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A multi-faceted analysis of the influence of state energy policies on spatial clustering of wind and solar farms in the U.S.

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ABSTRACT

This study examines the spatial clustering of large-scale wind and solar farms in the United States to evaluate the impact of state energy policies and natural resources on the distribution of renewable energy, utilizing the framework of artificial intelligence (AI) and geospatial analysis. We develop an AI-GIS workflow that translates unstructured state policy documents into comparable, dimension-specific policy scores using a rubric-guided large language model (LLM) and links these measures to statistically significant clustering patterns via hexagon-based overlay analysis. By integrating policy scores, analyzed using an LLM, clustering measures, and natural resource availability, we conducted an overlay analysis to identify patterns of co-occurrence. Results show that while solar farm development is strongly influenced by policy incentives, wind farm locations are primarily dictated by natural wind conditions. Unlike sunlight, which is available to some extent in most regions, wind energy requires specific speed thresholds for efficient power generation, making natural resource availability a more decisive factor. Our overlay results show that large-scale solar hot spots align most with strong policy environments, especially comprehensive climate strategies, renewable portfolio standards (RPS) presence, solar-specific support, and grid-readiness measures, whereas large onshore wind clustering aligns predominantly with high wind speeds, with policy variables (e.g., RPS and grid/interconnection readiness) playing a secondary, enabling role. These findings highlight technology-specific pathways, such as policy-responsive solar versus resource-constrained wind, and help identify policy-resource mismatches that may indicate unrealized deployment potential.

1. Introduction

Energy research is crucial today as the world faces increasing challenges and crises related to energy security, environmental sustainability, and climate change. The current problems include a heavy reliance on fossil fuels (Mercure et al., 2021; Perry, 2020), which significantly contribute to greenhouse gas emissions and global warming (Galimova et al., 2022; Johnsson et al., 2019). This dependency also leads to geopolitical tensions and economic vulnerabilities due to fluctuating fuel prices, limited resources, and the critical dependency on energy-dependent industries. The alternative to traditional energy sources is renewable-based energy, which is necessary to reduce the carbon footprint (Rozhkov, 2025; Al-Shetwi, 2022), diversify energy sources, and create a more resilient and sustainable overall energy system (Stokes and Warshaw, 2017). However, in the United States (U.S.), it was not a significant part of the conversation until the energy crises of the 1970s that significant attention was given to developing alternative energy sources (Rozhkov, 2023). Since then, there has been substantial growth in renewable energy adoption every decade, driven by technological advancements, policy support, and increasing awareness of environmental issues.

However, the development of renewable energy, particularly wind and solar, has been uneven across the U.S. due to a variety of factors, including political affiliations, local policies, and geographic conditions (Levenda et al., 2021; Haggerty et al., 2014; Sovacool, 2009). States with more progressive policies and strong political support for renewable energy have seen significant growth in wind and solar installations over the years (O'Shaughnessy et al., 2024; Burke and Stephens, 2018; Hess et al., 2016). These states have implemented various strategies, favorable incentives, subsidies, and mandates that encourage renewable energy development. In contrast, other states with less supportive political environments or policies have lagged in adopting renewables, often due to political resistance (Hess et al., 2016; Yi and Feiock, 2014), vested interests in fossil fuels (Vormedal et al., 2023), or a lack of infrastructure investment (Hashemizadeh et al., 2021). Additionally, state and municipal policies play a crucial role in shaping the renewable energy landscape, as they can initiate pioneering initiatives that move faster than federal directives (Rozhkov, 2023; Leonhardt et al., 2022). Local governments have considerable autonomy in developing their energy policies and can implement renewable energy targets, strategies, zoning laws, and incentives tailored to their specific needs and priorities. This can significantly impact the pace and extent of renewable energy development in various regions, ultimately benefiting local businesses and residents. This decentralized approach means that

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renewable energy growth in the U.S. is highly variable, reflecting the diverse political, economic, and social landscapes across the country (Balthasar et al., 2020; Busch and McCormick, 2014).

Energy policies in the U.S. are shaped by complex connections between federal and state governments, resulting in a unique system that differs significantly from the more centralized approaches seen in other regions, such as Europe (Rozhkov, 2023; Saurer and Monast, 2021). The decentralized approach in the U.S. allows states to be innovators in energy policy, experimenting with various strategies to promote renewable energy, energy efficiency, and grid modernization (Popp, 2020; Ryder, 2017). For example, states like California and Minnesota have implemented ambitious renewable energy standards and carbon reduction goals in California (California Clean Energy and Pollution Reduction Act - SB 350, 2015) or Minnesota's 2025 Energy Action Plan (2016), while others may focus more on traditional energy sources or resist such measures altogether.

At the federal level, the U.S. government establishes overarching energy policies and regulations, often aimed at ensuring national energy security, promoting economic growth, and addressing environmental concerns whenever possible (Guliyev, 2020; Doris et al., 2009). Federal initiatives may include tax incentives for renewable energy, funding for research and development, and regulations on emissions. However, the U.S. federal government typically provides just a framework that states can build upon or diverge from, depending on their priorities, so in the past years, it has been proven that the political shifts at the federal level have a limited influence, and states can oppose and become a driver of a change themselves (Giberson, 2016; Stokes and Warshaw, 2017).

To understand the factors influencing the development of current distributed energy systems, this work focuses on analyzing the locations and clustering of existing renewable energy sources (solar and wind) across the U.S. Clustering is very well explored in the various topics related to technology and sustainability, for instance in works about high-tech industries is a framework of sustainability (Zandiatashbar et al., 2019; Bibri, 2018), wind farm spatial clustering (Amjad et al., 2021), and renewable energy industries in general (Xu et al., 2022; Wang et al., 2019). In comparison to simple location analysis, measuring the spatial clustering of renewable farms is more important because it highlights areas of concentrated interest, which may indicate favorable policies, strong investment activity, or optimal environmental conditions. Clusters can serve as indicators of emerging energy hubs, technological advancements, or underlying economic and regulatory factors that drive renewable energy development. By examining whether the concentration (clusters) of wind and solar energy installations is more closely related to local policies or natural resource availability, this research aims to determine the extent to which policy environments influence the distribution of renewable energy.

Nevertheless, the existing literature applying clustering methods to renewable energy development exhibits several limitations. Most studies examine localized contexts or single-country case studies (e.g., Amjad et al., 2021; Wang et al., 2019), often without systematically accounting for the interaction between spatial concentration and policy heterogeneity across jurisdictions. Additionally, clustering has frequently been used in a purely techno-economic context, focusing on optimal siting or cost minimization, while overlooking the broader policy and governance dimensions that shape deployment patterns (Ren and Zhou, 2025; Zhao and Sun, 2022; Sovacool, 2009). This article advances the field by proposing a robust spatial overlay framework that simultaneously integrates geospatial clustering with policy intensity and natural resource potential.

This framework enables us to isolate the relative importance of state-level policy versus natural resource endowment in explaining renewable energy concentration, a question not adequately addressed in earlier works. Unlike traditional regression-based or econometric models, which assess associations but lack spatial nuance (Carley et al., 2018), clustering provides insights into co-location patterns and spatial dependencies that are essential for understanding the geography of renewable energy. As emphasized by Stokes and Breetz (2018), policy design is spatially embedded; thus, methods that fail to consider geography risk overlooking the real-world mechanisms of deployment. In this context, spatial clustering methods are uniquely valuable, offering the ability to identify not only where installations are dense, but also how those densities correlate with enabling conditions, both *natural* and *institutional*.

The study aims to answer critical questions about (1) how state policies contribute to the uneven development of renewables and (2) whether these policies align with the natural opportunities available in different regions. Our approach builds upon but significantly extends previous efforts by providing a replicable, multi-variable spatial analysis applicable across diverse jurisdictions. Additionally, by identifying these relationships, the research provides valuable insights that can help optimize renewable energy deployment in other states and inform future policy decisions, ensuring more strategic and effective growth of renewable energy across the country.

2. Materials and methods

This study examines the spatial clustering of wind and solar farms in the United States, aiming to understand the impact of state energy policies on their distribution. The methodology comprises data collection, data processing utilizing Artificial Intelligence (AI) – specifically, Large Language Models (LLMs) – and spatial statistical analysis employing Geographic Information System (GIS) tools (Fig. 1). In this study, we collected comprehensive datasets on solar and wind energy installations from the United States Geological Survey's (USGS) website. These datasets were critical for performing spatial analysis, specifically the United States Large-Scale Solar Photovoltaic Database (USPVDB) for solar installations (Hoen et al., 2018) and the United States Wind Turbine Database (USWTDB) for wind turbines (Fujita et al., 2023). Additionally, we compiled existing state energy strategic documents and created a unique dataset that was not previously available in a single location.

2.1. Solar energy data

The USPVDB, developed in collaboration between the Lawrence Berkeley National Laboratory and the USGS, provides a comprehensive dataset on large-scale solar photovoltaic (PV) installations across the U. S. The database, as of June 18, 2024, contains detailed information on 4160 solar projects with a total rated capacity of 69,718 MW, distributed across 47 states and the District of Columbia. The dataset is continuously updated to include the latest operational facilities, and the data is rigorously verified using aerial imagery and multiple quality checks to ensure positional accuracy, with the most recent installations from the third quarter of 2023 and older ones dating back to pre-1990. By integrating datasets from the U.S. Energy Information Administration, the Environmental Protection Agency, and the National Renewable Energy Laboratory, the USPVDB offers precise estimates of each solar facility's footprint. Available in a shapefile format, which is compatible with GIS software such as ESRI ArcGIS Pro, the data is well-structured for use in geospatial analysis.

2.2. Wind energy data

The USWTDB was created as a collaboration between the USGS, Lawrence Berkeley National Laboratory, and the American Wind Energy Association, as well as from the Federal Aviation Administration Digital Obstacle File (DOF) and Obstacle Evaluation Airport Airspace Analysis (OE-AAA). It offers a detailed and comprehensive record of wind turbines across the U.S. As of June 4, 2024, the dataset includes 74,511 turbines, representing a total rated capacity of 149,422 MW. These turbines are distributed across 45 states, as well as U.S. territories like Guam and Puerto Rico, reflecting the growing importance of wind

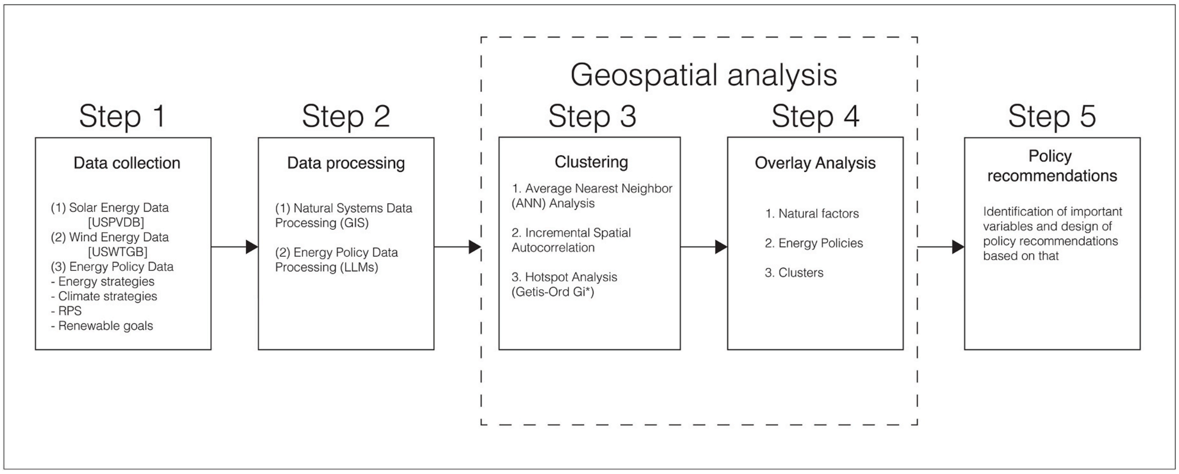

Fig. 1. Methodological workflow.

energy in diverse regions. The USWTDB tracks installation dates ranging from turbines established prior to 1990 to the most recent turbines, which became operational in the second quarter of 2024. Data for the USWTDB is sourced from a diverse range of sources, including federal agencies, industry groups, and individual wind projects, with a high degree of accuracy. Like the solar energy dataset, the wind turbine data is stored in a shapefile format, enabling seamless integration into the GIS.

2.3. Natural systems data

In our study of solar radiation and wind patterns across the U.S., we used data from the USGS and the National Renewable Energy Laboratory (NREL). For solar energy, we referred to the Direct Normal Irradiance (DNI) map, which shows the annual average of daily solar resources at a resolution of 4 km by 4 km (Fig. 2a – raster and 2b – vector). The insolation values from this map represent the solar energy available for systems like solar panels. For wind patterns, we used the Average Annual Wind Speed map, focusing on wind speeds at 100 m above sea level (Fig. 2c – raster and 2d – vector). The availability of solar and wind energy can vary significantly by location, making the operation of solar power plants and wind turbines more complex than simply building them. The intensity of sunlight depends on factors such as the time of day and location. It is highest at solar noon on clear, cloudless days. However, factors such as clouds, dust, and pollution can block sunlight, and objects like buildings or trees can cause shading at different times of the day and throughout the year. The farther a location is from the equator, the more its solar resources fluctuate throughout the year. For wind energy, turbine placement is critical. Ideal locations have an average wind speed of at least 9 miles per hour (mph) for small turbines and 13 mph for large, utility-scale turbines. To be able to process the data further, both raster maps were aggregated and converted into vector maps, aggregated at the same geographical level.

2.4. Energy policy data

The energy policy data were collected and processed semi-automatically, with the first and last steps of the analysis performed manually, while the middle steps were processed using LLMs.

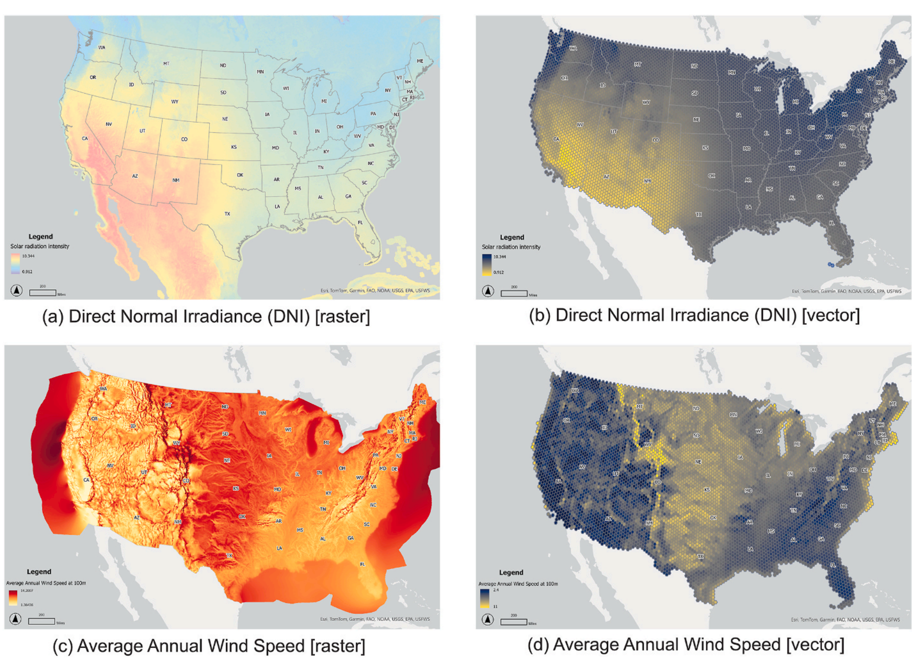

Fig. 2. Solar radiation and wind speed data.

(a) Data Collection

In this study, data on state and municipal energy policies were collected manually from various reports and documents published by organizations such as the National Association of State Energy Officials (NASEO), government agencies, and non-governmental bodies involved in the energy policymaking process. Unlike other datasets, such as those on wind and solar installations, energy policy data in the U.S. is not centralized or standardized across states, meaning there is no single database that compiles all relevant policies. Each state or municipality may have its own set of policies, often documented in different formats, including policy reports, government documents (such as bills), regulatory filings, or press releases. To gather this information, a manual review process was employed to collect the information. Policy documents were carefully reviewed to identify key details, including renewable energy mandates, strategies, incentives, tax credits, subsidies, and regulations that directly affect the development of wind and solar energy projects. We focused on coding these policies based on their relevance to renewable energy support, such as Renewable Portfolio Standards (RPS) and clean energy or climate goals that favor the deployment of renewable energy. This extraction process was necessary because the formats in which states document these policies vary significantly, with some states providing clear and accessible information, while others may only outline policies in broad legislative terms or present them in a fragmented manner across different reports.

(b) Data Analysis using Large Language Models

In our analysis, we utilized the LLM to systematically analyze patterns across a dataset of 58 full-text legislative documents related to energy policies, which were collected at the previous stage and spanned over 100 pages, making thorough analysis potentially time-consuming. The process utilizes state-of-the-art pre-trained AI methodologies based on deep learning transformers (Vaswani et al., 2017) to address the task, which is sometimes referred to as generative regulatory measurement (Singleton and Spielman, 2024; Bartik et al., 2023). LLMs, such as GPT or Gemini, are sophisticated AI models trained on large amounts of textual data, enabling them to interpret, summarize, and generate structured outputs from unstructured texts. In our case, we designed a specific framework using the ChatGPT-4o (OpenAI, 2024) model to evaluate and rank key components within legislative documents. This framework enabled us to extract relevant information, categorize legislative elements, as previously demonstrated (Bartik et al., 2023), and assign rankings to the various developed sections of each document using an LLM as a processing mechanism. The LLM's capacity for semantic understanding and contextual interpretation facilitated a structured and consistent approach to the analysis, allowing us to efficiently handle the complexity and volume of the data and produce rankings that reflect the relative maturity and focus of the energy policy components.

To validate the accuracy of the LLM-generated rankings and minimize errors (Zhao et al., 2023), we conducted a manual control analysis on a randomly selected control group of ten documents, which represents approximately 17 % of the dataset. This process involves applying our subject knowledge, reviewing documents independently of the LLM, identifying key legislative features, and assigning rankings to these components. When comparing the manually derived rankings with those produced by the LLM, we observed a high degree of alignment, with minimal variance between the two methods (less than 10 %). This result indicates that the LLM is capable of accurately parsing and ranking complex legislative content, with its output closely mirroring human analysis. The consistency of the LLM's performance, as demonstrated by this control group comparison, underscores the model's potential for large-scale automated analysis of legal and regulatory texts while still benefiting from occasional human oversight to mitigate the risk of errors.

(c) Data Classification

After the data analysis, the data were classified to evaluate state energy policies against a set of criteria that gauge their effectiveness, ambition, and clarity of goals, including measurable outcomes such as emission reduction, job creation, renewable energy targets, equity considerations, and timelines. Each policy is rated on a scale of 0–5, where "0" represents no measures, "1" represents weak or vague commitments, "2" indicates moderate but non-binding or incomplete plans, "3" indicates moderate targets, "4" indicates strong and concrete actions but with some limitations, and "5" represents strong, ambitious, and effective policies with comprehensive, well-funded, and legally binding framework. To make sure that there is a consistent and transparent approach to scoring, each metric was evaluated using a structured rubric that clearly defines the range of possible policy actions and outcomes. For example, the metric "Strength of Clean Energy Targets (M1)" was evaluated using the following tiered scale:

- Score 0: No renewable targets or entirely missing policy.
- Score 1: Vague or symbolic mentions of renewable energy without numeric targets or dates.
- Score 2: Weak or non-binding targets (e.g., "increase renewables over time" without specificity or enforcement).
- Score 3: Moderate goals with some numeric targets but long-term or non-binding (e.g., 35 % by 2050, advisory only).
- Score 4: Strong targets (e.g., 50–70 % by 2030–2040) with enabling mechanisms (like interim milestones) but lacking full legal enforceability or dedicated funding.
- Score 5: Comprehensive and binding policy with clear, ambitious targets (e.g., 90–100 % clean energy by 2030), legal mandates, interim targets, actionable steps and partners, and enforcement mechanisms.

This rubric format (with variations adjusted for each metric) was applied to all 12 metrics and derived from well-established energy policy evaluation frameworks (Carley et al., 2018; Burke and Stephens, 2017; Zhou and Solomon, 2021; Rozhkov, 2023). Using such a tiered ordinal scale is appropriate for evaluating qualitative regulatory texts because it captures varying degrees of policy ambition, clarity, and enforceability, which are core dimensions in comparative public policy research (Howlett and Rayner, 2013). While not entirely objective, this approach provides and improves replicability and interpretability compared to binary coding or unstructured subjective judgment.

These criteria were then encoded into a structured scoring rubric and supplied to the LLM model for evaluation. The LLM did not assign values arbitrarily but rather followed a guided rubric step-by-step, making sure that there was procedural consistency across all documents. Manual validation of a representative sample confirmed high alignment between the rubric and the LLM's scoring behavior. In states with more than one strategic policy document, scores for each document were generated independently using the same rubric. The final score for each metric in such cases represents the average across documents. This preserves the integrity of each policy assessment while accurately reflecting composite policy environments that evolve over time.

The analysis framework was divided into twelve distinct categories, which enabled the classification of policies into future successful and actionable implementations. The categories of the measures (M1-M12) are the following:

1. *Strength of clean energy targets* (M1). It measures the ambition and clarity of the policy in transitioning from fossil fuels to renewable energy (e.g., percentage goals, by which year). The measurable effect is in the percentage of renewable energy deployment or reduction in fossil fuel consumption over time.
2. *Timeline for implementation* (M2). It assesses how realistic and specific the timeline for achieving renewable energy goals is. The

measurable effect is in the progress monitoring over specified intervals (e.g., 5-year checkpoints).

3. *Green job creation* (M3). It assesses the degree to which the policy prioritizes job creation in the clean energy sector (e.g., solar, wind, electric vehicles). The measurable effect is the number of new green jobs created per year, clearly stated in the strategy.
4. *Energy efficiency initiatives* (M4). It evaluates the policy's focus on improving energy efficiency in residential, commercial, and industrial sectors. The measurable effect is energy savings and a reduction in overall energy demand.
5. *Carbon emissions reduction* (M5). It measures the extent to which the policy prioritizes reducing greenhouse gas emissions through mechanisms like carbon pricing, regulations, or incentives. The measurable effect is in annual reductions in CO_2 emissions, measured in tons.
6. *Equity and environmental justice* (M6). It measures how the policy addresses the impact of the energy transition on vulnerable communities, ensuring equitable access to clean energy. The measurable effect is in the number of programs and benefits directed toward vulnerable communities.
7. *Technological innovation and R&D support* (M7). It evaluates the policy's support for new technologies (e.g., battery storage, grid modernization, carbon capture) and investments in research and development. The measurable effect is reflected in the number of projects or new cutting-edge technology deployments that are funded.
8. *Public participation and transparency* (M8). It evaluates the policy's mechanisms for public engagement, stakeholder input, and transparency in decision-making processes. The measurable effect is in the number of public consultations held and the frequency of reports published.
9. *Financial incentives and funding mechanisms* (M9). It assesses whether the policy incorporates financial incentives (e.g., tax credits and grants) to facilitate the transition to renewable energy for businesses and consumers. The measurable effect is in the level of funding committed.
10. *Grid reliability and modernization* (M10). It assesses whether the policy addresses grid reliability and modernization to accommodate an increasing number of intermittent renewable energy sources. The measurable effect is evident in investments in grid infrastructure, a reduction in grid outages, or an increase in renewable energy integration.
11. *Wind energy support* (M11). It assesses the focus on wind energy systems development and integration into the state strategy. The measurable effect is in the amount of funding and the percentage of the total state energy production from wind sources.
12. *Solar energy support* (M12). It assesses the focus on developing and integrating solar energy systems into the state strategy. The measurable effect is in the amount of funding and the percentage of the total state energy production from solar sources.

All policy documents were given equal weight in the scoring process. This was a deliberate decision to provide consistency across jurisdictions to avoid subjective assessments of policy importance; a more detailed explanation of the overlay approach is provided later. Only documents that were officially adopted and signed into law, such as approved strategic plans, regulatory frameworks, and enacted legislation, were included in the evaluation. This makes sure that each input represents a legally binding or government-endorsed policy instrument. After scores for those individual measures are calculated; then, they are averaged with equal weights to get the final score. Importantly, the "appropriate" weighting of policy dimensions may differ across states because jurisdictions often pursue distinct transition pathways and priorities; for example, some states foreground workforce development and green jobs as primary levers for renewable deployment. However, these priorities cannot be considered in isolation, and the weights of different components may vary from state to state: policy mechanisms operate as interdependent bundles, where labor-force and supply-chain capacity are closely linked to enabling investments and reforms such as grid modernization. In particular, an aging transmission and distribution system can become a binding constraint that limits interconnection and the integration of new, especially large-scale, renewable generation; without grid modernization, job creation and incentive programs may not translate into new construction at the same rate. For this reason, we interpret the equal-weighted score as a screening measure of policy comprehensiveness and cross-domain readiness, and we avoid state-specific weighting schemes that would require externally validated evidence (potentially, through interviews with each state representative, which is outside of the scope of this article) on how heterogeneous policy mixes translate into deployment outcomes under different grid and labor contexts. If a state has more than one strategic document, those documents are evaluated independently, and their final scores are then averaged.

Also, in addition to energy strategies, four additional variables were collected:

13. The presence of the approved *climate strategy* (Center for Climate and Energy Solutions, 2024), not necessarily focusing on energy (1 – presented; 0 – not presented)
14. States with *Renewable Portfolio Standards* (NCSL, 2021) (1 – presented; 0 – not presented)
15. The strength of the *state's target for the percentage of renewables* (CleanEnergy States Alliance, 2024) (scale of 0–5)
    - Scores of 5: highest-rated strategies are those with a 100 % target in the near term (2030–2040), indicating strong commitment and higher impact.
    - Scores of 3–4: These strategies still have high targets but are for long-term goals (2045–2050).
    - Scores of 1–2: Moderate or minimum progress strategies (35–70 %), rated higher if they have nearer deadlines (2030) and lower if the targets are further into the future.
    - A score of 0: No progress or targets.
16. *Regulation/deregulation* of the energy market (1 – deregulated; 0 – regulated)

These variables were identified as important for the analysis because they provide a broader context for evaluating energy policies beyond just energy strategies. The presence of a climate strategy (13) reflects a state's commitment to comprehensive environmental planning in a nexus with other domains, such as food, water, transportation, economics, etc. (Rozhkov et al., 2025a,b; Zellner et al., 2023). Renewable Portfolio Standards (14) indicate how actively states are mandating renewable energy integration (Zhou and Solomon, 2021). The strength of renewable energy targets (15) measures the ambition and progressiveness of a state's renewable energy goals, which is critical for understanding policy outcomes in the energy transition (Burke and Stephens, 2017). Finally, energy market regulation (16) helps assess the flexibility of the energy market and its openness to competition, which in turn impacts policy effectiveness (Rozhkov, 2024; Daszkiewicz, 2020). Overall, our scoring summarizes policy intensity along specific dimensions (targets, technology-specific support, interconnection/grid readiness, permitting/market structure, equity/community measures), not a universal notion of 'better' policy. Because U.S. states are politically and institutionally heterogeneous, a higher score is not interpreted as uniformly more 'favorable'; rather, it indicates that a state is more policy-forward in that particular dimension. To respect this heterogeneity, we firstly report dimension-level results alongside any composite summaries, then use uniform, public definitions for all measures to preserve comparability, and, finally, interpret overlaps, emphasizing how clusters co-locate with specific policy dimensions.

2.5. Geospatial analysis

After the data processing and collection, we applied geospatial analysis to identify and quantify spatial clustering patterns of wind and solar farm locations in the contiguous U.S. – we excluded Alaska and Hawaii, as well as remote territories such as Guam, American Samoa, Puerto Rico and similar due to the lack of renewable resources there and to minimize the computational error resulting from the spatial discontinuity. We utilized several spatial statistical tools, such as Average Nearest Neighbor, Incremental Spatial Autocorrelation, and Hotspot Analysis. The primary workflow utilized ESRI ArcGIS Pro 3.3, a commercial license. All reported Z-scores and associated p-values follow the inferential framework implemented in ArcGIS Pro itself: each statistic is evaluated against an explicit null hypothesis of complete spatial randomness (CSR) and/or random spatial assignment of attribute values (randomization), and p-values are computed from the reference distribution associated with the reported Z-score (standard normal approximation), using a two-sided test unless stated otherwise.

(a) Average Nearest Neighbor (ANN) Analysis

The Average Nearest Neighbor (ANN) analysis assesses whether the spatial distribution of features (wind and solar farms) is clustered, random, or dispersed (ESRI, n.d., a). The ANN ratio is calculated using the following formula:

$$ANN = \frac{\overline{D}_O}{\overline{D}_E} \tag{1}$$

where $\overline{D}_O$ is the observed mean distance, which is the average distance from each feature to its nearest neighbor, and $\overline{D}_E$ is the expected mean distance, which is the average distance expected in a hypothetical random distribution of points within the study area, calculated as

$$\overline{D}_O = \frac{\sum_{i=1}^{n} d_i}{n} \tag{2}$$

$$\overline{D}_E = \frac{0,5}{\sqrt{n/A}} \tag{3}$$

where:

d_i is the distance between feature i and its nearest neighboring feature

n is the total number of features.

A is the area of a minimum enclosing rectangle around all features (area value).

An ANN Ratio less than 1 indicates clustering, equal to 1 suggests randomness and greater than 1 implies dispersion. The significance of the observed spatial pattern is determined using the Z-score:

$$z = \frac{\overline{D}_O - \overline{D}_E}{SE} \tag{4}$$

where:

SE is the standard error of the mean distance, calculated as:

$$SE = 0.26136 \Big/ \sqrt{n^2/A} \tag{5}$$

The ANN null hypothesis is that point locations are randomly distributed within the study area with CSR. The ANN Z-score compares the observed mean nearest-neighbor distance to its CSR expectation using the analytical standard error above; the corresponding p-value is obtained by referencing the Z-score to the normal distribution (two-sided), representing the probability of observing a deviation at least as extreme under CSR. The ANN formulation further assumes that points are free to locate anywhere within the study area (no barriers) and are located independently of one another; we only interpret ANN significance within a fixed study area definition because Z-scores and p-values are sensitive to the chosen area parameter. In our analysis, a high Z-score indicates statistically significant clustering at a significant confidence level and a strong intensity of the clustering. A Z-score near zero indicates that there is no apparent clustering within the study area.

(b) Incremental Spatial Autocorrelation

To identify the spatial scales at which clustering is most pronounced, we performed Incremental Spatial Autocorrelation using Moran's I statistic across multiple distance bands. Moran's I measures spatial autocorrelation by evaluating the similarity of a variable (e.g., the presence of wind farms) at nearby locations. The analysis calculates Moran's I and associated Z-scores at increasing distances to detect where spatial autocorrelation is strongest. Incremental Spatial Autocorrelation repeatedly executes Global Moran's I across an increasing sequence of distance bands; for each band, the approach computes an observed Moran's I, its expected value and variance under the randomization/CSR, and then reports a Z-score and p-value to test the null hypothesis that the analyzed attribute is randomly distributed among features (i.e., no spatial autocorrelation beyond chance). By observing Z-scores against distance bands, we identified peaks indicating distances where clustering is most significant. This informed the selection of an appropriate distance threshold for subsequent Hotspot analysis.

(c) Hotspot Analysis (Getis-Ord Gi*)

The Getis-Ord Gi* statistic identifies statistically significant Hotspots and Cold spots (Getis and Ord, 1992; ESRI, n.d., b) of wind and solar farms:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)\right]}{n-1}}} \tag{6}$$

where x_j is the attribute value for the feature j

$w_{i,j}$ is the spatial weight between feature i and j

n is equal to the total number of features

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{7}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2} \tag{8}$$

The Gi* statistic generates Z-scores and p-values indicating the intensity of clustering. High positive Z-scores and very low p-values represent Hotspots (clusters of high values). High negative Z-scores and very low p-values indicate Cold spots (clusters of low values).

(d) Overlay Analysis and Feature Selection

In the next step, after applying spatial pattern analyses such as ANN and Hotspot Analysis, we aggregated all variables to the hexagons. Hexagons are a common way to visualize spatial data, which goes beyond the natural or artificial boundaries or is presented as a combination of both, and which is also a regular shape that tessellates the plane with no gaps (Carr et al., 1992). We couple local Hotspot detection with geospatial overlays because overlay-based suitability/constraint mapping is a standard decision-support technique in renewable-energy siting: it contextualizes project distributions with resource, planning, and policy layers at screening scales used by agencies and system planners (Oakleaf et al., 2019; Kahatapitiya et al., 2023; Lopez et al., 2012; Sochi et al., 2023).

This family of methods, which is part of the multi-criteria GIS overlays and related composite indices, is routinely applied to identify suitable areas for solar and wind, supporting comparative, map-based assessments rather than causal inference (Cook and Pétursson, 2025; Zalhaf et al., 2021). Within this workflow, Getis-Ord Gi* is an established local statistic for detecting spatial clustering prior to overlay interpretation, including recent applications to energy/urban contexts (Battle 2025; Guerri et al., 2021). Consistent with the spatial policy literature, we therefore frame our analysis as associational: overlays quantify the co-occurrence between clusters and policy/resource contexts, while acknowledging, as a limitation, other drivers (grid topology, interconnection, land constraints, and community acceptance) that are documented in energy-transition research (Caragliu and Graziano, 2022; Wang et al., 2024). Importantly, these non-policy drivers are not "second-order" considerations but core siting determinants that can confound policy-deployment associations in cross-sectional spatial analyses. Resource endowment can mechanically generate clustering even under weak policy (e.g., high wind regimes), while strict land-use constraints, protected-area coverage, terrain, and local siting restrictions can limit deployment even under favorable policy frameworks. Similarly, interconnection feasibility, locations within certain regional transmission organization or independent system operator (RTOs/ISOs), and transmission availability can act as binding constraints that dominate project geography. Community acceptance can also shape both permitting timelines and the realized spatial footprint of development. Therefore, our objective is to provide a transparent screening-level description of where deployment clusters co-locate with policy and resource contexts, and to explicitly flag plausible confounding pathways when interpreting those patterns.

Our policy indicators reflect measures commonly tracked in siting/deployment studies and national datasets; to avoid injecting subjective priors where the literature offers no externally validated weights, we adopt equal weights for a transparent, screening-level index (an approach analogous to global development-potential and technical-potential overlays) (Oakleaf et al., 2019,2024; Lopez et al., 2012; Rozhkov et al., 2025a,b). This choice is also aligned with the scope of the paper: our aim is to characterize the breadth of state policy environments and their spatial co-location with observed deployment clusters at a national screening scale, not to estimate marginal policy effect sizes or claim a causal ranking of "most influential" instruments. In principle, detecting non-arbitrary policy weights would require co-produced inputs, for example, participatory mapping/modeling with affected communities and stakeholders, to surface locally salient constraints and knowledge (Voinov et al., 2016; Fagerholm et al., 2021; Brown et al., 2020). Complementarily, structured expert elicitation (e.g., Delphi panels or validated 'classical model' protocols) can formalize practitioner knowledge for weighting schemes; however, implementing these processes is nontrivial, context-specific (Hanna and Noble, 2015; Colson and Cooke, 2018; Cadham et al., 2022). Moreover, assigning higher weights to "technology-targeted" policies (e.g., explicit solar/wind provisions) would embed an additional assumption about relative effectiveness that is not externally validated and is likely to be context-dependent, because targeted incentives often operate only in combination with cross-cutting enabling conditions (e.g., interconnection processes, market structure, permitting, and transmission availability). Given our national screening scope and the absence of externally validated differential weights, the weighting mechanism is outside of the scope of this particular study; therefore, we adopt equal weighting as a transparent, conservative compromise that is widely used in composite indicators, with results interpreted as patterns of co-location rather than causal effects and they are subject to sensitivity considerations (Greco et al., 2019). In the same spirit, we do not attempt to "control for" grid/interconnection and siting constraints in a causal sense, because (a) nationally consistent, spatially explicit datasets capturing interconnection feasibility, local zoning/setbacks, and permitting friction are not available at comparable resolution across all states, and (b) several of these factors may be jointly determined with policy and deployment (i.e., potentially endogenous), making naive statistical adjustment in a cross-sectional setting difficult to interpret. Taken together, Gi*-based clustering plus GIS overlays provide an appropriate framework for descriptive attribution of where renewable-energy build-out coincides with policy and resource conditions.

The overlay analysis was designed to identify instances where two factors occur simultaneously within the same hexagonal cell on the study grid. The criteria for this co-occurrence were defined by (1) a high Z-score, representing a strong clustering with a 99 % confidence level (corresponding to bin = 3), and (2) either a score above 4.5 or the presence (value of 1) of each respective policy variable. This approach aims to ensure that only the most significant clusters and high-value variables are considered when assessing potential interactions between factors. A similar analysis was conducted for natural resources, specifically focusing on solar radiation and wind potential. In this case, scores above the mean were selected to represent significant values for comparison. For each variable, the number of hexagonal cells that met the established criteria was recorded, allowing for an assessment of spatial overlap.

By quantifying the number of cells that meet these criteria, this analysis provides a basis for examining possible relationships or influences between factors. When the count of these cells is high, it may indicate a spatial or statistical connection between the two factors, where the presence of one factor (e.g., a high clustering score) is associated with or potentially influences the occurrence of the other factor within the study area. However, we interpret high overlap as evidence of co-location rather than causation per se: we think that overlaps may also arise because both deployment and certain policy regimes correlate with third factors such as resource endowment, developable land, or grid accessibility. We therefore use these overlays to generate geographically explicit hypotheses for subsequent work (e.g., matched regional comparisons or designs that incorporate interconnection and land-constraint data where available), rather than as definitive estimates of policy effects.

3. Results and discussions

3.1. Energy policy classification

The first result of this work includes the classification and ranking of all states' energy and climate policies. The full results are provided in Table 1 and Fig. 3. To avoid conflating distinct priorities, we discuss dimension-specific overlaps (e.g., RPS/targets, grid/interconnection readiness, permitting/market structure, equity/community) before any composite view. The composite index, where shown, is a screening heuristic and should not be read as a normative ranking. Because deployment is jointly shaped by policy and non-policy siting conditions (resource quality, land constraints, and interconnection feasibility), we interpret these scores as policy "enabling context" rather than as standalone predictors of build-out. Policy can matter even in broadly comparable contexts; states share similar regional settings, political regimes, and resource potential but differ in policy design and observed clustering outcomes (e.g., Tennessee vs. North Carolina; Iowa vs. Nebraska). For example, Tennessee and North Carolina share a similar Southeastern electricity market context and a comparable political environment, yet they differ in policy design and associated deployment patterns. Similarly, Iowa and Nebraska provide a Midwest comparison, where resource endowments are broadly favorable and similar, but policy environments diverge. These contrasts are presented as descriptive checks, illustrating how policy context can align (or not) with observed clustering under comparable regional settings.

Table 1

State energy policy scoring. Columns *M1-M12* and *Policy Score* are related to the energy policy, and text type in the column *Policy Score* represents the performance (text in **bold** – the best; regular text – medium; text in *italic* – the worst), *Climate* – the climate policy, *RPS* – the presence of renewable portfolio standards, *Target Score* – analysis of the strength of the state's goal regarding the renewable energy profile and target, *Regulation* explains is state's energy market is regulated or deregulated.

State Name	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Policy Score	Climate	RPS	Target Score	Regulation
Alabama	2	3	0	3	4	1	1	3	2	0	1	2	1.8	0	0	0	0
Arizona	4	4	5	4	3	4	3	3	5	4	2	5	3.8	1	1	0	0
Arkansas	3	3	4	5	4	4	3	3	5	2	2	4	3.5	1	0	0	0
California	5	4.7	3.3	5	4.3	3.3	3.3	3.3	4.3	4.7	4.3	5	4.2	1	1	4.5	1
Colorado	5	5	4.3	5	5	4.7	4	3.6	5	5	5	5	**4.7**	1	1	4	0
Connecticut	4.5	4	4	3	4.5	4.5	3	4	3.5	4.5	2	4	4	1	1	5	1
Delaware	4	4	3	5	4	4	4	4	5	4	4	5	4.2	1	1	2.5	1
Florida	2	3	1	5	3	1	3	1	4	3	0	2	2.3	1	0	0	0
Georgia	4	4	3	5	4	3	4	3	5	5	4	5	4.1	0	0	0	0
Idaho	4	4	3	3	4	3	3	4	4	3	4	4	3.6	0	0	0	0
Illinois	5	5	5	5	5	5	4	4	5	5	4	5	**4.8**	1	1	3	1
Indiana	3	3	4	4	3	2	3	3	4	3	3	2	3.1	0	0	0	0
Iowa	5	5	4	4	5	3	4	4	5	5	5	5	4.5	1	0	0	0
Kansas	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	0	0	0
Kentucky	2.5	2.5	2	2	2.5	1.5	2	2	2.5	2.5	2.5	2.5	2.3	1	0	0	0
Louisiana	2	4	0	3	4	0	1	2	3	2	0	0	1.8	1	0	0	0
Maine	5	5	4	3.3	4.7	4.7	4.3	4	5	4.7	5	3.3	4.4	1	1	4	1
Maryland	5	5	5	3	5	5	4	4	5	4	5	5	**4.6**	1	1	3.5	1
Massachusetts	5	5	4	5	5	5	4	4	5	5	5	5	**4.8**	1	1	2.5	1
Michigan	5	5	4	4	5	4	4	4	5	5	5	5	**4.6**	1	1	0	1
Minnesota	5	5	4	5	5	4	4	4	5	5	5	5	**4.7**	1	1	5	0
Mississippi	2	4	0	3	4	0	1	2	3	2	0	0	1.8	0	0	0	0
Missouri	4	3	4	5	4	3	4	4	4	5	4	4	4	0	1	0	0
Montana	3	3.5	2	4	4	1.5	2.5	3	3.5	3.5	2	2	2.9	1	0	0	0
Nebraska	3	2	2	2	3	1	3	3	3	4	4	2	2.7	0	0	0	0
Nevada	4	3	4	3	3	2	5	3	4	5	4	5	3.8	1	1	4	0
New Hampshire	4	4	3	5	3	2	4	3	4	4	4	4	3.7	1	1	0	1
New Jersey	4	3.5	3.5	4	3	2	4.5	3	4	4.5	4	4.5	3.7	1	1	3.5	1
New Mexico	5	5	4	3	5	4	4	3	5	5	4	4	4.3	1	1	4.5	0
New York	5	5	4	5	5	4	5	4	5	5	4	5	**4.7**	1	1	4	1
North Carolina	5	5	4	5	5	4	5	4	4	5	4	5	**4.6**	1	1	4	0
North Dakota	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	0	0	0
Ohio	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	1	0	1
Oklahoma	3	2	3	4	3	2	5	3	4	4	5	4	3.5	0	0	0	0
Oregon	5	5	4	3	5	5	4	4	5	5	4	5	**4.5**	1	1	5	1
Pennsylvania	4	4	4	5	5	4	4	4	4	5	4	4	4.3	1	1	0	1
Rhode Island	4	4	3	5	5	3	4	4	4	5	5	4	4.2	1	1	5	1
South Carolina	3	3	1	2	2	3	4	4	4	3	0	5	2.8	1	0	0	0
South Dakota	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	0	0	0
Tennessee	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	0	0	0
Texas	0	0	0	0	0	0	0	0	0	0	0	0	*0*	0	1	0	1
Utah	3	3	4	3	3	2	5	3	4	5	3	4	3.5	0	0	0	0
Vermont	5	5	4	5	5	5	4	4	4	5	4	5	**4.6**	1	1	0	0
Virginia	5	5	4	5	5	4	4	4	4	5	5	5	**4.6**	1	1	4.5	1
Washington	5	5	4	5	5	4.5	4	4	4	5	4.5	5	**4.6**	1	1	4.5	0
West Virginia	2	3	2	3	4	0	3	1	3	3	1	1	2.2	0	0	0	0
Wisconsin	5	5	4	5	5	5	4	4	4	5	4	5	**4.6**	1	0	0	0
Wyoming	1	3	0	1	4	0	3	2	3	3	1	1	1.8	0	0	0	0

3.2. Renewable farms clustering pattern

According to the ANN, our data (both wind turbines and solar PV) shows a very strong clustering pattern. Given the resulting Z-scores (−64.76 for solar and −31.92 for wind) with very low p-values (close to 0; ≪ 0.01), there is less than a 1 % likelihood that this clustered pattern could be the result of random chance. This means that both wind and solar farms in the U.S. are not randomly distributed but are highly concentrated in certain regions.

The ANN analysis is effective for detecting clustering patterns at a global scale by measuring the overall spatial distribution of features. It identifies whether the locations exhibit significant clustering or dispersion across the entire study area. However, ANN alone doesn't provide detailed insights into the specific regions driving these patterns. To gain a deeper understanding of localized clusters, we conducted a Hotspot Analysis, which identifies regions with statistically significant concentrations of wind and solar farms, allowing us to pinpoint areas of high activity (hot spots) and low activity (cold spots), offering a more granular view of the spatial trends.

After mapping all the solar installations (Fig. 4a) and applying the Getis-Ord Gi* methodology, we observe that for solar farms, a clear spatial pattern emerges, with hot spots primarily concentrated along both coasts (Fig. 4b). On the West Coast, California stands out as a major hub for solar farms, with additional clustering in northern Oregon. On the East Coast, significant solar activity is observed from South Carolina up through New Hampshire and Vermont. A particularly strong cluster is evident in Minnesota, reflecting concentrated solar development in the region. Additionally, smaller clusters are observed around several major cities, including Chicago, Denver, Indianapolis, and Orlando, where urban energy demand and supportive policies likely contribute to the development of localized solar farms. However, if we consider the direct current (DC) capacity of solar panels, which refers to the maximum amount of DC electricity that they can produce, this capacity varies depending on the size and efficiency of the solar farms (Fig. 4c). Larger solar farms with higher DC capacity are located in the southern regions of both coasts, such as Southern California and the Southeast, primarily due to the higher solar irradiance in these areas, which maximizes energy production. Additionally, regions like Arizona, southern Nevada,

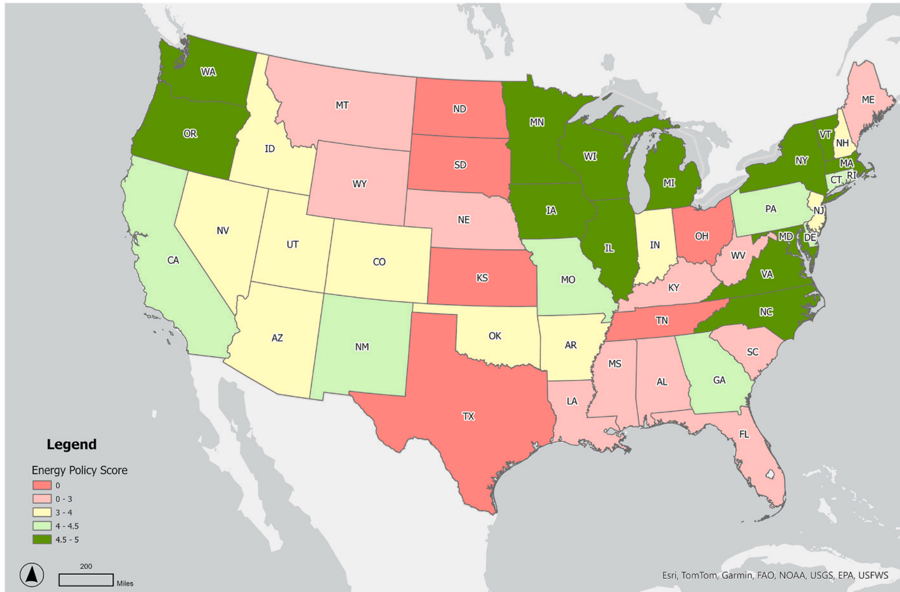

Fig. 3. Strength of energy policies in the U.S.

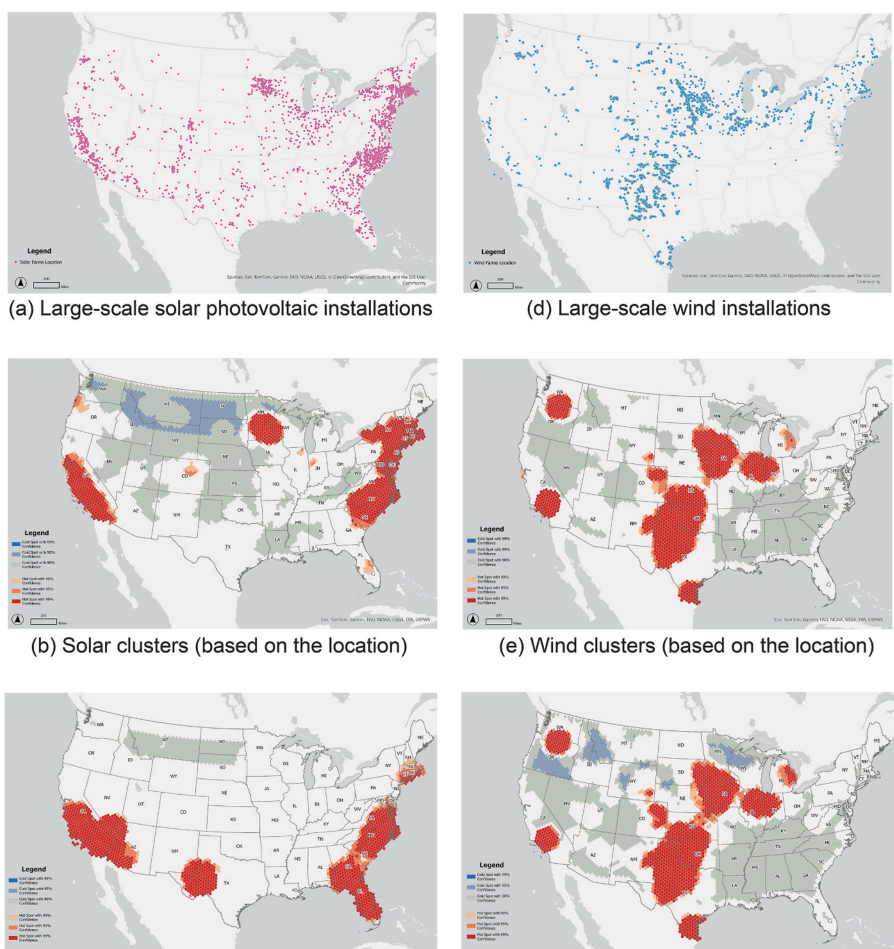
(a) Large-scale solar photovoltaic installations
(d) Large-scale wind installations
(b) Solar clusters (based on the location)
(e) Wind clusters (based on the location)
(c) Solar clusters (based on the DC capacity)
(f) Wind clusters (based on the installed capacity)

Fig. 4. Results of the spatial clustering of solar and wind farms.

western Texas, and all of Florida are home to large-scale solar farms because they receive abundant sunlight year-round, making them ideal for high-capacity solar installations. A useful within-region contrast is the Tennessee-North Carolina comparison: in our mapped patterns, North Carolina appears within the prominent East Coast solar hotspot corridor and exhibits substantial solar deployment, whereas Tennessee shows almost no clustering and no large installations, despite geographic proximity and a broadly similar regional context. This contrast is consistent with our broader framing, which suggests that policy environments may align differently with realized deployment, even among neighboring states.

For wind energy, both the spatial distribution (Fig. 4d and 4e) and capacity of wind farms (Fig. 4f) are largely concentrated primarily in the Midwest and central parts of the U.S. Most likely, this is because these areas offer some of the best wind resources in the country, with steady, strong winds that make large-scale wind energy production highly efficient. In the Midwest, states such as Iowa, Illinois, Indiana, Michigan, and Minnesota have become major hubs for wind energy due to their favorable wind conditions, relatively flat terrain, and ample land available for large installations. These states are home to some of the largest wind farms in the country, contributing significantly to the U.S. wind energy capacity. Similarly, central regions like Texas and Oklahoma are key players in wind energy production. Texas, in particular, leads the nation in installed wind capacity, driven by its massive open spaces and strong winds that might have encouraged wind development. The Panhandle and western parts of Texas, along with central Oklahoma, are locations with significant clusters of wind farms, benefiting from consistent wind speeds and a well-developed transmission network to transport electricity to demand centers. In addition to the Midwest and central U.S., there are smaller but significant pockets of wind farms in other regions, particularly in the mountainous areas of southern California and along the border between Washington and Oregon: the Columbia River Gorge area between Washington and Oregon features prominent wind farms due to the natural wind funneling effect in that region. The mountainous topography in these regions creates strong wind corridors that support the development of wind energy. Southern California, for example, is home to the Tehachapi Pass Wind Farm, one of the largest in the country, with around 710 MW produced by about 3400 wind turbines. It's also worth noting that compared to solar farms, the spatial distribution of wind farms is not significantly different from the distribution of wind farms based on their installed capacity. The comparison is shown in Fig. 4e and 4f. A notable contrast in the Midwest is between Iowa and Nebraska: Iowa forms one of the clearest wind capacity hotspots in our results, whereas Nebraska exhibits markedly weaker clustering and lower capacity concentration, despite sharing a broadly comparable Great Plains wind-resource context with the state. We treat this as a descriptive illustration that similar resource backdrops do not necessarily translate into similar realized build-out.

Based on these two clustering methods (by capacity and by location), we clustered solar sites by location and wind farms by capacity in our analysis. This was done intentionally because PV capacity reporting is heterogeneous (DC vs. AC) and varies with the inverter loading ratio (DC ratings are typically 10–30 % higher than AC ratings), and practices change over time, so capacity can be misleadingly inflated by a few oversized plants (U.S. Energy Information Administration, 2018). By contrast, wind nameplate capacity is consistently defined and directly tied to interconnection/transmission constraints that shape project siting and scale, making capacity-weighted clustering the more policy-salient metric (Energy Markets & Policy, 2024). We verified both metrics, and the spatial patterns did not change significantly (especially for wind farms), so we adopted the versions that are most comparable and robust for each technology.

3.3. Overlay analysis

To assess the relationship between policy, clustering, and natural resources, we performed an overlay analysis using a hexagonal grid system. Each hexagon was assigned values based on three key factors: policy scores, clustering intensity (categorized into bins with corresponding Z-scores), and the availability of natural resources. To ensure the results were both replicable and interpretable, we systematically selected and quantified overlaps within each hexagon, as detailed in the methodology section. The number of hexagons exhibiting these overlaps was then calculated to provide a clear spatial representation of these relationships.

Fig. 5 presents the overlay results between all strong policy measures and the high clustering of solar farms (pink color), highlighting areas where both factors align. A similar visualization for wind farms (blue color) is also shown, where clusters indicate locations with concurrent strong policies and significant wind farm development.

Fig. 6 extends this analysis with additional combined overlays, which allow us to draw conclusions. Fig. 6a illustrates the overlap between the average policy score (measures 1–12) and solar farm clustering, while Fig. 6b aggregates all policy measures, with color intensity representing the degree of overlap (dark purple with yellow boundaries indicating the highest overlap). Fig. 6c examines the correlation between high solar radiation and the clustering of strong solar farms. Notably, the number of hexagons identified through natural resource overlap is considerably lower (191 hexagons) compared to the average policy score overlap (452 hexagons), as summarized in Table 2. For wind farms, Fig. 6d follows the same approach as Fig. 6a, depicting the overlap of the averaged policy scores and wind farm clustering. Fig. 6e visualizes the aggregated policy measures with color intensity denoting overlap strength (dark blue with yellow boundaries for the highest overlap). Fig. 6f highlights areas where high wind speeds coincide with strong wind farm clustering. Unlike solar farms, where policies play a substantial role, wind farm clustering exhibits a stronger correlation with natural conditions, with 957 hexagons showing this overlap compared to just 181 hexagons for strong policy overlaps (as detailed in Table 2). In our analysis of scores, we do not claim that higher scores are universally preferable or that one policy approach (e.g., equity emphasis – ‘M6’ variable) dominates others. Instead, we show where renewable clusters co-occur with different policy dimensions. In practice, states legitimately pursue different objectives (affordability, reliability, equity, market efficiency), and trade-offs are context dependent. Our findings, therefore, inform which levers are spatially associated with observed clustering, without prescribing a single policy model.

Policy specificity and technology contrast. Reading Table 2, solar farm hot spots co-occur most frequently with strong policy variables rather than with high solar irradiance. In particular, overlaps are greatest for comprehensive climate strategies, the presence of RPS, solar-specific support (M12), and grid reliability/modernization (M10), followed by strong clean-energy targets (M1) and defined timelines (M2). By contrast, public-participation transparency (M8), equity (M6), and green jobs (M3) show comparatively few overlaps with solar clustering in our current configuration. For wind, the dominant co-occurrence is with high wind speeds, confirming that natural resource endowment is the primary driver of spatial concentration. Among policy variables, the strongest co-occurrences are observed for RPS, comprehensive climate strategies, grid reliability/modernization (M10), and market structure (deregulation), with clean-energy targets (M1, M2) and funding/carbon-reduction instruments (M9, M5) contributing but not substituting for resource quality. This suggests that solar farm development is more responsive to policy incentives, as solar energy can still be generated even in areas with moderate sunlight (while with much less efficiency), making policies a strong driver for project location. In contrast, wind farm development is far more dependent on wind conditions, as wind is not only more variable but also crucial for turbine efficiency: without sufficient wind speed, turbines cannot generate power. Unlike sunlight, which is present to some degree almost everywhere, wind resources are highly localized, requiring specific conditions to justify investment. Additionally, wind farms are more visually prominent, making their placement subject to greater public and environmental scrutiny, which can further limit their development to areas where wind conditions strongly justify construction. While policy can support wind energy expansion, it cannot compensate for the absence of

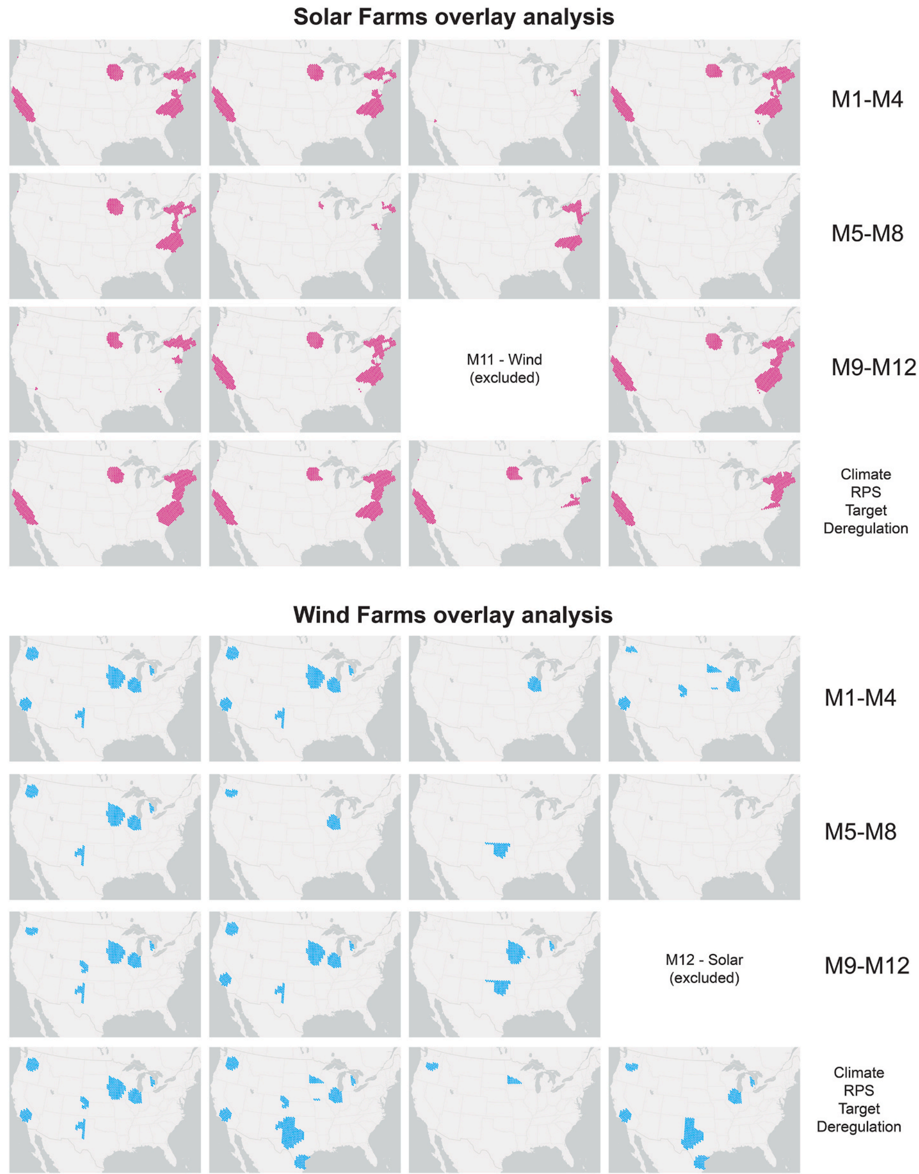

Fig. 5. Results of the overlay analysis between solar and wind farms clustering and various strong policy measures.

strong, consistent wind, making natural conditions the primary driver for wind farm clustering.

For utility-scale solar, the most actionable levers, consistent with our overlaps, are: (i) adopting or strengthening comprehensive climate strategies and RPS frameworks, by setting binding, escalating targets with interim milestones, credible alternative compliance payments, transparent REC markets (banking/borrowing rules), and technology-appropriate carve-outs; (ii) maintaining solar-specific support instruments, by using bankable long-tenor contracts, predictable tax abatement/Payment in Lieu of Taxes (PILOT) structures, and clear successor tariffs for large-scale interconnection; and (iii) accelerating grid readiness (interconnection timelines, hosting capacity, implementation of decentralized energy systems, and other related modernization), by publishing hosting-capacity maps, imposing statutory interconnection clocks with 'deemed-complete' rules, adopting cluster studies and cost-allocation reforms, and pre-permitting energy zones. Targets and clear timelines complement these levers by codifying one-stop siting authority, evidence-based permitting clocks, and consistent appeal/preemption pathways. For onshore wind, making sure that there is an access to high-quality resource corridors remains decisive; within that constraint, states can improve clustering outcomes by (i) planning and funding grid/interconnection in wind-rich areas through multi-year transmission plans, Competitive Renewable Energy Zones (CREZ)-style designated zones, advanced reconductoring, and cost-recovery mechanisms; (ii) sustaining RPS and climate strategies by running regular long-term procurement auctions with renewable energy certificate (REC) markets; and (iii) aligning market structure and permitting by establishing one-stop siting processes with statutory timelines, adopting evidence-based setback and wildlife mitigation standards, requiring early community-benefit agreements, and providing transparent interconnection queue management across jurisdictions.

4. Conclusions

The results of our analysis indicate that energy policies play a crucial role in determining the distribution of renewable energy farms across the U.S., with a particular focus on solar farms. Analysis reveals that policies, such as RPS and state-level incentives, are strong predictors of where large solar farms are located. In simple terms, while natural resources like solar irradiance are important, their role as predictors is not as strong as that of energy policies, climate policies, and RPS.

This highlights the significance of state policies in promoting

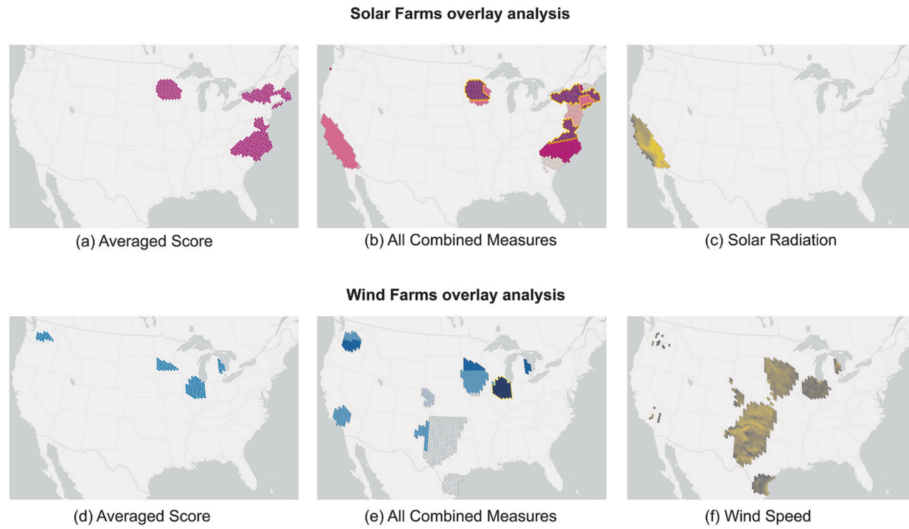

Fig. 6. Combined results of the overlay analysis between solar and wind farms clustering and various strong policy measures (a, b, d, e) and natural factors (c, f).

Table 2
Results of the overlay analysis: counts of hexagons where Hotspot clustering and a given factor coincide. For solar, the largest overlaps are with policy variables (climate strategy, RPS, solar support, grid readiness), not with irradiance; for wind, the largest overlap is with wind speed, with policy factors (RPS, climate strategy, grid readiness, market structure) providing supportive alignment.

Solar Farms overlay analysis																	
Solar Radiation	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Score	Regulation	Target	Climate Policy	RPS
191	686	661	18	707	497	68	271	0	305	706	–	782	452	502	365	824	745
Wind Farms overlay analysis																	
Wind Speed	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Score	Regulation	Target	Climate Policy	RPS
957	460	460	87	266	401	133	102	0	407	466	292	–	181	487	90	498	653

renewable energy development, particularly in states such as Illinois, Wisconsin, Minnesota, Iowa, Washington, Oregon, Virginia, North Carolina, New York, Vermont, and Massachusetts. Notably, some of these states, such as Vermont, Minnesota, and Massachusetts, do not have optimal natural conditions for solar power (e.g., limited sunlight), yet they still see significant renewable energy development due to strong policy frameworks. In states like New York, Minnesota, and Massachusetts, solar energy clusters are established in regions with less favorable natural conditions, but policy incentives compensate for these limitations. The opposite situation is observed in states like Arizona and New Mexico with solar farms: the natural conditions there are close to ideal, but there is no strong policy support and, as a result, a very weak presence of large-scale solar farms.

For wind farms, the situation is slightly different, with natural conditions playing a much more significant role compared to state energy policy. While climate policy and RPS are also important, they are not as strong as the average wind speed in the area. For instance, in states like Iowa and Texas, where wind farms cluster in areas with high wind potential, the distribution aligns well with natural resources. This suggests that while natural resources provide a foundation, the strength of state energy policies, such as RPS targets and regulatory frameworks, significantly influences where renewable energy projects are developed, often overriding natural limitations and potentially strengthening the development of large renewable farms. Worth noting that because priorities differ across states, composite screening scores can mask intentional policy choices. We therefore place interpretive weight on dimension-level results and describe the composite only as a convenience summary. Determining normative weights would require participatory or expert-elicited weighting; in their absence, equal weighting is used as a transparent compromise. Overall, based on the results, we see that the role of state legislation in energy policies is critical (even with different state priorities), with political and regulatory commitments being the most decisive factors in accelerating or impeding the shift toward renewable energy systems.

The use of AI, such as GPT-4o or similar, for analyzing legislative documents has proven to be an effective method for systematically evaluating complex regulatory texts, as demonstrated in our study. By leveraging the ability of LLMs to process and interpret large volumes of text, we generated structured insights and rankings across diverse legislative components. This approach holds significant promise for future research, where it can be applied to other domains of legal and regulatory analysis, with a potentially broader scope. In future studies, we plan to further explore and refine the application of LLMs, improving their ability to handle increasingly complex legislative frameworks and ensuring greater accuracy. Combined with traditional spatial analysis methodology, it creates a robust framework for future work in similar or other domains, both in the U.S. and internationally.

The work has limitations, and future research will focus on expanding this current study in various directions to deepen the understanding of the relationships, including potentially causal relationships, between renewable energy development and influencing factors. Because overlays capture co-occurrence, they cannot, on their own, isolate causal effects of policy. Potential confounders such as grid topology/interconnection queues, land-use exclusions, and community acceptance remain important drivers identified across the siting literature; we acknowledge these factors and treat our findings as descriptive patterns consistent with (but not proof of) policy influence. Future causal work could leverage quasi-experimental designs (e.g., policy timing, queue reforms) to separate channels. In future research, first, a more detailed examination of how specific policy mechanisms (such as tax incentives, subsidies, and grid access regulations) affect renewable energy deployment at a finer spatial scale could provide more actionable insights. Additionally, future research could investigate how evolving policies, like the expansion of RPS or carbon pricing mechanisms, influence the long-term growth of renewable energy infrastructure.

Another important area for future study is the integration of climate resilience and adaptation into the spatial planning of renewable farms. This could involve assessing how projected changes in climate conditions (e.g., shifting wind patterns or solar irradiance due to global warming) will impact the optimal locations for renewable energy over time. Since large renewable farms are a significant investment with a multi-decade payback period, changes in natural factors over time should be considered, transforming spatial analysis into spatiotemporal analysis. Furthermore, understanding the interaction between renewable energy clusters and energy storage technologies, such as batteries, could provide new insights into how energy systems can be optimized for reliability and efficiency. Finally, by incorporating social and economic factors, such as public acceptance and local job creation, and focusing on more local areas (including local energy policies), a more comprehensive view of the multifaceted drivers behind renewable energy development can be achieved. In our data, solar clustering aligns most closely with policy-rich environments, rather than irradiance alone, while wind clustering aligns primarily with wind resource quality, with policy acting as a crucial enabler. These technology-specific patterns suggest that states should prioritize grid/interconnection and durable demand signals everywhere, while focusing solar policy on broad policy packages (RPS, climate strategy, solar support) and wind policy on transmission/interconnection readiness in the best wind corridors.

CRediT authorship contribution statement

Anton Rozhkov: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Koyel Das:** Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Al-Shetwi, A.Q., 2022. Sustainable development of renewable energy integrated power sector: trends, environmental impacts, and recent challenges. Sci. Total Environ. 822, 153645.
Amjad, F., Agyekum, E.B., Shah, L.A., Abbas, A., 2021. Site location and allocation decision for onshore wind farms, using spatial multi-criteria analysis and density-based clustering. A techno-economic-environmental assessment, Ghana. Sustain. Energy Technol. Assessments 47, 101503.Balthasar et al., 2020 Balthasar, A., Schreurs, M.A., Varone, F., 2020. Energy transition in Europe and the United States: policy entrepreneurs and veto players in federalist systems. J. Environ. Dev. 29 (1), 3–25.
Bartik, A., Gupta, A., Milo, D., 2023. The Costs of Housing Regulation: Evidence from Generative Regulatory Measurement. Available at: SSRN.
Battle, C.R., 2025. The Clustering of Utility-Scale Solar Farms in Rhode Island: Empirical Evidence and Policy Implications. Available at: SSRN 5572815.
Bibri, S.E., 2018. A foundational framework for smart sustainable city development: theoretical, disciplinary, and discursive dimensions and their synergies. Sustain. Cities Soc. 38, 758–794.
Brown, G., Reed, P., Raymond, C.M., 2020. Mapping place values: 10 lessons from two decades of public participation GIS empirical research. Appl. Geogr. 116, 102156.
Burke, M.J., Stephens, J.C., 2017. Energy democracy: goals and policy instruments for sociotechnical transitions. Energy Res. Social Sci. 33, 35–48.
Burke, M.J., Stephens, J.C., 2018. Political power and renewable energy futures: a critical review. Energy Res. Social Sci. 35, 78–93.
Busch, H., McCormick, K., 2014. Local power: exploring the motivations of mayors and key success factors for local municipalities to go 100% renewable energy. Energy Sustain. Soc. 4, 1–15.
Cadham, C.J., Knoll, M., Sanchez-Romero, L.M., Cummings, K.M., Douglas, C.E., Liber, A., et al., 2022. The use of expert elicitation among computational modeling studies in health research: a systematic review. Med. Decis. Mak. 42 (5), 684–703.
California clean energy and pollution reduction act - SB 350. https://www.energy.ca.gov/rules-and-regulations/energy-suppliers-reporting/clean-energy-and-pollution-reduction-act-sb-350, 2015.
Caragliu, A., Graziano, M., 2022. The spatial dimension of energy transition policies, practices and technologies. Energy Policy 168, 113154.
Carley, S., Davies, L.L., Spence, D.B., Zirogiannis, N., 2018. Empirical evaluation of the stringency and design of renewable portfolio standards. Nat. Energy 3 (9), 754–763.
Carr, D.B., Olsen, A.R., White, D., 1992. Hexagon mosaic maps for display of univariate and bivariate geographical data. Cartography and Geographic Information Systems 19 (4), 228–236.
Center for Climate and Energy Solutions (C2ES), 2024. U.S. state climate action plans. https://www.c2es.org/document/climate-action-plans/.
CleanEnergy States Alliance, 2024. Table of 100% clean energy states. https://www.cesa.org/projects/100-clean-energy-collaborative/guide/table-of-100-clean-energy-states/.
Colson, A.R., Cooke, R.M., 2018. Expert Elicitation: Using the Classical Model to Validate Experts' Judgments. Review of Environmental Economics and Policy.
Cook, D., Pétursson, J.G., 2025. The role of GIS mapping in multi-criteria decision analysis in informing the location and design of renewable energy projects-A systematic review. Energy Strategy Rev. 59, 101765.
Daszkiewicz, K., 2020. Policy and regulation of energy transition. Geopolitic. Glob. Energy Trans. 203–226.
Doris, E., Cochran, J., Vorum, M., 2009. Energy Efficiency Policy in the United States: Overview of Trends at Different Levels of Government.
Energy Markets & Policy, 2024. Land-Based Wind Market Report: 2024 Edition. Berkeley Lab. https://emp.lbl.gov/publications/land-based-wind-market-report-2024.
ESRI. (n.d., a). How average nearest neighbor works. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-average-nearest-neighbor-distance-spatial-st.htm. ESRI, n.dESRI. (n.d,.b,How Hot Spot Analysis (Getis-Ord Gi*) works. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-hot-spot-analysis-getis-ord-gi-spatial-stati.htm.
Fagerholm, N., Raymond, C.M., Olafsson, A.S., Brown, G., Rinne, T., Hasanzadeh, K., et al., 2021. A methodological framework for analysis of participatory mapping data in research, planning, and management. Int. J. Geogr. Inf. Sci. 35 (9), 1848–1875.
Fujita, K.S., Ancona, Z.H., Kramer, L.A., Straka, M., Gautreau, T.E., Garrity, C.P., Robson, D., Diffendorfer, J.E., Hoen, B., 2023. United States Large-Scale Solar Photovoltaic Database (V2.0, August, 2024. U.S. Geological Survey and Lawrence Berkeley National Laboratory data release. https://eerscmap.usgs.gov/uspvdb/data/.
Galimova, T., Ram, M., Breyer, C., 2022. Mitigation of air pollution and corresponding impacts during a global energy transition towards 100% renewable energy system by 2050. Energy Rep. 8, 14124–14143.
Getis, A., Ord, J.K., 1992. The analysis of spatial association by use of distance statistics. Geogr. Anal. 24 (3), 189–206.
Giberson, M., 2016. Trump's policy may undermine pro-growth intentions. Nat. Energy 1 (10), 1–3.
Greco, S., Ishizaka, A., Tasiou, M., Torrisi, G., 2019. On the methodological framework of composite indices: a review of the issues of weighting, aggregation, and robustness. Soc. Indic. Res. 141 (1), 61–94.
Guerri, G., Crisci, A., Messeri, A., Congedo, L., Munafò, M., Morabito, M., 2021. Thermal summer diurnal hot-spot analysis: the role of local urban features layers. Remote Sens. 13 (3), 538.
Guliyev, F., 2020. Trump's "America first" energy policy, contingency and the reconfiguration of the global energy order. Energy Policy 140, 111435.
Haggerty, J.H., Haggerty, M., Rasker, R., 2014. Uneven local benefits of renewable energy in the US west: property tax policy effects. West. Econ. Forum 13 (1), 8–22.
Hanna, K., Noble, B.F., 2015. Using a Delphi study to identify effectiveness criteria for environmental assessment. Impact Assess. Proj. Apprais. 33 (2), 116–125.
Hashemizadeh, A., Ju, Y., Bamakan, S.M.H., Le, H.P., 2021. Renewable energy investment risk assessment in belt and road initiative countries under uncertainty conditions. Energy 214, 118923.
Hess, D.J., Mai, Q.D., Brown, K.P., 2016. Red states, green laws: ideology and renewable energy legislation in the United States. Energy Res. Social Sci. 11, 19–28.
Hoen, B.D., Diffendorfer, J.E., Rand, J.T., Kramer, L.A., Garrity, C.P., Hunt, H.E., 2018. United States wind turbine database v7.1 (august 14, 2024): U.S. geological survey. American Clean Power Association, and Lawrence Berkeley National Laboratory Data Release. https://eerscmap.usgs.gov/uswtdb/data/.
Howlett, M., Rayner, J., 2013. Patching vs packaging in policy formulation: Assessing policy portfolio design. Politics and Governance 1 (2), 170–182.
Johnsson, F., Kjärstad, J., Rootzén, J., 2019. The threat to climate change mitigation posed by the abundance of fossil fuels. Clim. Policy 19 (2), 258–274.
Kahatapitiya, C., Jayasooriya, V.M., Muthukumaran, S., 2023. GIS-based weighted overlay model for wind and solar farm locating in Sri Lanka. Environ. Sci. Pollut. Control Ser. 30 (44), 98947–98965.
Leonhardt, R., Noble, B., Poelzer, G., Fitzpatrick, P., Belcher, K., Holdmann, G., 2022. Advancing local energy transitions: a global review of government instruments supporting community energy. Energy Res. Social Sci. 83, 102350.
Levenda, A.M., Behrsin, I., Disano, F., 2021. Renewable energy for whom? A global systematic review of the environmental justice implications of renewable energy technologies. Energy Res. Social Sci. 71, 101837.

Lopez, A., Roberts, B., Heimiller, D., Blair, N., Porro, G., 2012. Us Renewable Energy Technical Potentials. a Gis-based Analysis. National Renewable Energy Laboratory (NREL), Golden, CO (United States). No. NREL/TP-6A20-51946).
Mercure, J.F., Salas, P., Vercoulen, P., Semieniuk, G., Lam, A., Pollitt, H., et al., 2021. Reframing incentives for climate policy action. Nat. Energy 6 (12), 1133–1143.
Minnesota's 2025 energy action plan. https://mn.gov/commerce/energy/policy-data-reports/energy-data-reports/mn-action-plan.jsp, 2016.
National association of state energy officials (NASEO). (n.d.) https://www.naseo.org.
NCSL, 2021. State renewable portfolio standards and goals. https://www.ncsl.org/energy/state-renewable-portfolio-standards-and-goals#:~:text=Renewable%20Portfolio%20Standards%20(RPS)%20require,production%20and%20encourage%20economic%20development.
Oakleaf, J.R., Kennedy, C.M., Baruch-Mordo, S., Gerber, J.S., West, P.C., Johnson, J.A., Kiesecker, J., 2019. Mapping global development potential for renewable energy, fossil fuels, mining and agriculture sectors. Sci. Data 6 (1), 101.
Oakleaf, J., Kennedy, C., Wolff, N.H., Terasaki Hart, D.E., Ellis, P., Theobald, D.M., et al., 2024. Mapping global land conversion pressure to support conservation planning. Sci. Data 11 (1), 830.
OpenAI, 2024. *ChatGPT* 4o (Oct 1, 2024) [large language model]. https://chat.openai.com/chat.
O'Shaughnessy, E., Barbose, G., Kannan, S., Sumner, J., 2024. Evaluating community solar as a measure to promote equitable clean energy access. Nat. Energy 9 (8), 955–963.
Perry, K.K., 2020. For politics, people, or the planet? The political economy of fossil fuel reform, energy dependence and climate policy in Haiti. Energy Res. Social Sci. 63, 101397.
Popp, D., 2020. Promoting clean energy innovation at the state and local level. Agric. Resour. Econ. Rev. 49 (2), 360–373.
Ren, J., Zhou, Y., 2025. How spatial clustering of resource-based enterprises affects air pollution: micro evidence from China. Environ. Dev. Sustain. 1–29.
Rozhkov, A., 2023. Harnessing European policies for energy planning in Illinois: overcoming barriers and transitioning to a climate-neutral society. Sustain. Cities Soc. 98, 104803.
Rozhkov, A., 2024. Applying graph theory to find key leverage points in the transition toward urban renewable energy systems. Appl. Energy 361, 122854.
Rozhkov, A., 2025. Decentralized renewable energy integration in the urban energy markets: a system dynamics approach. PLOS Complex Syst. 2 (12), e0000083.
Rozhkov, A., Zandiatashbar, A., Seyrfar, A., 2025a. Tackling transportation inequality through unveiling Chicago's transit deserts and vulnerable communities. J. Urban Plann. Dev. 151 (3), 04025030.
Rozhkov, A., Zellner, M., Murphy, J.T., Massey, D., 2025b. Identifying leverage points for sustainable transitions in urban – rural systems: application of graph theory to participatory causal loop diagramming. Environ. Sci. Pol. 164, 103996.
Ryder, S.S., 2017. Unconventional regulation for unconventional energy in Northern Colorado? Municipalities as strategic actors and innovators in the United States. Energy Res. Social Sci. 26, 23–33.
Saurer, J., Monast, J., 2021. Renewable energy federalism in Germany and the United States. Transnation. Environ. Law 10 (2), 293–320.
Singleton, A.D., Spielman, S., 2024. Segmentation using large language models: a new typology of American neighborhoods. EPJ Data Sci. 13 (1), 34.
Sochi, K., James, O.R., Aishwarya, B., Jeffrey, E.S., Vejnović, I., Kasandra, Z.D., et al., 2023. Mapping a Sustainable Renewable Energy Transition: Handbook for Practitioners.
Sovacool, B.K., 2009. Rejecting renewables: the socio-technical impediments to renewable electricity in the United States. Energy Policy 37 (11), 4500–4513.
Stokes, L.C., Breetz, H.L., 2018. Politics in the US energy transition: case studies of solar, wind, biofuels and electric vehicles policy. Energy Policy 113, 76–86.
Stokes, L.C., Warshaw, C., 2017. Renewable energy policy design and framing influence public support in the United States. Nat. Energy 2 (8), 1–6.
U.S. Energy Information Administration (EIA), 2018. Solar plants typically install more panel capacity relative to their inverter capacity. https://www.eia.gov/todayinenergy/detail.php?id=35372.
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I., 2017. Attention is all you need. Adv. Neural Inf. Process. Syst. 30.
Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., et al., 2016. Modelling with stakeholders–next generation. Environ. Model. Software 77, 196–220.
Vormedal, I., Bjander, J., Larsen, M.L., Lindberg, M.B., 2023. Technological change and the politics of decarbonization: a re-making of vested interests? Environ. Innov. Soc. Transit. 47, 100725.
Wang, Q., Kwan, M.P., Fan, J., Zhou, K., Wang, Y.F., 2019. A study on the spatial distribution of the renewable energy industries in China and their driving factors. Renew. Energy 139, 161–175.
Wang, X., Jin, W., Qin, M., Su, C.W., Umar, M., 2024. Pushing forward the deployment of renewable energy: do cross-national spillovers of policy instruments matter? Energy 301, 131643.
Xu, J., Lv, T., Hou, X., Deng, X., Li, N., Liu, F., 2022. Spatiotemporal characteristics and influencing factors of renewable energy production in China: a spatial econometric analysis. Energy Econ. 116, 106399.
Yi, H., Feiock, R.C., 2014. Renewable energy politics: policy typologies, policy tools, and state deployment of renewables. Policy Stud. J. 42 (3), 391–415.
Zalhaf, A.S., Elboshy, B., Kotb, K.M., Han, Y., Almaliki, A.H., Aly, R.M., Elkadeem, M.R., 2021. A high-resolution wind farms suitability mapping using GIS and fuzzy AHP approach: a national-level case study in Sudan. Sustainability 14 (1), 358.
Zandiatashbar, A., Hamidi, S., Foster, N., 2019. High-tech business location, transportation accessibility, and implications for sustainability: evaluating the differences between high-tech specializations using empirical evidence from US booming regions. Sustain. Cities Soc. 50, 101648.
Zellner, M., Massey, D., Rozhkov, A., Murphy, J.T., 2023. Exploring the barriers to and potential for sustainable transitions in urban–rural systems through participatory causal loop diagramming of the food–energy–water nexus. Land 12 (3), 551.
Zhao, M., Sun, T., 2022. Dynamic spatial spillover effect of new energy vehicle industry policies on carbon emission of transportation sector in China. Energy Policy 165, 112991.
Zhao, W.X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., et al., 2023. A Survey of Large Language Models. *arXiv preprint arXiv:2303.18223*.
Zhou, S., Solomon, B.D., 2021. The interplay between renewable portfolio standards and voluntary green power markets in the United States. Renew. Energy 178, 720–729.