which excludes Alaska and Hawaii as data for those states are not yet available in the DWEFS. While containing data for nearly 150 million parcels, some small fraction of missing parcel data results in select counties that are not represented in this analysis, primarily located in New Mexico, Kentucky, Indiana, South Dakota, Utah, Nevada, and Colorado. We have used an updated version of the DWEFS data from Lockshin et al. (2025), which is not yet published but developed with a similar methodology. Key improvements from the previously published data include updating technology costs, electricity rates and state compensation mechanisms to the latest available data (2024), and a more comprehensive evaluation of federal incentives. Importantly, these data assume a federal investment tax credit equivalent to 30% of project capital expenditures, and location-dependent credit bonuses (for energy communities, low-income communities and Tribal lands) which were present in 2024. In light of federal policy changes in 2025, the availability of these tax credits is expected to be reduced in future years, in turn reducing modeled cost-viable AEP. These potential changes in tax credit policy are beyond the scope of this study but may be considered in future or more localized analyses. The results presented here can be interpreted as an average or above-average estimate of market opportunity in a favorable policy environment.

This analysis does not directly incorporate weather-related variables (e.g., heating/cooling degree days) or housing characteristics (e.g., age, thermal efficiency), both of which can influence EB independent of income. Because EB is calculated from realized electricity expenditure, some of this variation is implicitly embedded in the data, but the models do not isolate it, so its influence on covariates such as poverty and agricultural employment cannot be ruled out. Future work incorporating these variables directly could refine the predictors identified here.

Economic and demographic data used in this analysis reflect the most recent available estimates rather than year-specific projections, as projected demographic and economic data at comparable county level resolution were not available for this study. Only DW generation potential and electricity demand vary by scenario year. This represents a data availability constraint rather than an assumption of no future change, and the framework presented here could be readily applied with updated demographic projections as they become available

Data on energy generation potential, EB, and modeled energy demand offsets are used by their corresponding scenario year (2025 or 2035) while other socioeconomic and demographic data correspond to the latest available datasets to reflect current demographics and economic characteristics across the contiguous United States.

Table 1. Summary of Data Sources

Data	Description and Source	Data Year
Cost-Viable AEP Values	Distributed Wind Energy Futures Study (Lockshin et al., 2025)	2022, 2025, 2035
Poverty and Income	U.S. Census Bureau, Small Area Income and Poverty Estimates Program (U.S. Census Bureau, 2023a)	2023
Gross Domestic Product (GDP)	U.S. Bureau of Economic Analysis, Gross Domestic Product by County, Industry and Metropolitan Area (U.S. Bureau of Economic Analysis, 2023)	2023
Ethnicity	U.S. Census Bureau, County Population by Characteristics: 2020–2023 (U.S. Census Bureau, 2023b)	2023
Energy Total Demand & Residential Electricity Expenditure	National Laboratory of the Rockies, Net Electricity and Natural Gas Consumption, State and Local Planning for Energy (NLR, 2025)	2025, 2035
Unemployment	U.S. Bureau of Labor Statistics, Local Area Unemployment Statistics Program (U.S. Bureau of Labor Statistics, 2023)	2023
Residential Units	U.S. Census Bureau, National, State, and County Housing Unit Totals. (U.S. Census Bureau, 2024)	2024

2.2 Metrics Description

To enable spatial consistency with representative datasets, we aggregate parcel-level data to the county level. The data include sector-specific electricity metrics for residential (household), commercial, and industrial consumers, which are also aggregated to county level by sector and normalized where appropriate.

We define the **AEP-to-demand ratio** (AEP_{demand}) as:

$$AEP_{\text{demand}} = \frac{AEP}{\text{Total Electricity Demand}} \quad (1)$$

100 where Total Electricity Demand is the sum of residential, commercial, and industrial electricity demand at the county level. For sector-specific analyses, the denominator is replaced by the corresponding sector's demand alone; for example, residential AEP_{demand} divides cost-viable residential AEP by residential electricity demand only. All demand values are drawn from the NLR SLOPE dataset, which provides county-level electricity consumption disaggregated by sector (NLR, 2025). This ratio standardizes DW generation relative to total electricity demand across residential, commercial, and industrial sectors
 105 accounting for variation in population density and consumption levels. Sector-specific analyses also use disaggregated demand components as needed. Higher values of AEP_{demand} indicate that potential DW generation could supply a relatively larger share of local electricity demand, suggesting greater opportunity for demand-offsetting generation. Lower values indicate that even substantial wind resources would cover only a small fraction of demand, limiting system-level impact of DW deployment.

Our primary affordability metric is **Energy Burden - EB**, which conceptually reflects residential-level affordability. In our
 110 analysis, we compute EB at the county level as the ratio of total residential electricity expenditure to the product of median household income and the number of residential units in the county:

$$EB = \frac{\text{Total Residential Electricity Expenditure}}{\text{Median Household Income} \times \text{Number of Residential Units}} \quad (2)$$

Higher EB values indicate greater energy cost burdens and lower affordability, meaning households must devote a larger fraction of income to electricity. Lower EB values indicate comparatively affordable electricity, where energy costs consume
 115 a smaller share of household income. This county-level aggregate formulation differs from conventional household-level EB metrics typically derived from survey data or census-tract scale estimates (Ross et al., 2018; Scheier and Kittner, 2022). The county-level aggregate approach is adopted here to maintain spatial consistency with the DWEFS parcel-level data aggregated to the county level, and to enable the spatial prioritization analysis that is the primary objective of this study.

At the county level, we extend this to **EB relative to GDP (EB_{GDP})**, which provides a broader perspective on county-level
 120 economic performance. Rather than focusing solely on residential metrics, this approach considers the county as an economic unit, viewing its GDP and energy expenditures as components of overall economic output:

$$EB_{\text{GDP}} = \frac{\text{Total County Energy Expenditure}}{\text{GDP}} \quad (3)$$

Higher values of EB_{GDP} indicate that a larger share of county-level economic output is absorbed by energy expenditures, reflecting greater macroeconomic energy intensity or stress. Lower values indicate that energy costs represent a smaller fraction
 125 of economic activity, suggesting greater economic resilience to energy prices.

We retain the EB nomenclature rather than alternative framings such as energy cost intensity to maintain consistency with the residential EB metric. Both metrics share the same ratio structure of energy expenditure relative to an income or output measure, and the parallel naming reflects this parallel construction within the study's analytical framework.

While EB measures the proportion of income spent on energy – offering a direct sense of affordability – it can produce distorted or infinite values for households with very low or near-zero income (Scheier and Kittner, 2022). **NER** addresses this by remaining mathematically defined and interpretable across the full income range, while also providing smoother statistical properties and a complementary interpretive angle. NER reflects the economic return or residual income relative to energy expenditure:

$$NER = \frac{\text{Household Income} - \text{Energy Expenditure}}{\text{Energy Expenditure}} \quad (4)$$

Because NER is an algebraic transformation of EB, they are mathematically linked as:

$$NER = \frac{1}{EB} - 1 \quad (5)$$

Higher NER values indicate greater residual income relative to energy spending and thus lower effective EB. Lower NER values indicate limited residual income after paying for electricity, reflecting higher affordability stress.

To parallel our EB_{GDP} measure and further extend the analysis to the macroeconomic level, we define a GDP-based version of NER: NER_{GDP} . This metric evaluates the return of economic output over energy spending at the county level:

$$NER_{GDP} = \frac{GDP - \text{Total County Energy Expenditure}}{\text{Total County Energy Expenditure}} \quad (6)$$

Higher values of NER_{GDP} indicate that economic output substantially exceeds energy expenditures, suggesting stronger economic returns per unit of energy cost. Lower values indicate that energy expenditures consume a relatively large share of economic output, signaling reduced economic efficiency.

While EB_{GDP} and NER_{GDP} are mathematically equivalent transformations of one another, they offer complementary interpretive framings: EB_{GDP} emphasizes the share of economic output absorbed by energy costs (a burden-oriented framing), while NER_{GDP} emphasizes economic return relative to energy spending (a resilience-oriented framing). Retaining both is consistent with the residential-level EB/NER pairing established above.

Together, these metrics – EB, EB_{GDP} , NER, and NER_{GDP} – provide a multidimensional view of energy affordability and serve as key response variables in our spatial correlation and modeling analyses.

While national policies typically define energy poverty as $EB > 6\%$ or $NER < 16\%$ (Colton, 2011; Drehobl et al., 2020), these thresholds include all energy sources (e.g., natural gas), whereas we calculate EB for electricity only. This is because DW electricity generation is only comparable to electricity costs, not other costs like natural gas consumption. Therefore, we define extreme values using state-specific distributions – identifying the top 10th percentile for EB and bottom 10th percentile for NER – to better capture localized energy stress in an electricity-specific context.

2.3 Correlations

This analysis examines correlations among NER, EB, and AEP_{Demand} for residential, commercial, industrial, and combined-sector demand at the county level. Notably, the spatial distribution of AEP_{Demand} might not necessarily align with areas of high EB. A state or county may exhibit high energy demand, but if the associated EB is low, the relationship between the two remains weak. Strong correlations emerge only when **both** conditions – high DW potential and high EB – are present, a pattern not uniformly observed across the country.

To assess the relationships between key variables, both parametric and nonparametric correlation methods were employed. This dual approach accounts for the non-normal distribution of EB and AEP_{Demand} in their raw forms. Box–Cox transformations (Kutner et al., 2004) were applied to normalize the data for Pearson correlation analysis while Kendall’s Tau was used as a robust, nonparametric alternative to capture rank-based associations under non-normal conditions.

Kendall’s Tau evaluates ordinal association by comparing all possible observation pairs (Kendall and Gibbons, 1990). A pair $(x_i, y_i), (x_j, y_j)$ is *concordant* if the ranks of both variables move in the same direction and *discordant* if they move oppositely. The coefficient is calculated as:

$$\tau = \frac{C - D}{\sqrt{(C + D + T_1)(C + D + T_2)}} \quad (7)$$

where C and D represent the number of concordant and discordant pairs, respectively, and T_1, T_2 account for ties in each variable. Positive values of τ indicate a direct association; negative values indicate an inverse relationship.

2.4 Weighted ranking and grouping

After computing both parametric and nonparametric correlations, we construct rankings at the state level and then combine them into a weighted ranking to identify states where DW deployment opportunity could be most strongly aligned with EB. The purpose of this ranking is not to maximize wind resource alone, but to prioritize locations where DW potential spatially coincides with affordability challenges, consistent with the primary objective of this study.

As shown in Eq. 8, the composite ranking assigns 50% of the total weight to correlation-based metrics. This emphasis reflects the central research question of this analysis: identifying where DW potential and EB are spatially aligned, rather than where either factor is independently high. Correlation strength is therefore treated as the primary diagnostic indicator of potential relevance for affordability-oriented DW deployment.

A weight of 50% was selected to ensure that correlation serves as the dominant but not decisive criterion in the composite ranking. Assigning less than half the total weight would allow scale-based metrics to outweigh alignment between DW potential and EB, undermining the central objective of the study. Conversely, assigning substantially more than half the weight would risk over prioritizing statistical alignment at the expense of deployment relevance and practical impact. The 50% threshold therefore represents a balance point at which correlation is guaranteed to influence rankings while preserving sensitivity to demand magnitude and generation scale.

To ensure that correlation-based rankings remain meaningful in terms of deployment scale and practical impact, we incorporate two additional counterbalancing components. First, AEP_{Demand} for both the 2025 and 2035 scenarios is included to represent relative DW opportunity normalized by electricity demand. Second, absolute electricity demand is included to account for scale effects and avoid disproportionately prioritizing low demand where standardized ratios may appear favorable despite limited potential impact.

Each component is ranked independently and combined using this weighted formulation:

$$\begin{aligned} \text{rank}_{\text{composite}} = & 0.5 \cdot (\text{rank}_{25} + \text{rank}_{35}) \\ & + 0.25 \cdot (\text{rank}_{AEP/D,25} + \text{rank}_{AEP/D,35}) \\ & + 0.25 \cdot (\text{rank}_{\text{Dem},25} + \text{rank}_{\text{Dem},35}) \end{aligned} \quad (8)$$

where rank_{25} and rank_{35} are the correlation-based ranks of DW potential and EB alignment for 2025 and 2035, $\text{rank}_{AEP/D,25}$ and $\text{rank}_{AEP/D,35}$ are ranks of DW opportunity normalized by electricity demand (AEP_{Demand}), and $\text{rank}_{\text{Dem},25}$ and $\text{rank}_{\text{Dem},35}$ are ranks of absolute electricity demand.

The selected weights are intentionally goal-driven and reflect a balance between (i) emphasizing spatial alignment between EB and DW potential, and (ii) maintaining sensitivity to deployment scale and demand magnitude. These weights are not derived from statistical optimization and alternative weighting schemes are possible; however, the chosen structure directly supports the study's focus on affordability-relevant siting rather than maximum energy generation. To assess the sensitivity of the rankings to the chosen weighting scheme, we evaluated several alternative formulations varying the components and weights assigned to correlation, AEP_{Demand} , and absolute demand.

Based on this framework, we classify states into two groups and a set of special cases, each designed to highlight a distinct type of deployment-relevant context.

Group 1 consists of states with the highest composite rankings in Eq. 8, reflecting a favorable combination of spatial alignment between EB and residential DW potential together with substantial demand scale. These states represent locations where affordability challenges and DW opportunity coincide geographically, making them priority candidates for affordability-oriented DW deployment. While correlation strength is a primary component of the ranking, inclusion in Group 1 does not require uniformly strong correlations across all states, but rather a balance between alignment and deployment relevance.

Group 2 is based on the absolute ranking of AEP_{Demand} , independent of the correlation strength with EB. These states exhibit high DW generation potential relative to demand but comparatively lower or weakly aligned EB. As such, the highlight regions where DW deployment may be attractive for broader energy or economic development goals.

Special cases include states that do not clearly fall into either group due to scale effects, extreme EB values, or weak spatial alignment between EB and DW potential. These states illustrate important boundary conditions of the framework, where high need or high resource exists but the spatial coincidence required for prioritization under the composite ranking is limited. Identifying these cases helps avoid overgeneralization and highlights the importance of sub-state or targeted deployment strate-

gies. This grouping framework is intended as an interpretive tool rather than a prescriptive prioritization scheme, providing a transparent and reproducible way to compare states across multiple, policy-relevant dimensions.

While AEP_{Demand} and EB-related metrics are computed for residential, commercial, and industrial sectors (Sect. 2.2), the composite ranking and grouping framework is based specifically on residential-sector metrics. This choice is guided by the empirical finding that residential AEP_{Demand} consistently shows the most robust correlation with residential EB across all sectors analyzed (Sect. 3), making it the most informative metric for identifying states where DW potential spatially aligns with energy affordability challenges. Commercial and industrial sector results are presented as descriptive context but do not directly influence group classification.

2.5 Mixed- and fixed-effects modeling of regional predictors

To identify key predictors of residential EB at the county level, we implement a mixed-effects linear regression model using nationwide data (Table 1). In this framework, county-level covariates – including poverty rate, percentage of agricultural employment, and percentage of the population identifying as non-white racial and ethnic groups – are treated as fixed effects, meaning that in this national model (granularity is studied later), their estimated relationships with EB are assumed to be consistent across the United States.

States are modeled as random effects to account for unobserved, state-specific factors that systematically influence EB but are not explicitly included in the model, such as differences in energy policy, utility regulation, climate, or electricity pricing structures. Modeling states as random effects allows the intercept of the regression to vary by state, capturing baseline differences in EB while still estimating a single set of national-level fixed-effect relationships.

This approach enables the estimation of fixed effects while allowing intercepts to vary by state, capturing regional deviations from the national baseline. The significance of the random state effect is supported by the intraclass correlation (ICC), which quantifies the proportion of total variance attributable to state-level differences, as reported in Sect. 3.

Following the identification of state-level variation, we conduct separate fixed-effects linear regressions (with and without interactions) for representative states from each of the groups defined in the ranking analysis (see Sect. 2.4). States were selected based on the composite ranking and grouping framework described in Sect. 2.4, with one or more representative states chosen from Group 1, Group 2, and the special cases. These states are not a random sample but rather illustrative of distinct deployment-relevant contexts identified through the spatial correlation and ranking analysis. These models provide more granular insights into how key predictors of EB differ across regional contexts and support the interpretation of group-level patterns observed in the correlation and ranking results. To ensure the validity of these models, we evaluate key diagnostics, including adjusted R^2 , residual distributions, variance homogeneity (homoskedasticity) and multicollinearity. Multicollinearity was assessed in the models without interactions using the Variance Inflation Factor (VIF) to verify that the main predictors were not highly correlated before including interaction terms.

This modeling framework identifies key demographic and economic factors statistically associated with EB. It does not imply that interventions such as DW deployment will directly alter the covariates involved. The mixed-effects and state-level regression models are therefore used as explanatory and diagnostic tools to contextualize the spatial correlation results and

composite ranking framework. These models are not used to determine the weights, thresholds, or group classifications directly, nor are they intended for prediction or causal inference. Instead, they serve three purposes: (i) to confirm that EB exhibits statistically significant variation across states, motivating a state-specific analysis framework; (ii) to identify socioeconomic factors consistently associated with elevated EB, providing interpretive context about high EB regions that emerge in the correlation analysis; and (iii) to assess whether states grouped by correlation patterns exhibit distinct EB drivers. In this way, the regression results support interpretation and validation of the grouping framework rather than defining it.

3 Results

This section presents the findings from our spatial, statistical, and modeling analyses using scenarios for current (2025) and future (2035) DW potential. We describe patterns of geographic variation in EB and NER, followed by an examination of the relationship between EB and the standardized DW generation potential metric AEP_{Demand} . We then report on state clustering patterns and present mixed-effects and state-level model results.

3.1 Energy burden and net energy return (residential level)

We analyze spatial patterns in EB and NER to understand how energy and cost burdens vary across the U.S. and how they may relate to DW opportunity. EB and NER vary significantly across U.S. counties and states. Southeastern states exhibit above-median residential EB (Alabama has the highest EB) while many western states fall below the national average in both scenarios. However, county-level analysis reveals substantial intrastate variation, suggesting that state-level aggregates may obscure local disparities. Figure 1a–1f presents residential EB distributions and spatial patterns for the 2025 and 2035 scenarios.

The EB distribution (Fig. 1e and 1f) is slightly right-skewed, with a median and mean around 1.7% for both scenarios (2025 and 2035) and a 90th percentile near 2.5% for 2025 and 2.4% for 2035. The geographic distribution is not even, which reinforces the earlier observation of intrastate heterogeneity.

Regarding the reported percentages, it is important to note a methodological distinction discussed in Section 2.2. Because DW is only comparable with electricity costs, and not other household energy uses such as natural gas or heating fuels, EB is calculated here using electricity expenditures only rather than total household energy costs. As a result, the reported EB values may appear lower than commonly cited EB estimates that account for all residential energy sources.

Moreover, as shown in Fig. 1c and 1d, the southeastern states of Alabama, South Carolina, and Georgia consistently exhibit the highest percentages of counties with EB above the 90th percentile nationwide. These patterns are further highlighted in Fig. 2, which presents the top 10 states with the largest share of counties exceeding this high EB threshold.

3.2 EB_{GDP} and NER_{GDP} (at a county level)

To further understand how regional economic capacity determines energy affordability and its implications for DW opportunity, we explore EB_{GDP} and compare it to residential EB. The EB_{GDP} metric shows less heterogeneity within states (Fig. 3a and 3b)

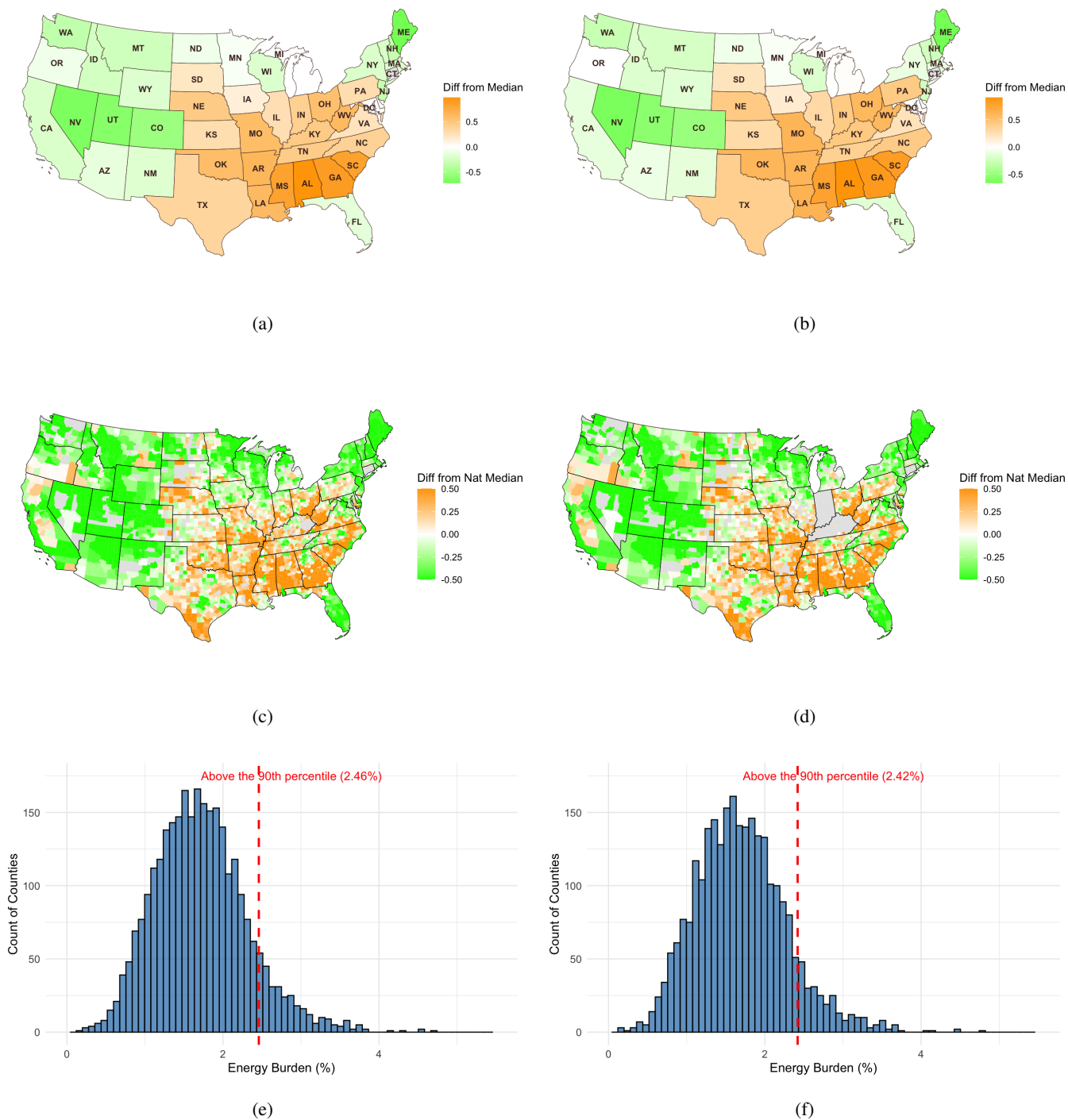


Figure 1. Residential EB across states ((a) 2025–(b) 2035 and county levels ((c) 2025 – (d) 2035). EB values above the national median in the Southeast and below in many western states across both scenarios (a–b). County-level results ((c) 2025 – (d) 2035) show intrastate variation, with some regional trends across state boundaries. The EB distributions (e–f) are slightly right-skewed, indicating that most counties have EB values below the mean.

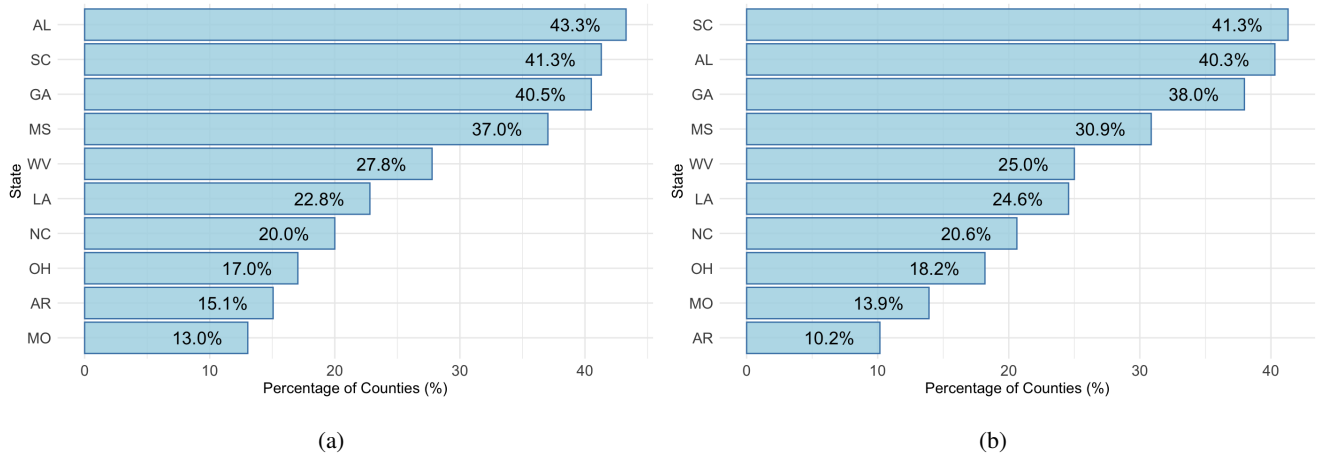


Figure 2. Top 10 states with the highest percentage of counties above the 90th percentile in EB. (a) 2025–(b) 2035.

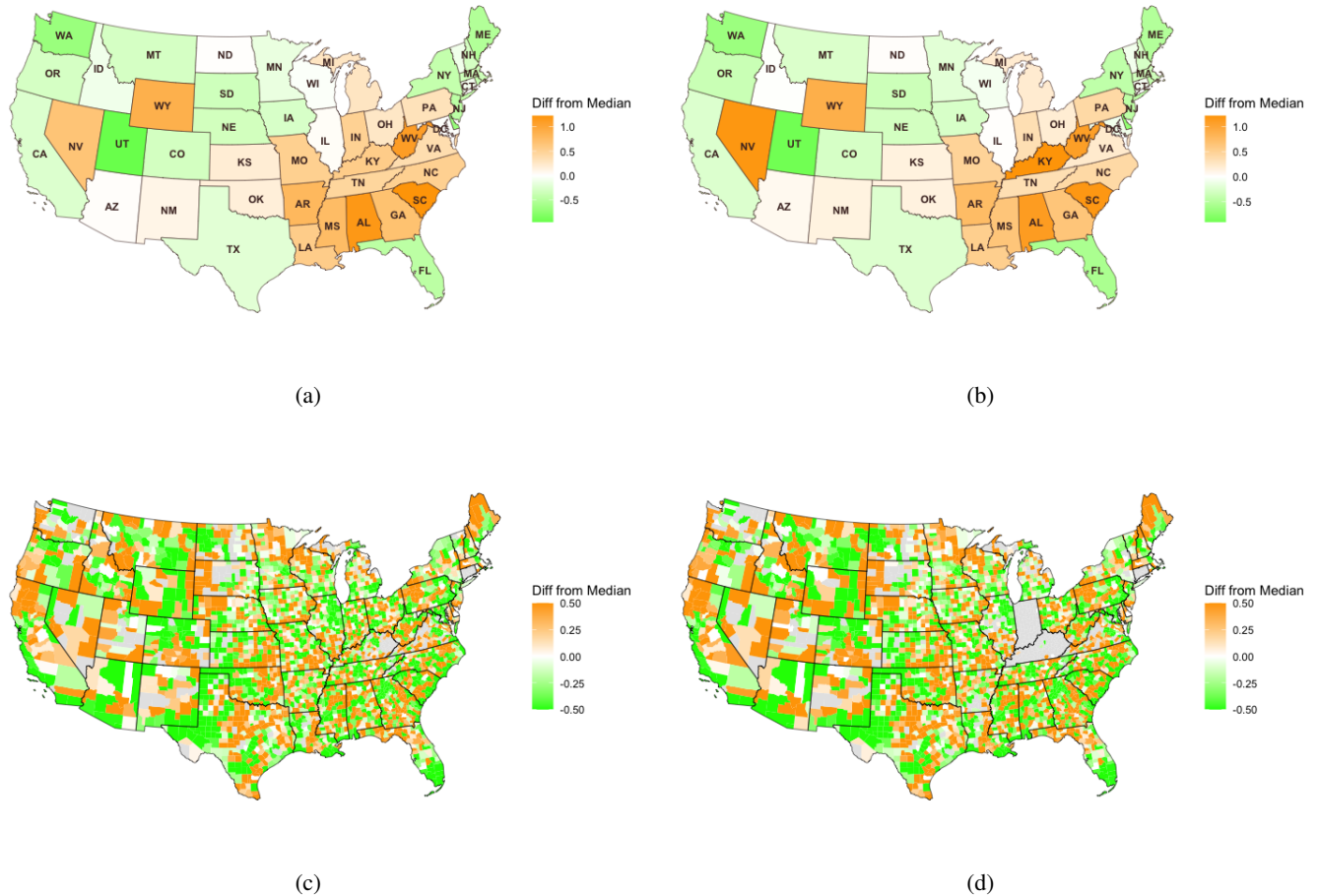
compared to the residential EB (Fig. 1), with state values generally clustering closer to the national median. However, noticeable regional patterns at a county level (Fig. 3c and 3d) still emerge, often crossing state boundaries. This result underscores the importance of conducting sub-state analyses. Taken together, these trends suggest that understanding energy affordability requires not only county-level granularity but also consideration of broader economic and geographic factors.

3.3 AEP-to-demand ratio

To enable consistent comparisons across places with different populations and demands, we apply the AEP-to-demand normalization described in Section 2.2, yielding the AEP_{Demand} metric. This ratio, like raw AEP, is highly right-skewed, with most parcels exhibiting low values relative to demand and a minority of outliers with high relative potential.

To facilitate statistical analysis, we apply the Box–Cox transformation (Fig. 4) solely for descriptive visualization and Pearson correlation diagnostics. These Pearson correlations (using Box–Cox–transformed variables) and Kendall’s Tau correlations (using untransformed variables) produced similar results on the rankings that we analyze later, indicating that the results are robust to transformation choice. However, all state rankings and group classifications are based on untransformed metrics and nonparametric (Kendall’s Tau) correlations, ensuring that the transformation does not influence the study’s prioritization results.

Several states, including Kansas, Illinois, Minnesota, and Nebraska, have both an absolute and proportionally higher number of counties exceeding the national median of AEP_{Demand} (Fig. 5). These states also consistently rank within the top 10 in total AEP_{Demand} , although in different order. These are areas of the United States where economically feasible DW opportunity meets or exceeds electrical demand, suggesting a strong potential for its deployment. Economically feasible DW potential in these states can result from a combination of numerous factors captured in the DWEFS data, including strong wind resource,



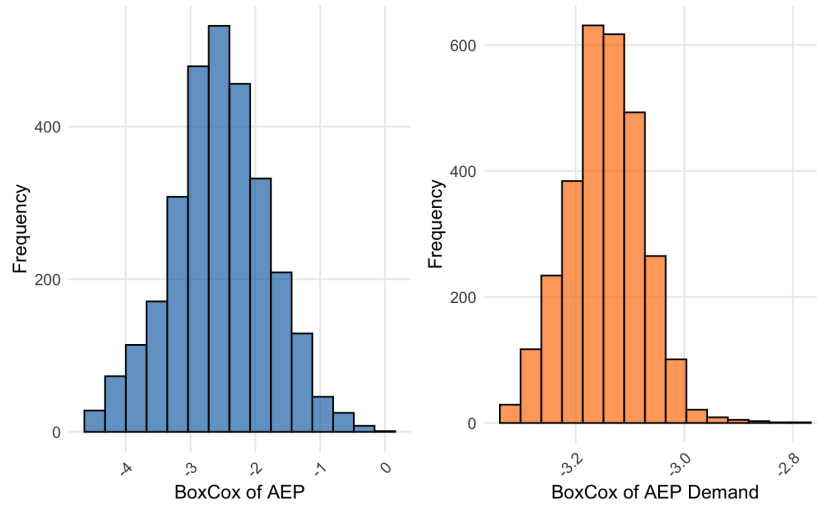


Figure 4. Nationwide distributions of Box–Cox–transformed AEP and AEP_{Demand} for BTM DW 2025. Before transformation, both metrics exhibit right-skewed distributions. They share the same Box–Cox transformation parameter ($\lambda = 0.2$). This transformation does not imply statistical equivalence between the two metrics, which remain distributionally distinct, but allows each to be analyzed within a comparable parametric framework where required.

favorable policies like net metering or local ordinances impacting siting, elevated utility rates that make DW costs competitive, amongst others (Lockshin et al., 2025).

In contrast, Texas and Georgia—while also ranking in the top 10 for total AEP_{Demand} by number of counties—achieve this largely due to their high overall county count. When considering the proportion of counties exceeding the national median, both states fall to midrange positions. This suggests that although total AEP is high, the distribution of DW potential across counties is uneven. As a result, these states may still offer strong opportunities for DW deployment but require more localized, county-level assessment to identify the most suitable areas.

We disaggregate AEP_{Demand} further by sector (residential, industrial, and commercial) to capture sector-specific dynamics. Across scenarios the residential sector consistently emerges as the most influential in explaining AEP_{Demand} variation in each scenario. Significant differences between scenarios are observed in all pairwise comparisons, confirmed using both parametric and nonparametric tests. These results highlight the dominant role of residential AEP_{Demand} in shaping spatial and temporal patterns in DW deployment potential.

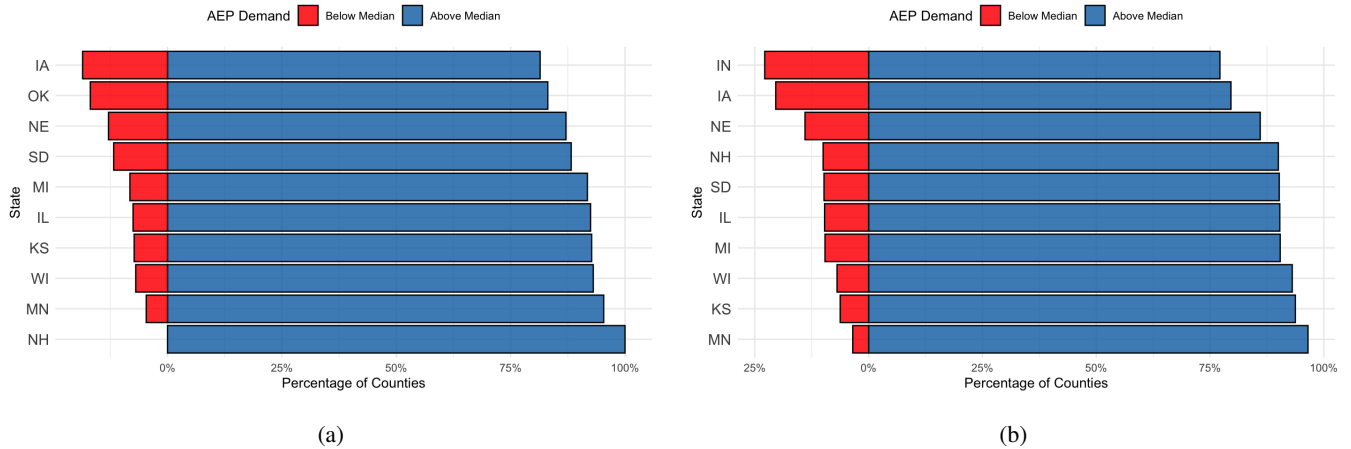


Figure 5. Top 10 states with the highest proportion of counties above the national median AEP_{Demand} (a) 2025–(b) 2035. Kansas, Illinois, Minnesota, and Nebraska show both high absolute and proportional county-level AEP_{Demand} , indicating widespread DW potential. In contrast, Texas and Georgia rank high in total counts but have more uneven distribution across counties.

3.4 Correlations between metrics

Correlations were examined across NER, EB (both residential and GDP-based), and AEP_{Demand} (residential and county total). Among these, the major finding is that residential AEP_{Demand} shows the strongest correlation with residential EB. Figures 6a and 6b show the correlation between EB and residential AEP_{Demand} .

To further investigate the nature of these correlations, we also analyzed the nonstandardized AEP values and the demand by sector. In some cases, states with large and internally diverse populations, such as Texas, exhibit high absolute demand and significant EB in certain areas yet show lower overall correlation. This internal variability, driven by differences in population density and economic capacity across regions within the state, dilutes the strength of the observed associations. These differences in correlation behavior motivated the classification of states into two distinct groups based on shared statistical and spatial patterns; Alabama and Texas were identified as special cases.

Spatial analysis of baseline scenarios for 2025 and 2035 revealed two distinct state groupings and special cases based on the correlation patterns between EB and AEP_{Demand} . Sensitivity analysis of the composite ranking using alternative weighting formulations showed that while the exact composition of groups varied across schemes, the overall framework consistently distinguished states with high spatial alignment between EB and DW potential from those with high DW potential but weaker EB alignment, supporting the interpretive value of the grouping approach even if specific state assignments may shift under alternative weights.

Group 1: High-Need/Demand, Favorably Correlated Potential. This group includes North Carolina, Georgia, Iowa, Louisiana, and California (Table 2). These states rank highest according to the composite score defined in Eq. (8), which shows high EB aligned with high DW generation potential in the residential sector in the same counties (county level). They also

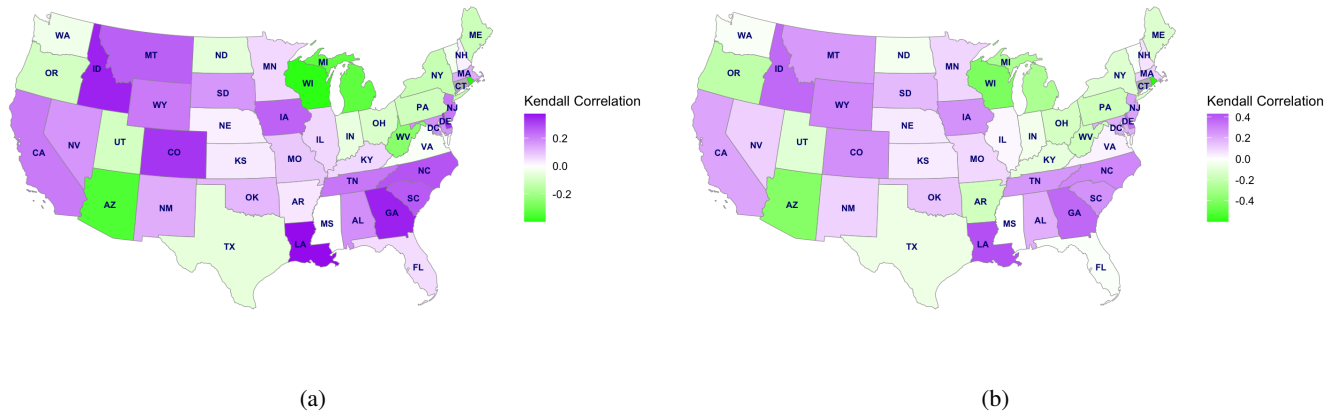


Figure 6. State-level nonparametric correlation between residential AEP_{Demand} and EB. This is the strongest correlation with EB among all metrics considered. States such as Georgia, Idaho, Louisiana, and Colorado consistently exhibit the most pronounced correlations nationwide in both the 2025 (a) and 2035 (b) scenarios.

rank more highly in energy demand and the AEP_{Demand}. The results for Georgia, shown in Fig. 7, are representative of these patterns.

States like Iowa, North Carolina, California, and Georgia are in the top 20 states with highest absolute AEP and residential AEP (moreover, North Carolina is in the top 10 for AEP_{Demand}) and also show consistent patterns across other sectors, including industrial and commercial DW potential. Even though these states do not necessarily have the highest absolute AEP_{Demand} compared to other states, they are in the top 20 and perform well when considering the weighted combination of residential AEP_{Demand} and its correlation with EB. This suggests these states may have relatively less DW opportunity, but the available opportunity is well located to potentially alleviate EB.

Louisiana, while ranked only 28th in residential AEP_{Demand} and 32nd in total AEP, exhibits high EB values and most pronounced correlation. This indicates that, within Louisiana, counties experiencing higher EB consistently coincide with counties that have relatively greater DW opportunity, despite the state's limited absolute wind resource. Importantly, Georgia, Louisiana, and North Carolina are among the top 10 states with the highest share of counties above the 90th percentile in EB in both 2025 and 2035 scenarios (Fig. 2).

In the case of California, while the state exhibits high total AEP (ranks 14th), its residential and total AEP_{Demand} are relatively lower. This is due to high electricity demand diluting the per-unit metric, especially in the industrial and commercial sectors. The correlation in California is weaker than in other Group 1 states. Nevertheless, when correlation is evaluated jointly with demand-normalized opportunity and absolute demand—consistent with Eq. (8)—California ranks highly overall. This indicates that, while alignment is less pronounced statistically, the scale of demand and available residential DW opportunity remains sufficiently large for EB-relevant deployment, justifying its classification alongside other high-opportunity states.

Importantly, inclusion in Group 1 does not imply that a state has a high absolute wind resource or is suitable for large-scale utility wind development. Rather, Group 1 identifies states where within state spatial variation in residential DW potential tends to align with spatial variation in EB at the county level, and at the same time accounts for the DW potential and demand scale. In these states, counties with higher EB generally coincide with relatively higher AEP_{Demand} , while counties with lower EB coincide with lower DW potential, producing generally positive—and in many cases strong—spatial correlations even when absolute wind resources are moderate.

Table 2. Summary of Group 1 state-level models and correlations for BTM 2025 scenario

State	Parametric correlation	Nonparam. correlation	EB median (%)	Residential $AEP_{Demand} \times 10^{-5}$	Total $AEP_{Demand} \times 10^{-5}$	Key EB predictors (interactions)	Model fit (adj. R^2)
North Carolina	0.41	0.28	1.80	2.51	9.25	Poverty, Ag, NWREG% x Poverty, Pov x Unemp.	High (0.78)
Georgia	0.51	0.37	2.31	3.71	4.23	Poverty, Poverty x Ag	Moderate (0.67)
Iowa	0.41	0.26	1.54	2.51	9.25	Unemp., NWREG%, Ag x NWREG%	Moderate (0.45)
Louisiana	0.57	0.37	2.02	7.90	4.76	Poverty, Unemp.	High (0.70)
California	0.25	0.22	1.20	3.29	2.33	Ag, NWREG%, Unemp. x Ag, Unemp. x NWREG%	Moderate (0.55)

Note: Ag = Agriculture; NWREG% = Percentage of the population identifying as non-White racial and ethnic groups; Unemp. = Unemployment

Group 2: High AEP_{Demand} , Low-EB States. This group includes the states of Wisconsin, Minnesota, and Kansas which demonstrate high AEP_{Demand} but low EB, resulting in low correlation across evaluated counties. Wisconsin results are shown in Fig. 8 as an example. Although the correlation with EB is low, the states' high AEP_{Demand} alone indicates high DW deployment potential (summarized in Table 3). It is also important to note that while the high EB in these states does not align with areas of high DW opportunity, EB itself is associated with factors such as a strong agricultural economy. Since DW deployment means increased energy generation, this could present additional economic benefits for the agricultural regions.

Special Cases: Texas, and Alabama. While these states do not fully align with Group 1 or Group 2, they exhibit distinct features that justify separate consideration, such as high total wind potential, very high EB, or demographic scale.

– **Texas:** Texas ranks second in total (nonstandardized) AEP, alongside Wisconsin and Minnesota (both in Group 2). Yet, like California, its vast energy demand lowers the standardized AEP_{Demand} . Although its EB is above the national median, the correlation between EB and DW potential is near zero, indicating almost no spatial overlap between EB and opportunity and ultimately limiting its prioritization within the current framework.

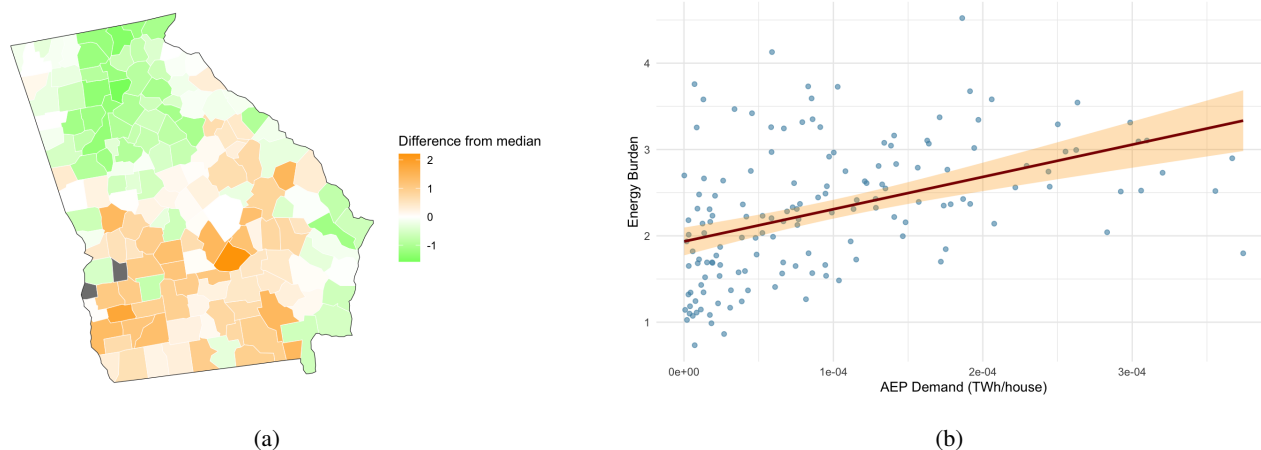


Figure 7. Georgia: Spatial and statistical patterns, 2025. (a) Energy burden (distance from the state median), (b) Correlation EB with AEP_{Demand}

Table 3. Summary of Group 2 state-level models and correlations

State	Parametric correlation	Nonparam. correlation	EB median (%)	Residential $AEP_{Demand} \times 10^{-5}$	Total $AEP_{Demand} \times 10^{-5}$	Key EB predictors (interactions)	Model fit (adj. R^2)
Wisconsin	-0.54	-0.38	1.21	19.9	21.1	Ag, Unemp., Pov., Ag $\times$ Unemp., Unemp. $\times$ Pov.	Moderate (0.48)
Minnesota	0.15	0.06	1.37	26.7	15.8	Ag, Pov., Pov. $\times$ Ag, Ag $\times$ NWREG%	Moderate (0.47)
Kansas	0.12	0.04	1.70	21.8	15.1	Unemp., Ag $\times$ NWREG%, Unemp. $\times$ NWREG%	Moderate (0.42)

Note: Ag = Agriculture; NWREG% = Percentage of the population identifying as non-White racial and ethnic groups; Unemp. = Unemployment; Pov = Poverty

- **Alabama:** Alabama represents a boundary case where EB is the highest but DW alignment is comparatively weak. Alabama occupies an intermediate position in terms of DW potential, ranking near the national median for both total and residential AEP_{Demand} . While its wind resource is substantially lower than that of traditional wind states, it is not negligible but it does not meet the top composite thresholds and ranks 7th in the Group 1 classification. However, Alabama is noteworthy for its high level of EB. It ranks first nationally for median EB in both the 2025 and 2035 scenarios and has the highest proportion of counties above the 90th percentile of EB (Fig. 2) in 2025 and the second in 2035 scenario. This underscores a need to find solutions for EB alleviation, even if wind alignment is less pronounced than in

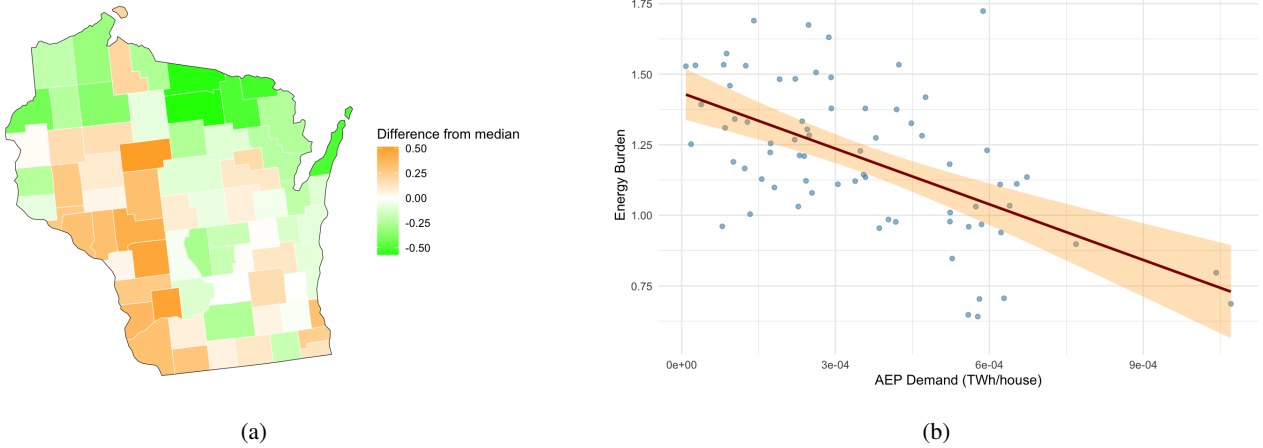


Figure 8. Wisconsin: Spatial and statistical patterns, 2025. (a) Energy burden (distance from the state median), (b) Correlation EB with AEP_{Demand}

Group 1 states. Consequently, DW in Alabama could be viewed as a conditional and localized opportunity—potentially relevant in select counties—but unlikely to serve as a primary or statewide solution for reducing or alleviating EB.

Table 4. Summary of Special cases

State	Parametric correlation	Nonparam. correlation	EB median (%)	Residential AEP _{Demand} $\times 10^{-5}$	Total AEP _{Demand} $\times 10^{-5}$	Key EB predictors (interactions)	Model fit (adj. R^2)
Alabama	0.30	0.21	2.39	7.90	4.76	Poverty, Pov. $\times$ Ag, Ag $\times$ NWREG%.	High (0.70)
Texas	-0.08	-0.05	1.20	5.20	4.51	Ag, Poverty, NWREG%, Unemp. $\times$ Ag, Pov $\times$ Ag, Unemp. $\times$ NWREG%, Ag $\times$ NWREG%	Moderate (0.57)

Note: Ag = Agriculture; NWREG% = Percentage of the population identifying as non-White racial and ethnic groups; Unemp. = Unemployment; Pov = Poverty

3.5 Mixed-effects modeling and state-level regression models by group

Mixed-effects models reveal that poverty rate and the presence of the agriculture industry at the county level are both significantly and positively associated with higher EB, with substantial variability across states. The state-level random effect accounts for approximately 40% of the total variance in EB (intraclass correlation = 0.40), confirming substantial interstate variability beyond what is explained by the fixed-effect covariates alone, which motivates the subsequent state-level analyses

presented below and indicates that regional economic and policy differences play a meaningful role in explaining this variation. Diagnostics of the mixed-effects model show no multicollinearity, but reveal mild deviations from normality and significant
385 heteroskedasticity in the residuals. These issues arise because the model treats covariates as fixed at the national level, pooling variation across all states. As described in the following paragraph, these limitations are addressed by conducting separate state-level regressions, which improve residual diagnostics and overall model performance.

To further investigate variation at the state level, we conducted separate linear regressions for key states representing the two identified groups and the special cases under the two scenarios (2025 and 2035). These models demonstrate stronger statistical
390 performance – exhibiting higher coefficients of determination, reduced heteroskedasticity (constant variance of residuals), no multicollinearity among main-effect predictors ($VIF \leq 5$) and more normally distributed residuals – enhancing the reliability of their results. Overall, the state-level regressions broadly align with national trends, consistently identifying poverty and agricultural employment as key covariates of the EB model. Summaries of these models, including coefficients and correlation metrics, are provided in Tables 2, 3 and 4. County-level correlation maps are presented in Figs. 7 and 8.

395 4 Discussion

Our findings reveal substantial spatial and economic variation in EB and DW generation potential as measured by AEP_{Demand} and also highlight states or regions with an important correlation between both metrics. While these results do not establish causality between the two metrics, they highlight a substantial opportunity for deploying DW technologies within broader efforts to potentially increase energy affordability. As the underlying analysis considers only those land parcels with favorable
400 technical and economic conditions, we assume these cost savings would be enabled through a direct return on investment for the landowners and/or ratepayers. Our mixed-effects model confirms that EB varies significantly by state, motivating the use of state-specific linear regression models. These state-level regressions reveal that EB is frequently associated with indicators of economic hardship, including poverty rates, unemployment, and agricultural activity, which are consistent with the ones identified in (Ross et al., 2022). Given that in some states the elevated generation potential in DW aligns with these EB
405 associated factors, these findings suggest there are targeted pathways through which DW energy generation could help alleviate EB, which is associated with the mentioned variables of economic hardship, particularly in rural sectors. It should be noted, however, that spatial correlation between EB and DW potential does not account for policy environment, permitting constraints, utility structures, financing availability, or technology adoption barriers, all of which play a critical role in actual deployment outcomes and must be considered alongside the spatial patterns identified here.

410 Our results show that correlation analyses and scenario comparisons consistently highlight that the residential sector is most strongly associated with variation in AEP_{Demand} , and exhibits higher correlations with EB. This suggests that the residential sector could be particularly responsive to localized energy interventions and highlights the potential role of residential energy systems in shaping energy affordability outcomes. It also highlights the opportunity of aligning DW deployment with areas of high residential EB, where even modest generation capacity may yield meaningful economic relief.

415 In contrast to residential-focused metrics, the consistently lower correlations between AEP_{Demand} and broader economic indicators (EB_{GDP} and NER_{GDP}) can be explained by the fact that both metrics incorporate demand from the residential, commercial, and industrial sectors. Commercial and industrial sectors could have, in significant cases, energy requirements that exceed what BTM DW can meet in terms of capacity, siting, and mode (i.e., natural gas vs. electricity). Therefore, the inclusion of these more energy-intensive sectors dilutes the alignment between DW generation potential and overall EB in
420 GDP-based metrics. This mismatch helps explain the weaker correlations, reinforcing the idea that residential-focused metrics provide a more accurate lens for assessing the impacts of DW deployment.

4.1 Implications of state differences

A key contribution of this study is demonstrating that DW deployment relevance depends not only on absolute wind resource, but also on how DW opportunity spatially aligns with EB within states in many cases. The grouping framework intentionally
425 prioritizes spatial correlation between EB and AEP_{Demand} , rather than maximum DW potential alone. Also, an important result from this study is the heterogeneity of results both between and within states. We identified two distinct groupings of states based on the EB– AEP_{Demand} relationship and two special cases:

- **Group 1: High-Need/Demand, Favorably Correlated Potential** (e.g., North Carolina, Georgia, Iowa, Louisiana, and California) rank highest in the weighted score (Eq. (8)), due to most pronounced positive alignment between residential
430 EB and residential AEP_{Demand} at the county level. Inclusion in this group does not imply uniformly high or utility-scale wind resources. Instead, it indicates that, within these states, counties with higher EB systematically coincide with counties that have relatively greater DW opportunity, while lower-EB counties coincide with lower opportunity. This distinction is particularly important for states such as Georgia and Louisiana. Although these states have lower absolute wind resources compared to traditional wind states, the observed correlations indicate that the limited DW potential that
435 does exist is geographically well matched to areas of high EB. In such contexts, even modest BTM or small community-scale systems could potentially provide energy affordability benefits relative to their generation size.

States such as Iowa, North Carolina, and California appear in Group 1 for complementary reasons. Iowa and North Carolina rank highly in both absolute and standardized DW metrics, reinforcing their suitability across multiple deployment scales. California, despite lower standardized AEP_{Demand} due to exceptionally high electricity demand, remains strategically
440 important because of its large population, economic scale, and localized pockets where EB and DW opportunity intersect.

Louisiana, while ranked only 28th in residential AEP_{Demand} and 32nd in total AEP, exhibits one of the strongest EB– AEP_{Demand} correlations nationally. In this context, “potential” reflects relative, localized suitability rather than statewide wind abundance, suggesting that targeted, BTM or community-scale deployment in specific counties may be impactful even in
445 low-wind resource states.

- **Group 2: High AEP_{Demand} , Low EB States** (e.g., Minnesota, Kansas, Wisconsin) display strong DW generation potential but relatively low or inconsistent EB. The values of total and residential AEP_{Demand} in Table 3 are much higher

than those in Table 2. Notably, agricultural indicators frequently emerge as key covariates for EB explanation (Table 3), pointing to the potential for sector-specific deployment, as discussed in the next section. They represent viable zones where DW may act as a broader economic development stimulus, even if not directly addressing energy hardship.

- **Special cases** (e.g. Texas and Alabama) do not clearly fit into either group but merit consideration. Texas has significant total AEP, but high electricity demand reduces its standardized AEP_{Demand} , weakening their composite ranking. Alabama illustrates a nuanced case where extreme EB coincides with only moderate DW potential. Although Alabama ranks near the national median in AEP_{Demand} , it ranks first nationally in EB and has the highest share of counties above the 90th percentile (Fig. 2), these signals are insufficient to justify broad deployment prioritization. Instead, they suggest that DW may be feasible in select local contexts, but should be treated as a potential supplementary rather than primary affordability intervention. This case reinforces the importance of distinguishing between non-negligible DW opportunity and deployment relevance at scale, and underscores the need for complementary strategies in states where wind alignment is limited.

These findings illustrate the diverse nature of EB and demand dynamics across the United States. Interpreting these relationships effectively requires a geographically-nuanced approach, often down to the county level or beyond, since DW siting depends on localized wind resource and economics. Local economic structure, energy infrastructure, and policy environment all shape how EB and energy demand interact. The influence of agricultural economies, in particular, often crosses state lines, as explored in the mixed-effects modeling.

4.2 Key drivers of energy burden

Consistent with prior research (Ross et al., 2018), our models show that poverty and agricultural employment are reliable associated factors of higher EB, although some global studies report mixed results (Meng and Kozybay, 2024). Agricultural employment likely reflects broader rural economic characteristics (such as lower and more variable incomes, older housing stock or limited access to utility programs) rather than a direct causal effect of agricultural activity on energy costs, and should therefore be interpreted as a proxy for rural economic disadvantage. The interaction between unemployment and agriculture in states like Wisconsin also highlights complex dynamics between industry structure and energy vulnerability. These findings suggest that DW planning should account for both demographic and economic context, not just technical feasibility.

It is important to clarify that while variables like unemployment and poverty frequently emerge as key covariates in explaining EB, this does not imply that DW deployment will directly reduce those underlying socioeconomic conditions. However, by potentially lowering energy costs in areas where these conditions are prevalent, DW may help ease energy-related hardship through activities like income generation and workforce development and indirectly contribute to improved quality of life.

This study demonstrates that a significant opportunity exists for targeted DW deployment to potentially alleviate economic hardships in high-EB states and counties with viable DW potential. However, implementation must consider disparities in conditions and environmental factors. Even in states with high overall AEP, deployment may be directed to counties where the benefits of energy cost reduction are most needed. Similarly, DW potential does not by default indicate energy cost savings, so

care must be taken to ensure there will be reasonable savings before DW project design or implementation. In some areas, strong wind resources exist alongside relatively low EB; these contexts may require different strategies or benefit rationales, such as other forms of economic development, independence, or resilience objectives rather than energy affordability. Households or communities with elevated EB may also find investments in DW projects unaffordable, especially without suitable financing or funding options, even if there are identified long-term economic benefits.

5 Conclusions

This study explores the potential for DW deployment in the contiguous United States, focusing on the relationship of DW with EB and residential energy demand. We found that the residential sector plays a central role in determining the impact of DW, as it better explains changes in AEP compared to industrial and commercial sectors. The analysis demonstrated that while residential EB is the most strongly correlated with AEP_{Demand} , EB_{GDP} also aligns with the economic conditions of states and counties but is less heterogeneous. As previously described, these results are based on the key assumption of projects receiving a federal investment tax credit and location-specific credit bonuses. Reduced availability of these tax credit per federal policy changes are likely to reduce cost-viable generation potential across all states, thus warranting additional scenario or localized analyses with these different economic considerations.

We also identified two distinct groupings of states and two special cases, each with varying levels of opportunity for DW deployment, driven by factors such as EB, economic conditions, and demographic characteristics. DW deployment could provide benefits to targeted areas facing significant economic hardship or could serve as a stimulus for agricultural regions, where energy needs may be high.

While the statistical relationships presented here are robust, it should also be highlighted that this study is descriptive and correlational, i.e., the model findings do not confirm causality and are limited in accuracy to that of the data upon which they are defined. For instance, EB estimates depend on the accuracy of demand projections and income data, both of which are subject to uncertainty at fine geographic scales. Similarly, correlation results do not indicate definitive cost savings, but they highlight an opportunity to explore energy hardship relief through strategic deployment of DW technologies. Future research could improve the resolution of the techno-economic data through the integration of residential-level data, explore cost-benefit analyses of DW deployment in specific counties, or explore policy scenarios (such as community wind incentives or rate design). Future research should also examine wind resource sufficiency at the parcel level, quantify projected electricity bill savings under realistic ownership and financing scenarios, and assess the degree to which EB would decrease under different deployment configurations, building on the spatial prioritization framework presented here.

Another important direction for future research is the integration of additional co-benefits, such as emissions and air quality impacts, into the prioritization framework for DW deployment. While preliminary steps have been taken under the DWEFS, they are limited by the availability of datasets. Improved access to high-resolution datasets would enable a more comprehensive assessment of these co-benefits, supporting a more strategic and impactful approach to DW deployment. Equally important, future research and implementation should also account for impacts on wildlife, ecosystems, and local land use to ensure that

DW projects deliver net-positive outcomes across environmental and economic dimensions. A holistic framework that balances energy and ecological concerns will be critical for responsible and effective deployment.

Taken together, these findings enhance our understanding of where DW deployment could be most relevant to affordability challenges and offer guidance on where such solutions are most likely to have a meaningful impact. The presented results could be leveraged by state- and county-level decision-makers to initiate more localized explorations and planning processes aligned with local goals, particularly for those states identified in Groups 1 or 2. This may include efforts to understand state, county and city Climate Action Plans or other energy strategies and how DW may help advance them, or what policies and regulations exist that enable or restrict DW project installations. Collaboration and coordination with other entities advancing energy affordability or economic development efforts may also be necessary to identify stakeholders and areas that could benefit from DW projects. To further aid decision-makers, future research should delve into local dynamics, examine the long-term effects of DW across different economic landscapes, and refine deployment strategies to optimize resulting benefits.

Code availability. The code used in this analysis will be made available at <https://github.com/NREL> upon publication.

Data availability. The DWEFS data supporting this study are publicly available at the U.S. Department of Energy's Wind Data Hub at <https://wdh.energy.gov/ds/dw/btm>.

Author contributions: SAG conducted methodology, formal analysis, and visualization. SAG and PP performed validation of data analysis and, together with CP, interpreted the results. JL, SP, and PC conducted data production and aggregation. SAG, PP, and CP prepared the manuscript with contributions from all authors.

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