

Spatial and economic prioritization for distributed wind

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Abstract. This study investigates how distributed wind (DW) 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 ~~-,including algebraic transformations of energy burden-~~ 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. 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 ~~burden-it~~ is closely tied to poverty rates and agricultural activities. ~~Based on these patterns~~ While noting that these associations do not imply causal effects, we group states ~~into two categories and special cases reflecting based on~~ correlation strength and DW potential, ~~highlighting-~~ This highlights potential opportunities to improve energy affordability through targeted siting of distributed wind projects whose 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 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). Distributed wind systems typically consist of a single wind turbine or several turbines at ~~heights~~ hub heights generally between 30 and ~~60 m~~ 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 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

*NLR was formerly known as the National Renewable Energy Laboratory

household or consumer energy costs by offsetting retail electricity purchases, avoid some utility charges, reduce the need for extensive transmission upgrades, and stimulate local economic development [through opportunities for workforce development and income generation](#) when appropriately cited ([U.S. Department of Energy, n.d.](#)).

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 ~~3~~[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 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 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 ~~National Renewable Energy Laboratory's~~ Distributed Wind Energy Futures Study (DWEFS) (~~Lockshin et al., 2025~~), [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 ~~distributed-wind-under-DW~~. [The latest data 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 ~~distributed-wind-DW~~ potential across both 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 ~~distributed-wind-DW~~ in areas with energy-related financial stress. Specifically, we examine where ~~distributed-wind-DW~~ could be deployed to potentially alleviate EB and increase NER, ~~with a particular focus on~~ [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 Crook et al. \(2025\) particularly across croplands throughout CONUS.](#) While our analysis does not imply causality, it ~~reveals meaningful statistical relationships~~ [identifies meaningful spatial and statistical associations](#) between DW potential and ~~indicators of economic vulnerability~~ [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 ~~distributed-wind-DW~~ potential, providing insights into where targeted investments might yield the greatest community benefit.

2 Methods

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), and NER from 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 racial-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 distributed-wind-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 distributed-wind-energy production, 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.

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 socioeconomic-economic characteristics across the contiguous United States.

Table 1. Summary of Data Sources

Data	Description and Source	Data Year
<u>Cost-Viable</u> AEP Values	Distributed Wind Energy Futures Study (Lockshin et al., 2025)	2022, 2025, 2035
Poverty and In- come	U.S. Census Bureau, Small Area Income and Poverty Estimates Program (U.S. Census Bureau, 2023a)	2023
Gross Domes- tic 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	National Renewable Energy Laboratory <u>Laboratory of the Rockies</u> , 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~~ Description

To enable spatial consistency with representative datasets, we aggregate parcel-level data to the county level. The data include
90 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:

$$AEP_{\text{demand}} = \frac{AEP}{\text{Total Electricity Demand}} \tag{1}$$

This ratio standardizes ~~distributed-wind~~ DW generation relative to total electricity demand across residential, commercial,
95 and industrial sectors 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.

100 Our primary affordability metric is **Energy Burden - EB**, which conceptually reflects residential-level affordability. In our 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:

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

105 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 a smaller share of household income.

At the county level, we extend this to **EB relative to GDP (EB_{GDP})**, which provides a broader perspective on county-level 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:

110
$$EB_{GDP} = \frac{\text{Total County Energy Expenditure}}{\text{GDP}} \quad (3)$$

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 of economic activity, suggesting greater economic resilience to energy prices.

While EB measures the proportion of income spent on energy – offering a direct sense of affordability – we also include
115 **NER** (Scheier and Kittner, 2022), which provides smoother statistical properties and a complementary interpretive angle. Rather than indicating energy cost burden, 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:

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

120 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:

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

125 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.

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.

130 While national policies typically define energy poverty as $EB > 6\%$ or $NER < 16\%$ (Colton, 2011), these thresholds include all energy sources (e.g., natural gas), whereas we calculate EB for electricity only. This is because ~~distributed-wind-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.

135 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 ~~demand-and-high-burden-DW~~ potential and high
140 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.

145 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
150 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 ~~generate~~ construct rankings at the state level and then combine them into a weighted ranking to identify states where ~~distributed wind deployment~~ DW deployment opportunity could be most ~~effective at improving residential energy affordability~~ strongly aligned with EB. The purpose of this ranking
155 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, ~~this ranking emphasizes correlation strength by assigning it~~ 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
160 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 ~~. To support a more comprehensive and scalable assessment, we also incorporate key metrics like residential AEP_{Demand} in~~ 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
165 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 ~~and total residential is~~
170 included to represent relative DW opportunity normalized by electricity demand. Including key metrics ensures that states with low demand are not inadvertently over-prioritized due to the standardization inherent in the AEP_{Demand} calculation. The final weighted score is computed by ranking each variable individually, then combining them using the formula: 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.

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

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

where rank₂₅ and rank₃₅ are the correlation-based ranks of DW potential and EB alignment for 2025 and 2035, rank_{AEP/D,25} and rank_{AEP/D,35} are ranks of DW opportunity normalized by electricity demand (AEP_{Demand}), and rank_{Dem,25} and rank_{Dem,35} are ranks of absolute electricity demand.

180 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. Alternative weighting schemes are possible; however, the chosen structure directly supports the study's focus on affordability-relevant siting rather than maximum energy generation.

Based on this ~~weighted ranking and the absolute values of AEP_{Demand}~~ framework, we classify states into two groups and a set of special cases. ~~Group 1 is defined by~~, each designed to highlight a distinct type of deployment-relevant context.

Group 1 consists of states that rank highly according to the composite ranking in Eq. 8 ~~while Group 2~~, 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}. ~~This classification helps highlight potential priority areas for distributed wind deployment and offers insight into the underlying factors driving regional variation in energy performance and affordability~~, 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.

Transparency note: During the initial design, rankings based solely on standardized AEP_{Demand} skewed disproportionately toward low-demand states. To correct this methodological distortion, we included residential demand as a counterbalancing factor. This adjustment improves the alignment of the ranking with the study's aim: identifying meaningful and potential opportunities for distributed wind deployment that serve both high-need and high-impact regions. 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 strategies.

205 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.

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), ~~with states modeled as random effects to account for unobserved heterogeneity across regions, and~~. In this framework, county-level covariates – including poverty rate, percentage of agricultural employment, and percentage of the population identifying as ~~non-White 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.

215 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.

220 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 evaluated using likelihood ratio testing to confirm substantial interstate variability in EB outcomes.

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). These models offer provide more granular insights into ~~the performance of key predictors across different~~ how key predictors of EB differ across regional contexts and ~~contribute to the statistical robustness of the EB model~~ 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, ~~and~~ 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.

230 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

240 This section presents the findings from our spatial, statistical, and modeling analyses using scenarios for current (2025) and future (2035) ~~distributed wind~~ DW potential. We describe patterns of geographic variation in EB and NER, followed by an examination of the relationship between EB and the standardized ~~distributed wind~~ 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)

245 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 ~~distributed-wind~~ 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–~~1d~~ 1f presents residential EB distributions and spatial patterns for the 2025 and 2035
250 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
255 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. ~~1a and 1b~~ 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
260 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 ~~distributed-wind~~ 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) compared to the residential EB (Fig. 1), with state values generally clustering closer to the national median.
265 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 ~~the Methods section~~ Section 2.2, yielding the AEP_{Demand} metric. This ratio, like raw AEP, is highly
270 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 ~~–also detailed in the Methods section. While this alters the ranking of some states relative to raw AEP, it preserves overall distributional patterns~~ (Fig. 4) –solely for descriptive visualization and Pearson correlation diagnostics. These Pearson correlations (using Box–Cox–transformed variables) and
275 Kendall’s Tau correlations (using untransformed variables) produced similar results on the rankings that we analyze later.

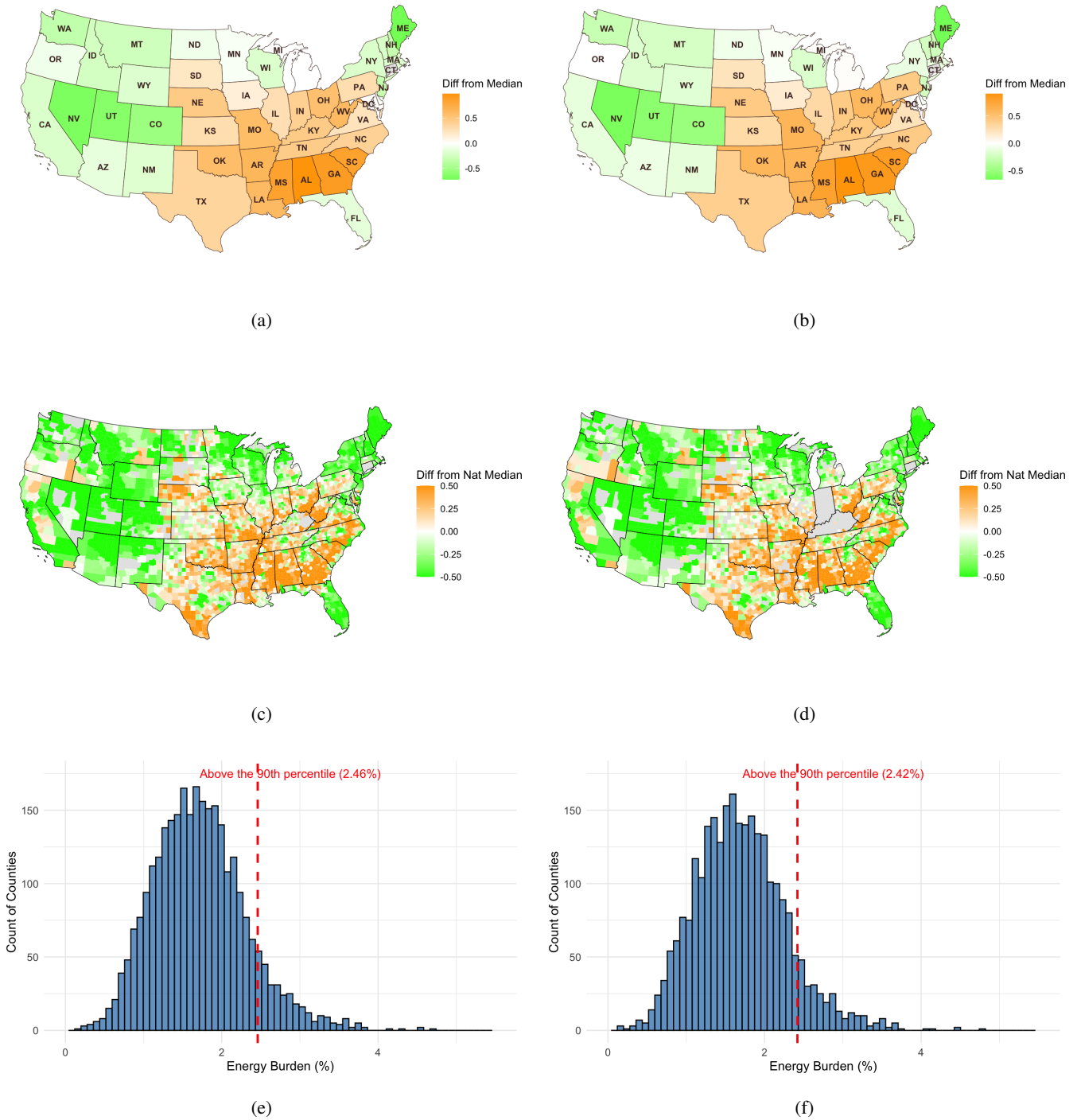


Figure 1. Residential EB across ~~state-states~~ ((a) 2025 – 2025 – (b) 2035 –) and county levels ((c) 2025 – (d) 2035). EB values above the national median in the Southeast and below in many western states across both scenarios (a–b). County-level ~~results~~ ((e) 2025 – (f) 2035) ~~shows-show~~ intrastate 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.

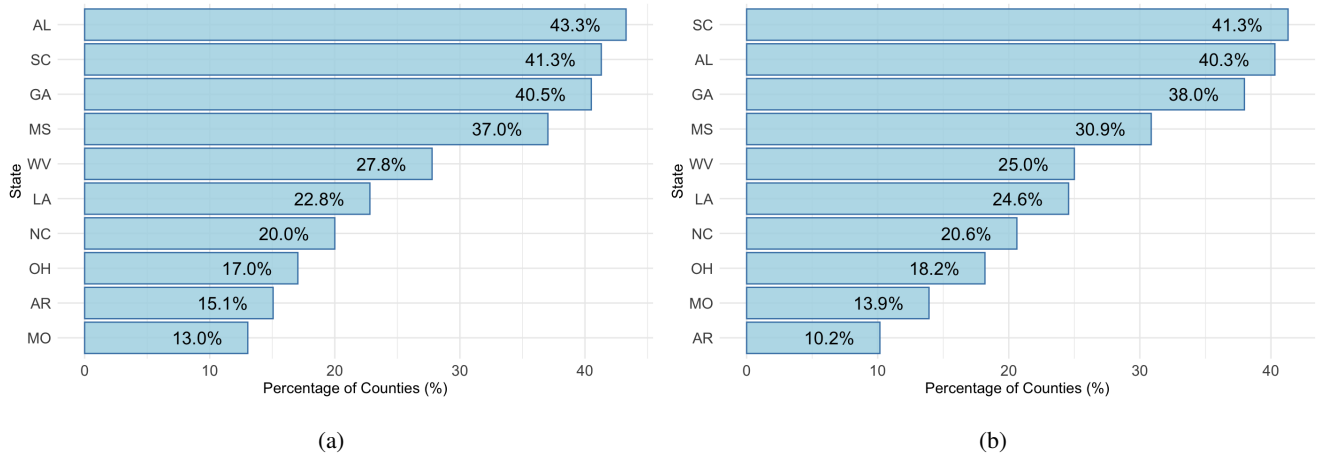


Figure 2. Top 10 states with the highest percentage of counties above the 90th percentile in ~~energy-burden~~EB. (a) ~~2025~~—2025—(b) 2035.

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 ~~favorable distributed wind-feasible DW~~ opportunity meets or exceeds electrical demand, suggesting a strong potential ~~to shift energy-generation to distributed wind from other sources~~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, favorable policies like net metering or local ordinances impacting siting, elevated utility rates that make distributed wind costs competitive, amongst others (Lockshin et al., 2025).

In contrast, Texas and ~~Georgia—while Georgia—while~~ also ranking in the top 10 for total AEP_{Demand} by number of ~~counties—achieve 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 ~~wind-DW~~ potential across counties is uneven. As a result, these states may still offer strong opportunities for ~~distributed wind-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 ~~energy-DW~~ deployment potential.

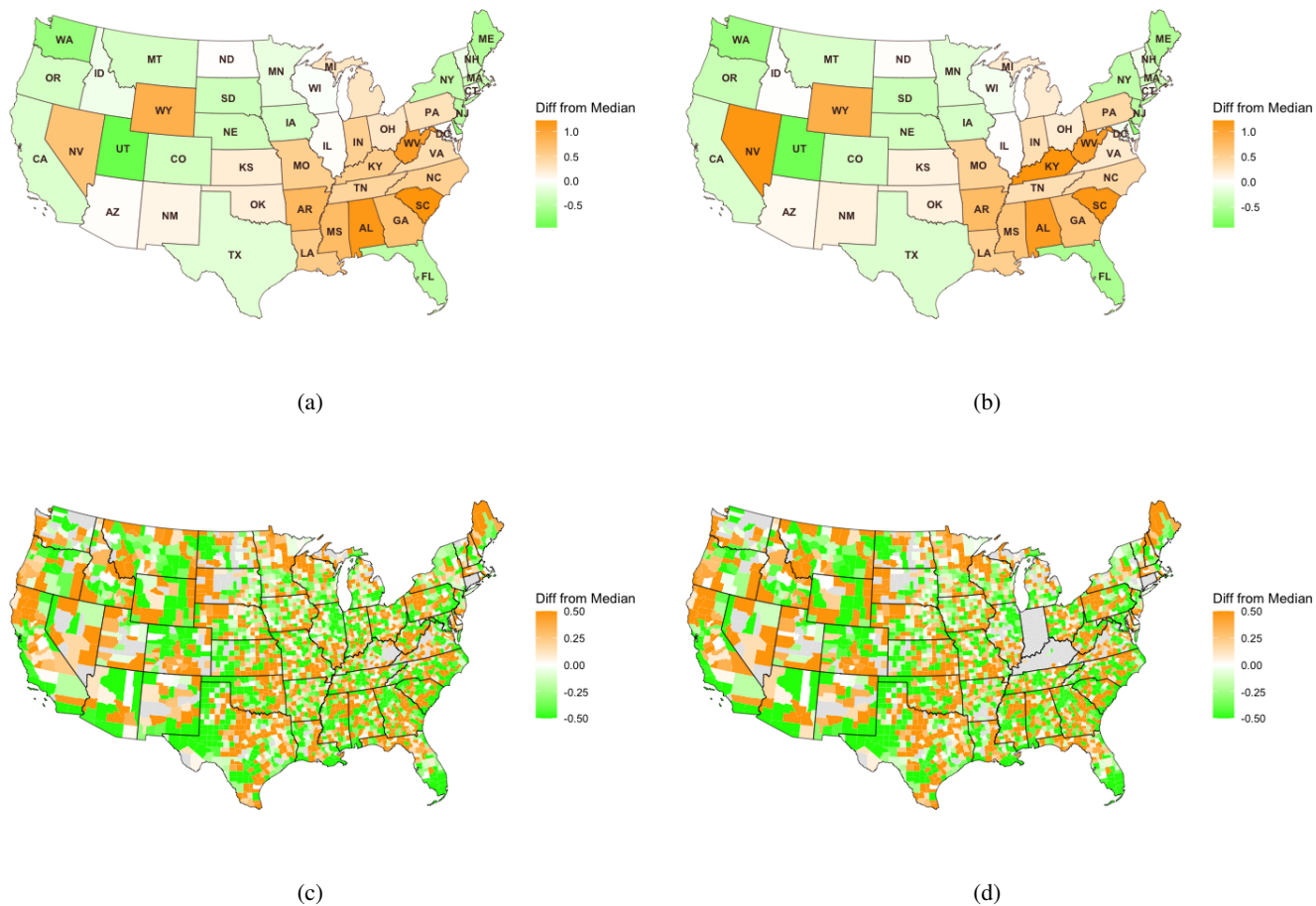


Figure 3. Comparison of energy burden relative to GDP (EB_{GDP}) in 2025 and 2035 across state ((a) 2025 – (b) 2035) across state and county levels ((c) 2025 – (d) 2035, 2035 county levels). The EB_{GDP} metric shows less intrastate variation than residential EB, with most state-level values clustering near the national median (a–b). In contrast, county-level patterns (c–d) reveal pronounced regional disparities that often extend across state boundaries.

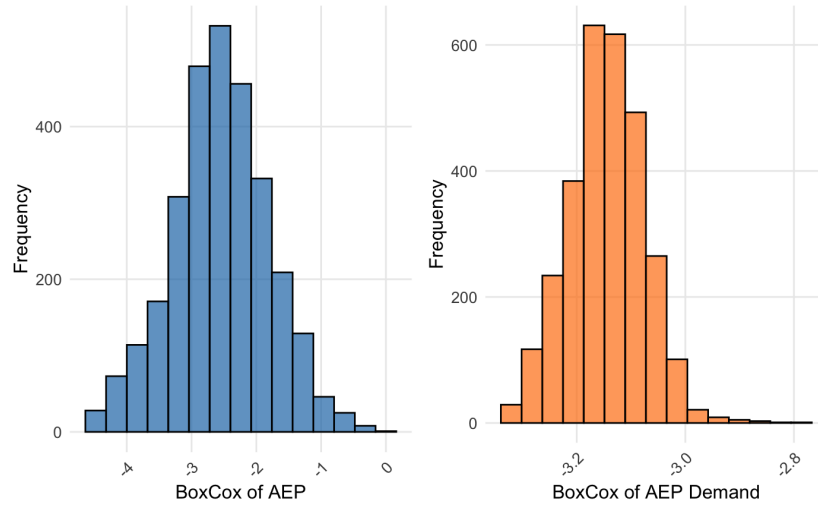


Figure 4. Nationwide distributions of Box–Cox–transformed AEP and AEP_{Demand} for BTM DW 2025. Before transformation, both metrics exhibit ~~similar~~-right-skewed distributions. They share the same Box–Cox transformation parameter ($\lambda = 0.2$), ~~indicating that normalization preserves the underlying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

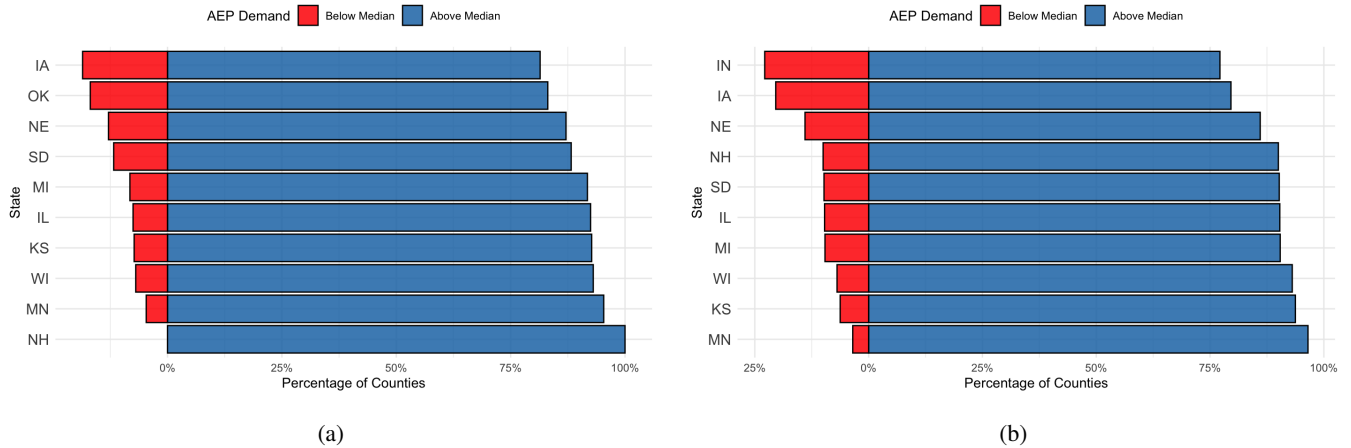


Figure 5. Top 10 states with the highest proportion of counties above the national median AEP_{Demand} (a) ~~2025~~—~~2025~~—(b) 2035. Kansas, Illinois, Minnesota, and Nebraska show both high absolute and proportional county-level AEP_{Demand}, indicating widespread ~~distributed wind~~ ~~DW~~ potential. 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 ~~correlations EB correlation with AEP_{Demand}~~ residential 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 ~~California~~ 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.

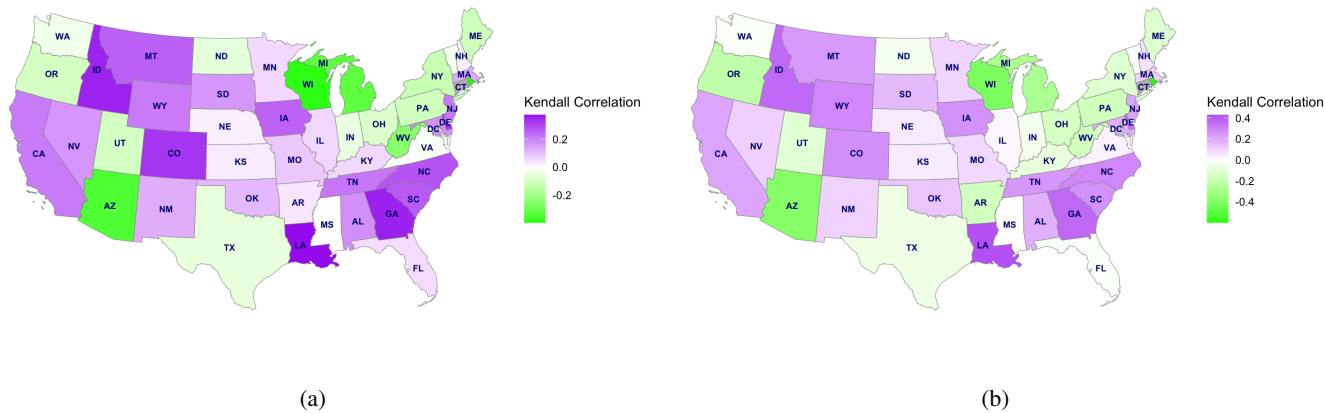


Figure 6. State-level nonparametric correlation between residential AEP_{Demand} and EB. This is the strongest correlation with EB among all metrics considered. States such as Georgia, Idaho, Louisiana, and Colorado consistently exhibit the highest correlations nationwide in both the 2025 (a) and 2035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

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} .

Group 1: High-Need/Demand, ~~High-Potential~~ States 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 ~~wind~~ DW generation potential in the residential sector in the same counties (county level). They also 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 ~~AEP~~ residential 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 ~~distributed wind~~ 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 ~~distributed wind~~ DW opportunity, but the available opportunity is well located to ~~reduce~~ potentially alleviate EB.

320 Louisiana, while ranked only 28th in residential AEP_{Demand} and 32nd in total ~~AEP~~ AEP, exhibits high EB values and strong 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).

325 In the case of California, while ~~it 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, ~~special~~ 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
330 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.
335 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.

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 ~~at across~~ evaluated counties. Wisconsin results are shown
340 in Fig. 8 as an example. Although the correlation with EB is low, the states' high AEP_{Demand} alone indicates high ~~distributed wind~~ DW deployment potential (summarized in Table 3). It is also important to note that while ~~high the high~~ EB in these states does not align with areas of high ~~distributed wind (DW)~~ DW opportunity, EB itself is ~~influenced by~~ 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.

345 **Special ~~cases~~ 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, ~~extreme~~ very high EB, or demographic scale.

- **Texas:** Texas ranks second in total (nonstandardized) ~~AEP~~ 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

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

State	Parametric correlation	Nonparametric Nonparam. correlation	EB median (%)	Residential AEP _{Demand} ×10 ⁻⁵	Total AEP _{Demand} ×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 × 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. × Ag, Unemp. × NWREG%	Moderate (0.55)

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

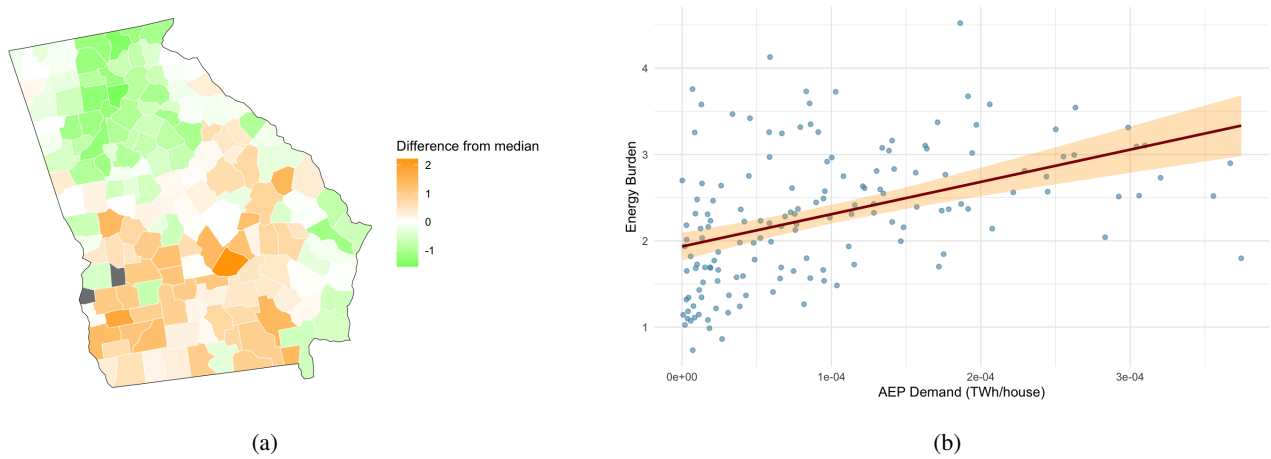


Figure 7. Georgia: Spatial and statistical patterns, 2025. (a) Energy burden (distance ~~form~~from the state median), (b) Correlation EB with AEP_{Demand}

350 median, the correlation between EB and ~~wind~~DW potential is near zero, indicating almost no spatial overlap between ~~need~~EB and opportunity and ultimately limiting its prioritization within the current framework.

– **Alabama:** Alabama ~~shows a light positive correlation between generation potential and EB~~, particularly in certain ~~regions as illustrated in Table 4~~, 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

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

State	Parametric correlation	Nonparametric correlation	EB median (%)	Residential AEP _{Demand} × 10 ⁻⁵	Total AEP _{Demand} × 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 × Unemp., Unemp. × Pov.	Moderate (0.48)
Minnesota	0.15	0.06	1.37	26.7	15.8	Ag, Pov., Pov. × Ag, Ag × NWREG%	Moderate (0.47)
Kansas	0.12	0.04	1.70	21.8	15.1	Unemp., Ag x NWREG%, Unemp. × NWREG%	Moderate (0.42)

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

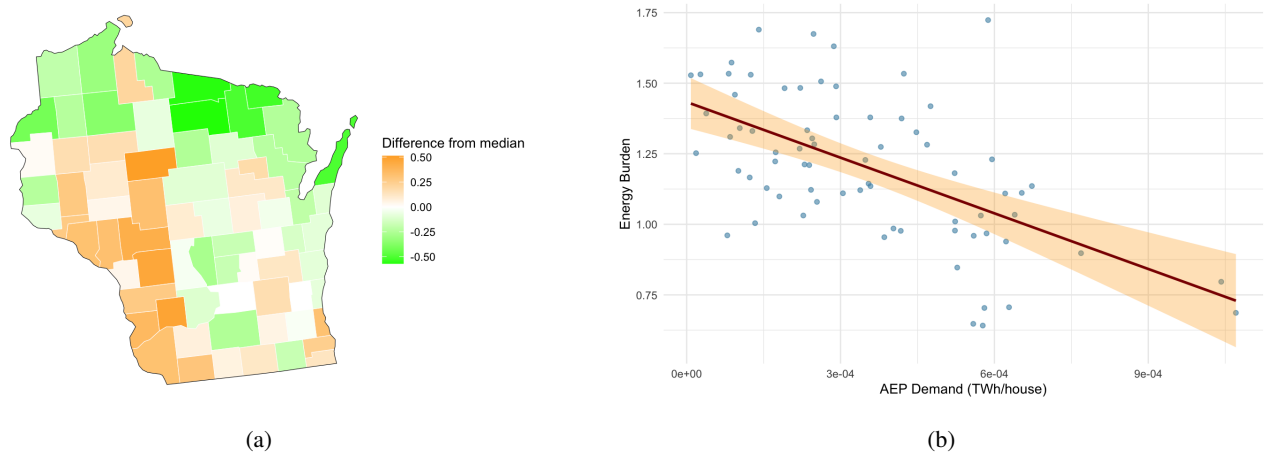


Figure 8. Wisconsin: Spatial and statistical patterns, 2025. (a) Energy burden (distance from the state median), (b) Correlation EB with AEP_{Demand}

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 an urgent need a need to find solutions for EB alleviation, even if wind alignment is less pronounced than in 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	Nonparametric correlation <u>Nonparam. correlation</u>	EB median <u>EB median</u> (%)	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, Ag -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 significance of the state-level random effect supports the use of a state-based grouping framework and 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 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.

3.6 ~~State-level regression models by group~~

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 performance – exhibiting higher coefficients of determination, reduced heteroskedasticity (constant variance of residuals), no multicollinearity among main-effect predictors ($VIF < 5$) 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 ~~predictors of EB~~covariates of the EB model.

Summaries of these models, including coefficients and correlation metrics, are provided in Tables 2and 3, 3 and 4. County-level correlation maps are presented in Figs. 7 and 8.

4 Discussion

Our findings reveal substantial spatial and economic variation in EB and ~~distributed-wind-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 ~~to deploy distributed-wind for deploying~~
385 DW technologies within broader efforts to potentially increase energy affordability. As the underlying analysis considers only those land parcels with favorable 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
390 consistent with the ones identified in ~~a prior study~~ (Ross et al., 2022). Given that in some states the elevated generation potential in ~~distributed-wind-DW~~ aligns with these EB ~~drivers, these finding-associated factors, these findings~~ suggest there are targeted pathways through which ~~distributed-wind-DW~~ energy generation could help alleviate EB, which is associated with the mentioned variables of economic hardship, particularly in rural ~~areasectors~~.

Our results show that correlation analyses and scenario comparisons consistently highlight that the residential sector is most
395 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 ~~distributed-wind-DW~~ deployment with areas of high residential EB, where even modest generation capacity may yield meaningful economic relief.

In contrast to residential-focused metrics, the consistently lower correlations between AEP_{Demand} and broader economic
400 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 ~~distributed-wind-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 ~~distributed-wind-DW~~ generation potential and overall EB in GDP-based metrics. This mismatch helps explain the weaker correlations, reinforcing the idea that
405 residential-focused metrics provide a more accurate lens for assessing the impacts of ~~distributed-wind-DW~~ deployment.

4.1 Implications of state differences

~~An~~ 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 prioritizes spatial correlation between EB and AEP_{Demand} , rather than maximum DW potential alone. Also, an
410 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, High-Potential States** Favorably Correlated Potential (e.g., North Carolina, Georgia, Iowa, Louisiana, and California) rank highest in the weighted score (Eq. (8)), ~~indicating the presence of both high~~

residential wind potential and high EB. These states also exhibit elevated AEP_{Demand} and comparatively high residential energy demand relative to other CONUS states. This combination highlights significant opportunities for distributed wind deployment aimed at alleviating energy burden (EB), as wind resources more closely align with areas experiencing substantial economic stress. Georgia, due to strong positive alignment between residential 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 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, California and Iowa are consistent, as they also rank highly across other distributed wind potential indicators. Although Louisiana shows weaker overall distributed wind potential, its strong EB 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 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} correlation suggests that targeted (strategic) 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 still be impactful even in low-wind resource states.

It is important to remark that in the case of California, its large population and high economic activity make it a strategically relevant case in the Group 1.

– **Group 2: High AEP_{Demand} , Low EB States** (e.g., Minnesota, Kansas, Wisconsin) display strong wind-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 distributed wind-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 ranks 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), despite weaker wind potential. Nonetheless, these states present important

sub-state opportunities, particularly in regions where high poverty rates and agricultural industry coincide with viable wind resources. Within the context of EB reduction efforts, they may be considered a secondary priority for distributed wind deployment, with localized deployment potentially yielding significant benefits. 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~~ geographically nuanced approach, often down to the county level or beyond, since ~~distributed wind 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 ~~predictors~~ associated factors of higher EB, although some global studies report mixed results (Meng and Kozybay, 2024). The interaction between unemployment and agriculture in states like Wisconsin also highlights complex dynamics between industry structure and energy vulnerability. These findings suggest that ~~distributed wind 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 ~~distributed wind DW~~ deployment will directly reduce those underlying socioeconomic conditions. However, by potentially lowering energy costs in areas where these conditions are prevalent, ~~distributed wind DW~~ may help ease energy-related hardship and through activities like income generation and workforce development and indirectly contribute to improved quality of life.

This study demonstrates ~~there is that~~ a significant opportunity ~~for targeted distributed wind exists for targeted DW~~ deployment to potentially alleviate economic hardships in high-EB states and counties with viable ~~wind 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, ~~distributed wind DW~~ potential does not by default indicate energy cost savings, so care must be taken to ensure there will be reasonable savings before ~~distributed wind 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 ~~distributed-wind~~DW deployment in the contiguous United States, focusing on the relationship of ~~distributed-wind~~DW with EB and residential energy demand. We found that the residential sector plays a central role in determining the impact of ~~distributed-wind~~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 ~~distributed-wind~~DW deployment, driven by factors such as EB, economic conditions, and demographic characteristics. ~~Distributed-wind~~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 ~~distributed-wind technologies.~~

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 ~~distributed-wind~~DW deployment in specific counties, or explore policy scenarios (such as community wind incentives or rate design).

An Another important direction for future research is the integration of additional co-benefits, such as emissions ~~offset potential~~and air quality impacts, into the prioritization framework for ~~distributed-wind~~DW deployment. While preliminary steps have been taken under the DWEFS, they are limited by ~~available~~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 ~~distributed-wind deployment.~~

DW deployment. Equally important, future research and implementation ~~must~~should also account for impacts on wildlife, ecosystems, and local land use. ~~It is essential~~ to ensure that ~~distributed-wind~~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 ~~how distributed-wind could impact energy affordability 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. ~~Future~~The presented results could be leveraged by state- and county-level decision-makers to

515 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
520 research should delve into local dynamics, examine the long-term effects of ~~distributed-wind~~ 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>.

525 *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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