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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 is closely tied to poverty rates and agricultural activities. Based on these patterns, we group states into two categories and special cases reflecting correlation strength and DW potential, highlighting potential opportunities to improve energy affordability through targeted siting of distributed wind projects.

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 between 30 and 60 m 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 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 when appropriately sited.

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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 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 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 could be further explored as a potential avenue for relief.

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), which provides parcel-level techno-economic assessments for distributed wind under recent (2025) and projected future (2035) scenarios. 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 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 to construct an energy-economy framework that evaluates the deployment potential of distributed wind in areas with energy-related financial stress. Specifically, we examine where distributed wind could be deployed to potentially alleviate EB and increase NER, with a particular focus on high-poverty, rural, and agricultural contexts. While our analysis does not imply causality, it reveals meaningful statistical relationships between DW potential and indicators of economic vulnerability. Our results highlight that counties that simultaneously experience high EB (or low NER) often have substantial distributed wind 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 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 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

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economic hardship. Second, we conduct a spatial correlation analysis to assess the relationship between distributed wind 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, 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. 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 characteristics across the contiguous United States.

Table 1. Summary of Data Sources

Data	**Description and Source**	**Data Year**
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 (US 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, Net Electricity and Natural Gas Consumption, State and Local Planning for Energy (NREL, 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

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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:

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

This ratio standardizes distributed wind generation relative to total electricity demand across residential, commercial, and industrial sectors accounting for variation in population density and consumption levels. Sector-specific analyses also use disaggregated demand components as needed.

Our primary affordability metric is **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:

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

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:

$$EB_{\text{GDP}} = \frac{\text{Total County Energy Expenditure}}{\text{GDP}} \tag{3}$$

While EB measures the proportion of income spent on energy – offering a direct sense of affordability – we also include **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:

$$NER = \frac{\text{Household Income} - \text{Energy Expenditure}}{\text{Energy Expenditure}} \tag{4}$$

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

$$NER = \frac{1}{EB} - 1 \tag{5}$$

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:

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$$NER_{\text{GDP}} = \frac{\text{GDP} - \text{Total County Energy Expenditure}}{\text{Total County Energy Expenditure}} \tag{6}$$

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), these thresholds include all energy sources (e.g., natural gas), whereas we calculate EB for electricity only. This is because distributed wind 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 $\text{AEP}_{\text{Demand}}$ for residential, commercial, industrial, and combined-sector demand at the county level. Notably, the spatial distribution of $\text{AEP}_{\text{Demand}}$ 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 – 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 $\text{AEP}_{\text{Demand}}$ 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:

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

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 generate a weighted ranking to identify states where distributed wind deployment could be most effective at improving residential energy affordability.

As shown in Eq. **??**, this ranking emphasizes correlation strength by assigning it half the total weight. To support a more comprehensive and scalable assessment, we also incorporate key metrics like residential $\text{AEP}_{\text{Demand}}$ in both the 2025 and

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2035 scenarios and total residential electricity demand. Including key metrics ensures that states with low demand are not inadvertently over-prioritized due to the standardization inherent in the $\text{AEP}_{\text{Demand}}$ calculation. The final weighted score is computed by ranking each variable individually, then combining them using the formula:

v

Based on this weighted ranking and the absolute values of $\text{AEP}_{\text{Demand}}$, we classify states into two groups and a set of special cases. Group 1 is defined by the composite ranking in Eq. **??** while Group 2 is based on the absolute ranking of $\text{AEP}_{\text{Demand}}$. 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.

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.*

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 county-level covariates – including poverty rate, percentage of agricultural employment, and percentage of the population identifying as non-White racial and ethnic groups—treated as fixed effects. 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 for representative states from each of the groups defined in the ranking analysis (see Sect. 2.4). These models offer more granular insights into the performance of key predictors across different regional contexts and contribute to the statistical robustness of the EB model. To ensure the validity of these models, we evaluate key diagnostics, including adjusted R^2, residual distributions, and variance homogeneity (homoskedasticity).

3 Results

This section presents the findings from our spatial, statistical, and modeling analyses using scenarios for current (2025) and future (2035) distributed wind 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 generation potential metric $\text{AEP}_{\text{Demand}}$. We then report on state clustering patterns and present mixed-effects and state-level model results.

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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 distributed wind opportunity. EB and NER vary significantly across U.S. counties and states. Southeastern states exhibit above-median residential EB (Alabama has 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 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 90^{th} 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.

Moreover, as shown in Fig. 1a and 1b, 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 $\mathrm{EB_{GDP}}$ and $\mathrm{NER_{GDP}}$ (at a county level)

To further understand how regional economic capacity determines energy affordability and its implications for distributed wind opportunity, we explore $\mathrm{EB_{GDP}}$ and compare it to residential EB. The $\mathrm{EB_{GDP}}$ 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. 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, yielding the $\mathrm{AEP_{Demand}}$ 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, 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).

Several states, including Kansas, Illinois, Minnesota, and Nebraska, have both an absolute and proportionally higher number of counties exceeding the national median of $\mathrm{AEP_{Demand}}$ (Fig. 5). These states also consistently rank within the top 10 in total $\mathrm{AEP_{Demand}}$, although in different order. These are areas of the United States where economically favorable distributed wind opportunity meets or exceeds electrical demand, suggesting a strong potential to shift energy generation to distributed wind from other sources.

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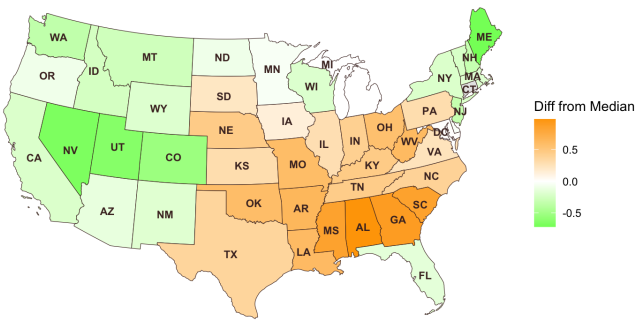
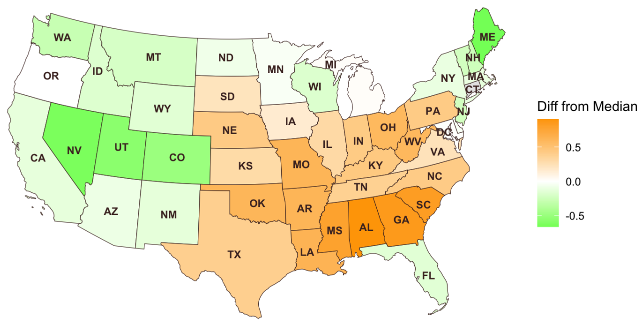
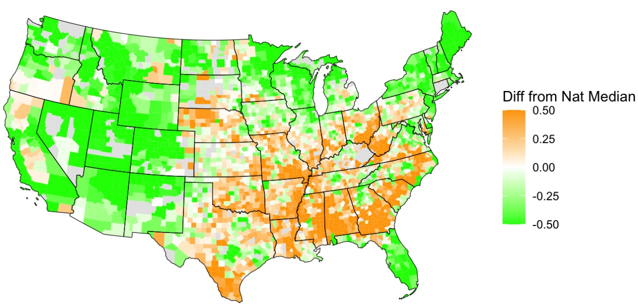


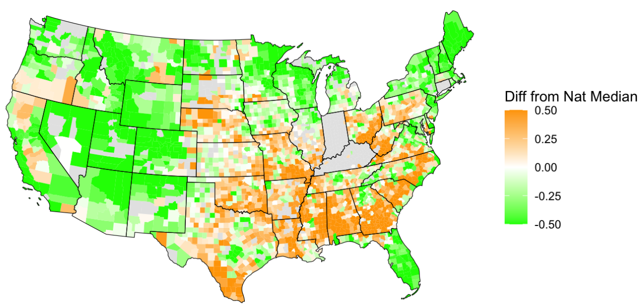
(a)



(b)



(c)



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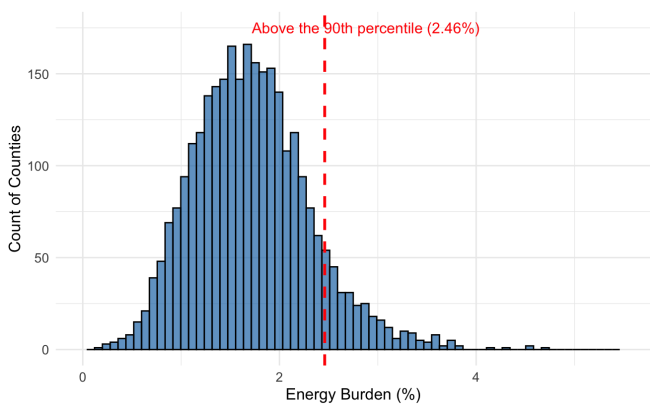
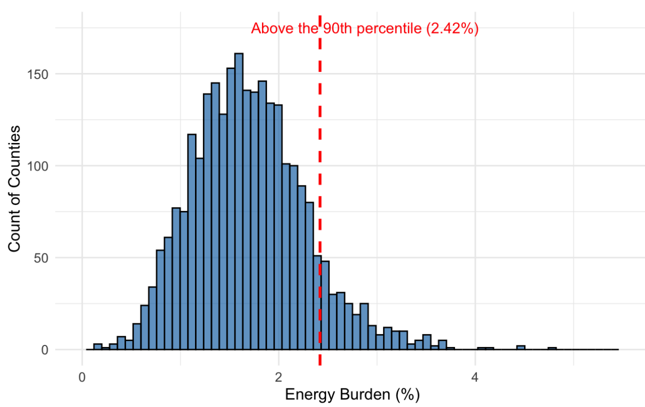


(e)



(f)

Figure 1. Residential EB across state ((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 ((e) 2025 – (f) 2035) shows 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.

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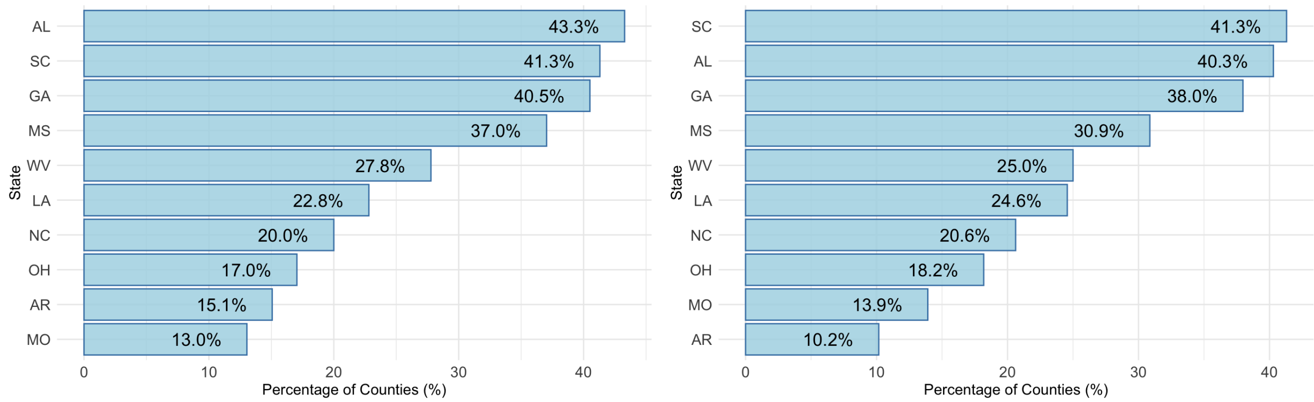

(a) (b)

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

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 wind potential across counties is uneven. As a result, these states may still offer strong opportunities for distributed wind 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 deployment potential.

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.

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, 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.

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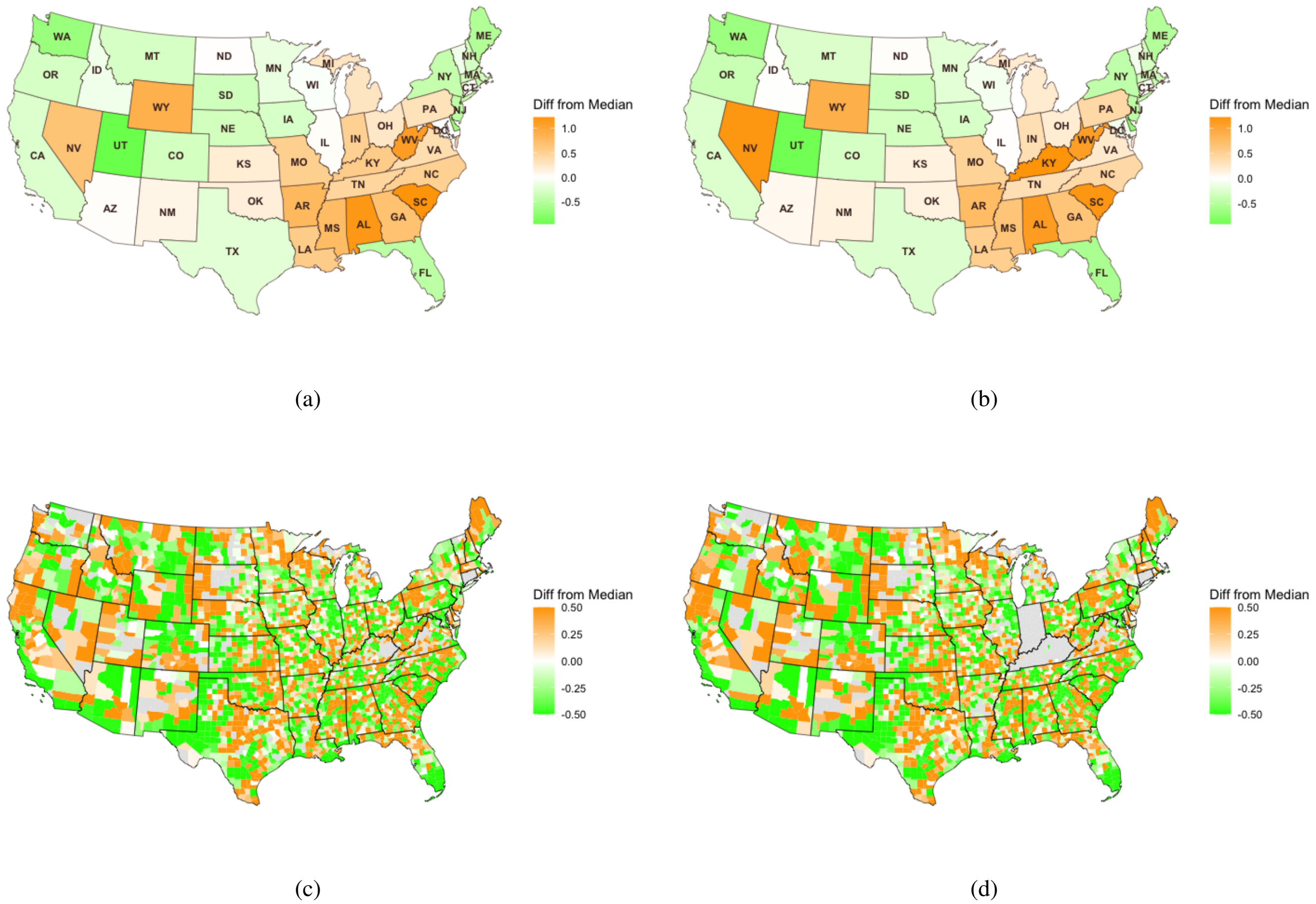

Figure 3. Comparison of **energy burden relative to GDP (EB_{GDP})** in 2025 and 2035 across state ((a) 2025 – (b) 2035) and county levels (c) 2025 – (d) 2035. The EB_{GDP} metric shows less intrastate variation than residential EB, with most state-level values clustering near the national median (a–b).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

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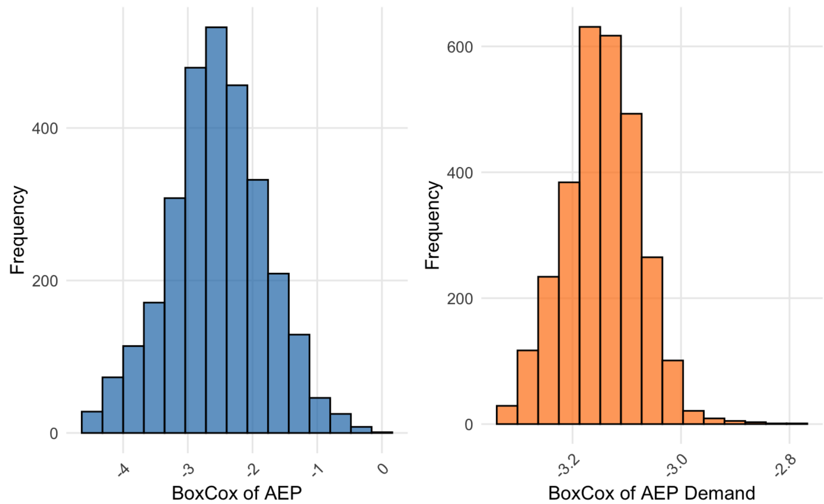
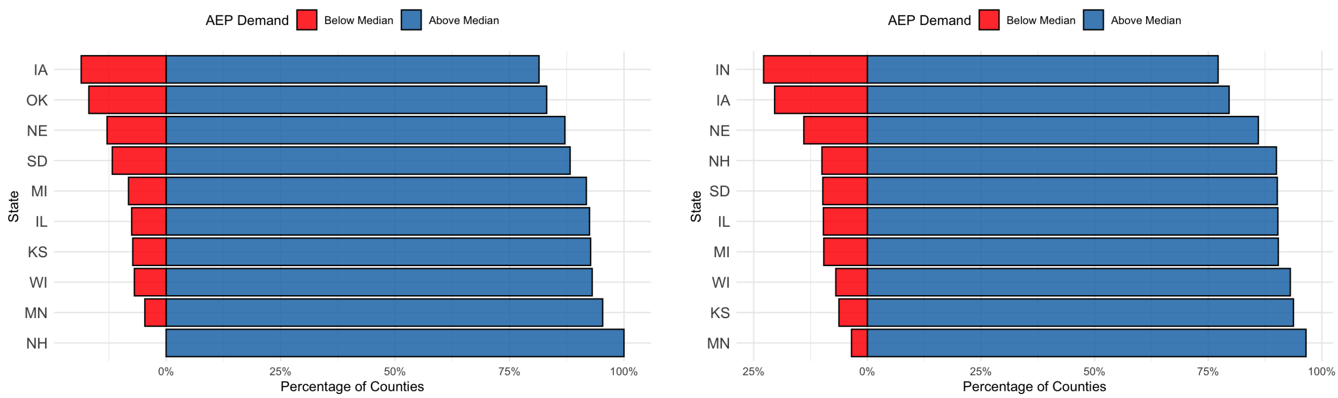


Figure 4. Nationwide distributions of Box–Cox–transformed AEP and AEP_{Demand} for BTM DW 2025. Before transformation, both metrics exhibit similar right-skewed distributions. They share the same Box–Cox transformation parameter ($\lambda = 0.2$), indicating that normalization preserves the underlying distributional shape. This suggests that AEP_{Demand} can be analyzed using the same statistical framework as raw AEP.



(a) (b)

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 distributed wind potential. In contrast, Texas and Georgia rank high in total counts but have more uneven distribution across counties.

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}.

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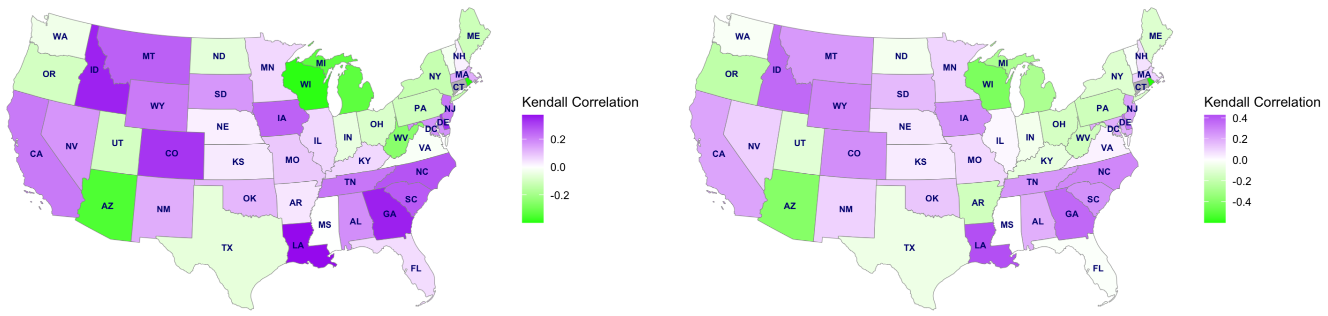

(a) (b)

Figure 6. State-level nonparametric correlation between residential AEP_{Demand} and EB. This is 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.

Group 1: High-Need, High-Potential States. This group includes North Carolina, Georgia, Iowa, Louisiana and California (Table 2). These states rank highest according to the composite score defined in Eq. (**??**), which shows high EB aligned with high wind 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 (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 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 opportunity, but the available opportunity is well located to reduce EB.

Louisiana, while ranked only 28th in residential AEP_{Demand} and 32nd in total AEP, exhibits high EB values and strong correlation. 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 it 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, specially in the industrial and commercial sectors.

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 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 distributed wind deployment potential (summarized in Table 3). It is also important to note that while thigh EB in these states does not align with areas of high distributed wind (DW) opportunity, EB itself is influenced by factors such as a strong agricultural economy.

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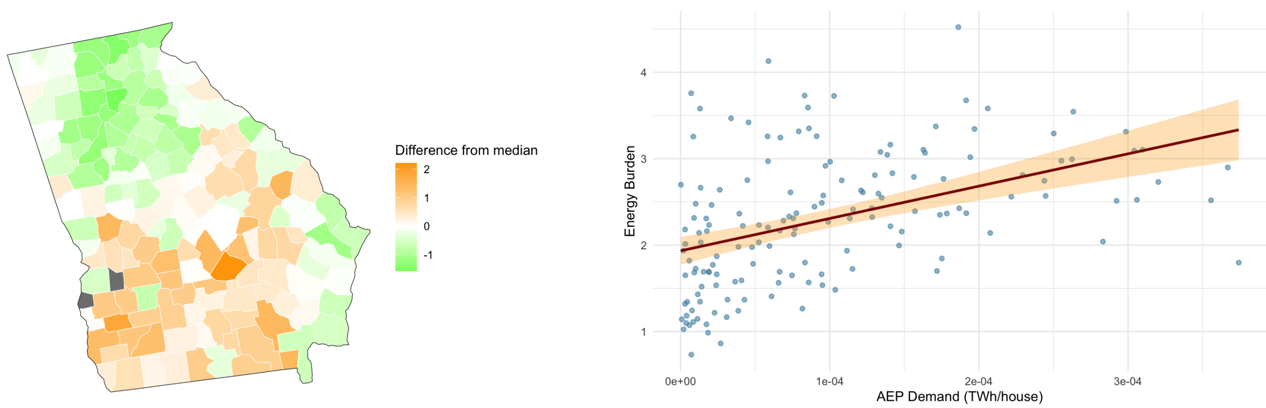
Table 2. Summary of Group 1 state-level models and correlations for BTM 2025 baseline scenario

State	**Parametric correlation**	**Nonparametric correlation**	**EB median (%)**	**Residential $\mathbf{AEP_{Demand}}$ $\times 10^{-5}$**	**Total $\mathbf{AEP_{Demand}}$ $\times 10^{-5}$**	**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 × Unemp.	High (0.78)
Georgia	0.51	0.37	2.31	3.71	4.23	Poverty, Poverty × 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



(a) (b)

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

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, extreme EB, or demographic scale.

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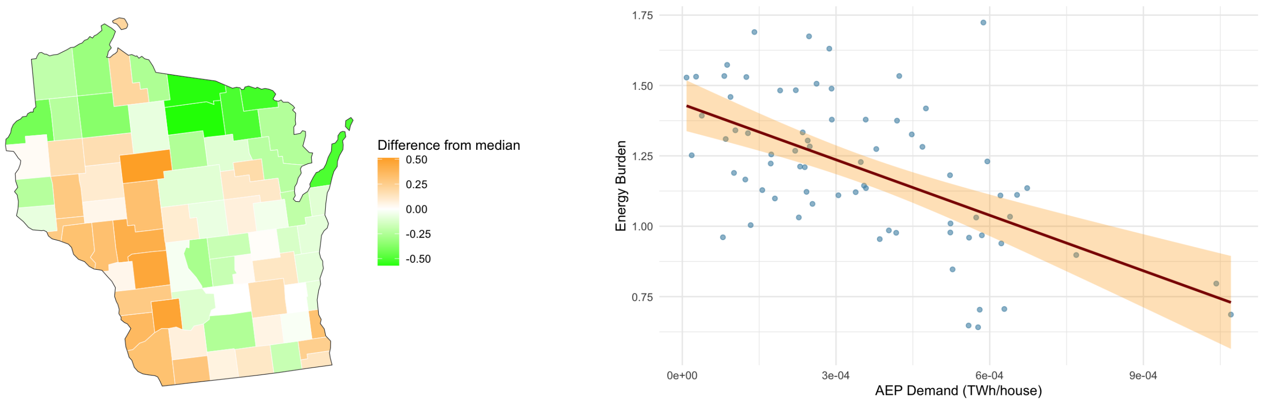
Table 3. Summary of Group 2 state-level models and correlations

State	Parametric correlation	Nonparametric 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 × 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



(a) (b)

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

- **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 wind potential is near zero, indicating almost no spatial overlap between need 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, 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

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second in 2035 scenario. This underscores an urgent need, even if wind alignment is less pronounced than in Group 1 states.

Table 4. Summary of Special cases

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

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 indicates that regional economic and policy differences play a meaningful role in explaining this variation.

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 scenarios (2025 and 2035). These models demonstrate stronger statistical performance – exhibiting higher coefficients of determination, reduced heteroskedasticity (constant variance of residuals), 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.

Summaries of these models, including coefficients and correlation metrics, are provided in Tables 2 and 3. 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 generation potential as measured by $\text{AEP}_{\text{Demand}}$ and also highlight states or regions with 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 technologies

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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 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 aligns with these EB drivers, these finding suggest there are targeted pathways through which distributed wind energy generation could help alleviate EB, which is associated with the mentioned variables of economic hardship, particularly in rural areas.

Our results show that correlation analyses and scenario comparisons consistently highlight that the residential sector is most strongly associated with variation in $\mathrm{AEP}_{\mathrm{Demand}}$, 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 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 $\mathrm{AEP}_{\mathrm{Demand}}$ and broader economic indicators ($\mathrm{EB}_{\mathrm{GDP}}$ and $\mathrm{NER}_{\mathrm{GDP}}$) 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 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 generation potential and overall EB in 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 distributed wind deployment.

4.1 Implications of state differences

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–$\mathrm{AEP}_{\mathrm{Demand}}$ relationship and two special cases:

- **Group 1: High-Need, High-Potential States** (e.g., North Carolina, Georgia, Iowa, Louisiana and California) rank highest in the weighted score (Eq. (**??**)), indicating the presence of both high residential wind potential and high EB. These states also exhibit elevated $\mathrm{AEP}_{\mathrm{Demand}}$ 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, 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–$\mathrm{AEP}_{\mathrm{Demand}}$ correlation suggests that targeted (strategic) deployment in specific counties may still be impactful.

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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 $\mathbf{AEP_{Demand}}$, Low EB States** (e.g., Minnesota, Kansas, Wisconsin) display strong wind 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 may act as a broader 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 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 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 distributed wind 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 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 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 deployment will directly reduce those underlying socioeconomic conditions. However, by potentially lowering energy costs in areas where these conditions are prevalent, distributed wind may help ease energy-related hardship and indirectly contribute to improved quality of life.

This study demonstrates there is a significant opportunity for targeted distributed wind deployment to potentially alleviate economic hardships in high-EB states and counties with viable wind 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 potential does not by default indicate

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energy cost savings, so care must be taken to ensure there will be reasonable savings before distributed wind 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.

5 Conclusions

This study explores the potential for distributed wind deployment in the contiguous United States, focusing on the relationship of distributed wind with EB and residential energy demand. We found that the residential sector plays a central role in determining the impact of distributed wind, 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 $\mathrm{AEP}_{\mathrm{Demand}}$, $\mathrm{EB}_{\mathrm{GDP}}$ also aligns with the economic conditions of states and counties but is less heterogeneous. We also identified two distinct groupings of states and two special cases, each with varying levels of opportunity for distributed wind deployment, driven by factors such as EB, economic conditions, and demographic characteristics. Distributed wind 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.

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

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

Equally important, future research and implementation must also account for impacts on wildlife, ecosystems, and local land use. It is essential to ensure that distributed wind 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 and offer guidance on where such solutions are most likely to have a meaningful impact. Future research should delve into local

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dynamics, examine the long-term effects of distributed wind 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 data supporting this study are publicly available from the U.S. Department of Energy's Wind Data Hub at https://wdh.energy.gov/project/dw/data.

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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