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Charting the Landscape of Data Envelopment Analysis in Renewable Energy and Carbon Emission Efficiency

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Abstract

This study explores the intellectual landscape and methodological evolution of Data Envelopment Analysis (DEA) in the context of renewable energy and carbon emission efficiency. Using bibliometric techniques and data extracted from the Web of Science Core Collection (2389 publications from 2000 to 2024), the research identifies influential authors, institutions, and thematic clusters shaping the field. The results reveal that DEA has evolved from a traditional efficiency assessment tool into a comprehensive analytical framework supporting sustainable energy transition and carbon mitigation policies. Six major research clusters were identified, encompassing carbon emission measurement, efficiency benchmarking, methodological innovations, industrial applications, circular economy perspectives, and international productivity comparisons. Notably, Asian scholars, particularly from China and Taiwan, dominate the research landscape, reflecting strong regional leadership in empirical and methodological advancements. The findings demonstrate that recent studies increasingly adopt advanced models such as network DEA, dynamic DEA, DEA–Malmquist, and hybrid DEA–machine learning approaches to address complex energy systems. Comparative insights highlight DEA’s advantages over Stochastic Frontier Analysis (SFA) in handling multi-dimensional, non-parametric data, while emphasizing the need for hybrid frameworks to improve robustness. This study contributes to the ongoing discourse on energy sustainability by mapping knowledge structures, revealing methodological trajectories, and providing guidance for future research on efficiency and carbon reduction strategies.

Keywords: DEA; renewable energy efficiency; carbon emission reduction; environmental benchmarking; sustainable energy transition; bibliometric analysis



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1. Introduction

The accelerating pace of climate change and the depletion of fossil fuel reserves have compelled governments, industries, and research communities to pursue sustainable energy transitions [1]. According to the International Energy Agency, renewable energy is projected to supply nearly 50% of global electricity demand by 2050, underscoring its central role in decarbonizing the energy sector [2]. Solar photovoltaics, wind energy, biomass, geothermal, and hydropower have emerged as major contributors to this transformation [3]. However, their rapid expansion is accompanied by challenges related to efficiency, resource allocation, intermittency, and environmental trade-offs [4]. Measuring and benchmarking performance across these diverse energy systems has therefore become an essential prerequisite for improving operational outcomes and guiding investment and policy decisions [5].

Parallel to the rise of renewable energy is the global urgency to mitigate greenhouse gas emissions [6]. Carbon dioxide (CO₂) accounts for nearly three-quarters of global greenhouse gas emissions, with the energy sector responsible for the majority of these outputs [7]. International agreements such as the Paris Accord and the pursuit of net-zero emission targets have heightened the demand for robust methodologies that can assess carbon emission efficiency at multiple levels, ranging from individual power plants and firms to national energy systems [8]. This dual imperative, improving renewable energy performance while reducing carbon emissions, has created fertile ground for methodological innovations in efficiency analysis.

Among the available efficiency assessment tools, Data Envelopment Analysis (DEA) has become particularly prominent. Originally introduced by Charnes, Cooper, and Rhodes in 1978, DEA is a non-parametric linear programming approach that measures the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs [9]. Unlike parametric approaches such as Stochastic Frontier Analysis (SFA), DEA does not require explicit functional form assumptions, making it especially useful in complex energy systems where diverse factors interact in nonlinear ways.

In the energy domain, DEA has been applied extensively to evaluate the efficiency of electricity generation companies, renewable energy technologies, regional energy systems, and national energy policies [10]. For instance, studies have employed DEA to benchmark the performance of wind farms, compare the operational efficiency of thermal versus renewable power plants, and analyze the energy–environmental efficiency of countries with varying emission profiles [11,12]. DEA has also been extended through models such as dynamic DEA, network DEA, Malmquist productivity indices, and slack-based measures, which allow researchers to capture temporal changes, multi-stage processes, and undesirable outputs such as CO₂ emissions [13]. These methodological advancements have substantially enriched the analytical capacity of DEA to address contemporary challenges in energy and environmental policy.

Despite its widespread application, the literature on DEA in renewable energy and carbon emission efficiency remains fragmented and dispersed across multiple disciplinary outlets [14]. Much of the research is dominated by case studies that focus on specific countries, technologies, or time periods. While these contributions offer valuable insights, they do not collectively provide a comprehensive overview of how DEA has been employed across different contexts, nor do they reveal the evolution of scholarly interest over time.

A few review studies have discussed efficiency assessment methods in energy or environmental economics more broadly [15,16], but these reviews tend to either:

1. Examine DEA alongside other methods (thus providing only a limited treatment of DEA itself); or
2. Focus on narrow applications such as electricity generation or national-level carbon efficiency, thereby overlooking the broader spectrum of renewable and emission-related studies.

As a result, several critical questions remain unanswered. How has the application of DEA in renewable energy and carbon emission efficiency evolved over the past two decades? Which regions and institutions are leading this field? What are the dominant methodological and thematic directions? And most importantly, what gaps exist that could guide future research in advancing both renewable energy adoption and carbon emission reduction? Addressing these questions requires a systematic knowledge mapping approach that goes beyond individual case studies to capture the structure, dynamics, and trajectory of the field.

Using bibliographic data extracted from the Web of Science Core Collection, this work applies advanced analytical and visualization techniques to uncover publication trends,

thematic clusters, influential authors, and collaboration networks. In doing so, it provides a panoramic view of how DEA has contributed to the twin objectives of renewable energy performance improvement and carbon emission reduction.

The contributions of this study are fourfold. First, it offers the first consolidated mapping of DEA applications in this domain, thereby creating a reference point for both new and experienced researchers. Second, it identifies key methodological developments, such as the integration of DEA with frontier productivity indices and environmental extensions, which have expanded the scope of analysis. Third, it highlights geographical and institutional patterns of research, providing insight into how global collaboration is shaping this field. Finally, it proposes a research agenda that emphasizes future directions, including the application of DEA to emerging energy technologies (e.g., hydrogen energy, energy storage, and smart grids), integration with machine learning techniques, and policy-oriented assessments aligned with net-zero targets [17].

The remainder of this paper is structured as follows. Section 2 outlines the methodology, including data collection procedures, search strategy, and the bibliometric tools employed for analysis. Section 3 presents the results, covering publication trends, authorship patterns, geographic and institutional contributions, and thematic structures revealed through keyword and citation analyses. Section 4 discusses these findings in light of the role of DEA in renewable energy efficiency and carbon emission reduction, while also comparing DEA with other methods of efficiency analysis. Section 5 develops a future research agenda, highlighting promising directions for integrating DEA with emerging technologies and policy frameworks. Finally, Section 6 concludes with key insights, implications, and recommendations for scholars, policymakers, and practitioners engaged in the energy transition.

2. Literature Review

2.1. DEA in Energy Efficiency Research

Data Envelopment Analysis (DEA) has become a cornerstone in evaluating efficiency within the energy sector. Its appeal lies in its ability to accommodate multiple inputs and outputs without assuming a predefined production function. Traditional efficiency methods such as stochastic frontier analysis (SFA) are often constrained by functional form specifications and statistical assumptions, whereas DEA provides greater flexibility in handling heterogeneous data typical of energy systems [18].

Early applications of DEA in energy research focused primarily on electricity generation, where the method was used to benchmark the technical efficiency of power plants [19]. Studies examined coal-fired, gas, and hydroelectric facilities, providing insights into operational performance and resource utilization. Over time, these analyses expanded to incorporate renewable energy sources, such as solar and wind power plants, which introduced new complexities due to intermittency, geographic dispersion, and evolving technological benchmarks [20].

The evolution of DEA models has further enriched energy applications. Extensions such as the Malmquist productivity index have enabled temporal analysis of efficiency changes, while network DEA has been employed to capture multi-stage processes in energy production [21]. Slack-based measures (SBM) have been introduced to better account for input and output slacks, particularly relevant in contexts where energy losses or unutilized capacity are significant [22]. These methodological advancements have made DEA a preferred approach for evaluating energy efficiency under conditions of technical, economic, and environmental complexity.

2.2. DEA in Renewable Energy Evaluation

As the global push for clean energy accelerated, DEA found increasing application in renewable energy evaluation. Researchers have employed DEA to benchmark the efficiency of wind farms, solar photovoltaic installations, biomass facilities, and hybrid renewable systems [23]. In many cases, DEA was used to assess not only technical efficiency but also financial and environmental performance, providing a holistic view of renewable energy deployment [24,25].

For example, DEA has been applied to evaluate the operational efficiency of wind power projects across different countries, highlighting how factors such as turbine size, location, and government subsidies influence performance outcomes [26]. Solar energy studies have used DEA to benchmark the productivity of photovoltaic plants, focusing on variations in geographic conditions and technological adoption [27]. In the case of biomass and biofuel facilities, DEA has been employed to evaluate energy conversion efficiency while simultaneously considering by-products and waste management [28].

DEA has also been extended to policy analysis in renewable energy. For instance, cross-country DEA studies have compared national renewable energy portfolios, providing insights into which countries allocate resources most effectively to maximize renewable generation [29]. These analyses have informed policy recommendations on subsidy design, grid integration, and research investment. The ability of DEA to handle multiple objectives has proven especially valuable in renewable energy, where technical efficiency, cost considerations, and environmental impact often need to be assessed simultaneously [30].

2.3. DEA and Carbon Emission Efficiency

In addition to renewable energy evaluation, DEA has played a central role in analyzing **carbon emission efficiency**. The method's ability to incorporate "undesirable outputs," such as CO₂ emissions, makes it uniquely suited for assessing environmental performance. DEA-based environmental efficiency models have been widely used to examine the trade-offs between energy use, economic growth, and carbon reduction [31].

At the macro level, DEA has been applied to compare the carbon efficiency of countries and regions. These studies assess how effectively nations convert energy inputs into economic output while minimizing emissions. Findings often reveal significant disparities across regions, reflecting differences in industrial structure, technological development, and policy stringency. For instance, some studies have shown that while developed economies achieve higher technical efficiency, emerging economies may perform better in terms of carbon emission reduction due to rapid adoption of cleaner technologies [32,33].

At the micro level, DEA has been used to evaluate carbon performance in specific industries, such as manufacturing, transportation, and energy-intensive sectors. By incorporating CO₂ emissions as undesirable outputs, these studies highlight the importance of environmental considerations in operational benchmarking [34]. Extensions such as the slack-based measure and dynamic DEA have provided more nuanced insights, capturing inefficiencies that traditional DEA might overlook.

DEA has also been integrated with life cycle assessment (LCA) and carbon accounting methods, allowing for more comprehensive evaluations of emission reduction strategies. This integration underscores the growing recognition of DEA as not only a tool for efficiency measurement but also a methodological framework for advancing environmental sustainability [35].

2.4. Methodological Advancements in DEA for Energy and Environment

As shown in Table 1, the versatility of DEA in energy and environmental applications has been enhanced through several methodological innovations:

Table 1. Methodological innovations in DEA for energy and environment.

Methodological	Description	Sources
Dynamic DEA	Captures changes in efficiency over time, useful for monitoring renewable energy adoption and emission reduction progress.	[36,37]
Network DEA	Models multi-stage processes, such as energy generation, transmission, and distribution, or production processes with intermediate outputs.	[38,39]
Slack-Based Measure (SBM) DEA	Explicitly accounts for input and output slacks, improving the realism of efficiency measurement in energy systems.	[40,41]
Malmquist Index DEA	Assesses productivity change over time, particularly relevant for tracking progress toward carbon neutrality.	[27,42]
DEA with Undesirable Outputs	Incorporates pollutants and emissions, making it directly applicable to carbon efficiency analysis.	[27,43]
Hybrid DEA Models	Combine DEA with machine learning, fuzzy logic, or econometric methods to improve robustness and predictive power.	[23,44]

These advancements demonstrate that DEA has evolved far beyond its original formulation, becoming an adaptable and powerful framework for addressing complex questions in energy sustainability and environmental policy.

3. Research Methodology

3.1. Data Collection

The study adopts a systematic review approach to map the application of Data Envelopment Analysis (DEA) in renewable energy and carbon-emission efficiency. Data were collected exclusively from the Web of Science (WoS) Core Collection, a database widely recognized for its comprehensive coverage of high-quality academic literature. Although the search was performed using a single query within Web of Science (WoS), the WoS Core Collection aggregates multiple citation indices (e.g., SCI-E, SSCI, ESCI). When a publication is indexed in more than one collection, it can appear multiple times in the raw export. After merging records from these indices, automated de-duplication was performed using WoS export metadata (DOI, title, author combination). To ensure rigor and replicability, we applied an advanced search strategy combining key terms such as “Data Envelopment Analysis,” “DEA,” “renewable energy,” “energy efficiency,” and “carbon emission” on 31 December 2024. Furthermore, to enhance methodological rigor, we have provided detailed documentation of the search strategy, including the use of specific keywords, Boolean operators, and field codes. This level of detail allows other researchers to replicate or adapt the search for related studies, ensuring consistency in bibliometric analyses. By explicitly stating the search parameters and potential limitations, such as database updates or indexing delays, we aim to promote transparency and reliability in the research process.

Although DEA originated in the late 1970s, its systematic adoption in renewable energy performance assessment and carbon-efficiency evaluation gained traction only after 2000. A preliminary scoping search confirmed that publications prior to 2000 were scarce and did not reflect modern renewable energy technologies, contemporary climate-policy frameworks, or methodological advances such as network DEA, dynamic DEA, and hybrid DEA–machine learning models. Therefore, the time frame was restricted to 2000–2024 to capture the relevant evolution of research alongside global sustainability imperatives.

Only English-language journal articles were retained to maintain consistency in data interpretation and ensure standardized citation records. While conference papers and book chapters may undergo peer review, they often lack standardized indexing, citation traceability, and structured metadata. To preserve analytical comparability and ensure data quality, we narrowed the scope to peer-reviewed journal articles only. The final search yielded 2389 records for further screening and analysis.

3.2. Data Screening and Filtering

To enhance methodological transparency, this study followed the PRISMA 2020 reporting guideline to structure the identification, screening, eligibility assessment, and final inclusion steps [45]. Because the objective of this research is bibliometric mapping rather than clinical intervention evaluation, PRISMA was applied to document workflow and reporting transparency, rather than to appraise article quality through the 27-item checklist, which is not directly applicable to bibliometric studies. Specifically, PRISMA guidance was used to record the process, including database identification, duplicate removal, title/abstract screening, full-text relevance confirmation, and final inclusion. The PRISMA framework was used to structure the four key stages of the review process: identification, screening, eligibility assessment, and final inclusion. First, duplicate records were removed to ensure data consistency. Second, titles and abstracts were screened to exclude studies unrelated to energy applications of DEA (e.g., banking, agriculture, healthcare). Third, a full-text evaluation was conducted to verify relevance to renewable energy systems, energy efficiency assessment, or carbon emission performance. Finally, only studies applying DEA or its methodological extensions within the energy domain were retained.

PRISMA Workflow (Text Description)

Accordingly, the use of PRISMA in this work focuses on documenting the filtering protocol rather than evaluating the methodological quality of each article. The detailed screening process is presented visually in the PRISMA flow diagram (Table 2). PRISMA citation has been added to acknowledge the standardized reporting structure supporting our workflow. The initial Web of Science Core Collection search yielded 4280 records. After removing 3920 duplicates, 2890 unique publications remained for title–abstract screening. Applying database index filters (SCIE and SSCI) resulted in 2398 eligible records. Subsequent filtering by document type (Article, Review, and Proceedings Paper) refined the dataset to 2392 studies, of which 2389 were identified as English-language publications. All 2389 records were evaluated at full-text level and confirmed as eligible for inclusion in the final bibliometric analysis.

Table 2. PRISMA-Style Flow Diagram.

Records identified through WoS search (<i>n</i> = 4280)	
↓	
Duplicates removed (<i>n</i> = 3920)	
↓	
Records screened (title/abstract) (<i>n</i> = 2890)	Records excluded (not SSCI/SCIE) (<i>n</i> = 492)
↓	
SSCI and SCIE records (<i>n</i> = 2398)	Excluded (not Article/Review/Proceeding) (<i>n</i> = 6)
↓	
Articles/Reviews/Proceedings (<i>n</i> = 2392)	Excluded (non-English) (<i>n</i> = 3)
↓	
English-language articles (<i>n</i> = 2389)	
↓	
Full-text articles assessed for eligibility (<i>n</i> = 2389)	
↓	
Final articles included in the analysis (<i>n</i> = 2389)	

3.3. Research Methods

For bibliometric analysis, this study employs VOSviewer 1.6.20, two widely used tools for scientific mapping. VOSviewer is utilized to construct and visualize networks of co-authorship, co-citation, and keyword co-occurrence, thereby identifying collaboration patterns, influential publications, and thematic clusters [46].

The calculation method for average citations has now been explicitly stated in the manuscript and table notes to ensure clarity and transparency. The study adopts an adjusted approach to account for differences in publication age, defined as:

$$\text{Average yearly citations} = \frac{\text{Total citations}}{\text{Years since publication} + 1}$$

This formula prevents division-by-zero issues for publications in 2025 and provides a more accurate representation of citation impact over time.

To support the methodological choice, references have been added that demonstrate precedent for this adjusted citation-window normalization in bibliometric analyses. Notably, Egghe and Rousseau (2000) and Harzing and Alakangas (2016) provide justification for using similar adjustments, reinforcing the robustness and validity of the approach in evaluating research impact [47,48].

The choice of a bibliometric method is particularly suitable for this topic as it not only quantifies the research output but also uncovers latent connections between concepts and disciplines. By analyzing publication trends, geographic distributions, and thematic clusters, this study provides valuable insights into how DEA has been applied to address pressing energy and environmental challenges. Moreover, the methodology facilitates the identification of gaps in literature, paving the way for future research on methodological innovations and practical applications of DEA in sustainability contexts.

4. Results

4.1. Publication Trends

The analysis of publication trends from 2000 to 2025 in Figure 1 reveals a clear upward trajectory in scholarly output, moving from only 2 records in 2000 to a peak of 340 in 2022. During the early stage (2000–2010), publication activity remained minimal, with fewer than 15 publications per year. This period indicates that research in this field was still emerging and had not yet attracted substantial academic attention.

From 2011 to 2018, the field entered a growth phase, with records increasing from 26 in 2011 to 184 in 2018. This steady rise reflects a growing recognition of the topic's importance within academic and professional discourse. The acceleration phase followed between 2019 and 2022, when publications more than doubled in just four years. The year 2022 marked the highest output with 340 records, suggesting strong global interest likely driven by technological advancements, policy debates, and post-pandemic recovery research.

After 2022, publication counts exhibited a modest decline, with 244 articles in 2023, 211 in 2024, and 127 in 2025. However, the lower figure for 2025 is likely due to incomplete indexing and data availability rather than a true reduction in research output, as records from the most recent year are often still undergoing database processing. This suggests that the apparent downward trend should be interpreted cautiously.

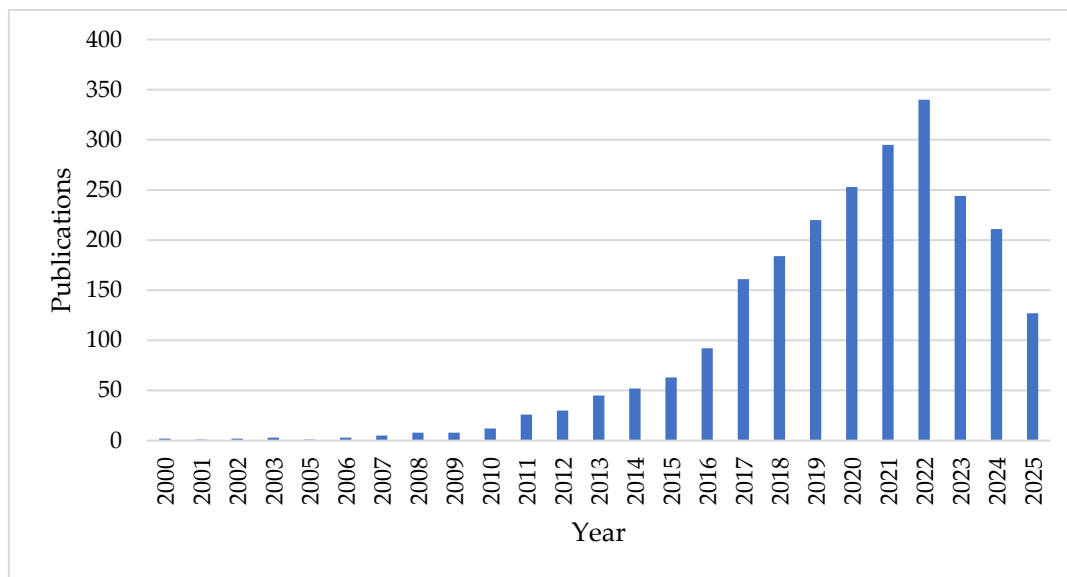


Figure 1. Growth trajectory of DEA-related studies in energy & carbon emission.

Beyond indexing delays, the fluctuation may also relate to evolving academic priorities and funding allocations as countries reassess their strategies toward carbon neutrality. For instance, some research initiatives may be shifting toward integrated evaluation frameworks, combining DEA with machine learning, ESG scoring, or life-cycle assessment, leading to potential dispersion of publications across broader sustainability journals. In addition, increasing interdisciplinary collaboration could redistribute DEA-based studies into domains such as environmental sciences, urban planning, and industrial engineering, temporarily affecting publication concentration.

Despite the short-term variability, the continued appearance of DEA-related studies in renewable energy and carbon-efficiency assessment indicates that the field remains active. Long-term patterns reinforce the sustained relevance of DEA as a quantitative tool for guiding sustainability decision-making, and future years are expected to reflect further growth once indexing records are fully updated.

Overall, the findings highlight several key insights. As shown in Figure 1, the field has experienced exponential growth since 2010, achieving maturity between 2019 and 2022. The peak in 2022 indicates the height of global scholarly attention, while the slight decline afterward should be interpreted cautiously, as it may reflect cyclical publishing patterns or incomplete indexing. Given the consistently high output since 2019, the research area is now well-established and continues to hold significant academic potential.

4.2. Geographic and Institutional Distribution

The analysis of publication output across countries and regions reveals a clear imbalance in research contributions (shown in Figure 2). China emerges as the predominant contributor, producing 1581 publications—far surpassing all other nations. This leading position reflects China’s consistent investment in research and development and its alignment with long-term national strategies aimed at carbon mitigation and energy transition. Existing literature shows that Chinese scholars frequently focus on carbon emission efficiency, the impacts of environmental regulations, and methodological innovations such as network and dynamic DEA models. These research directions mirror China’s broader pursuit of carbon neutrality and modernization of its energy infrastructure. Collectively, this dominant presence underscores not only China’s robust research capacity but also its

expanding role in shaping both the methodological approaches and thematic priorities of DEA-based energy research on a global scale.

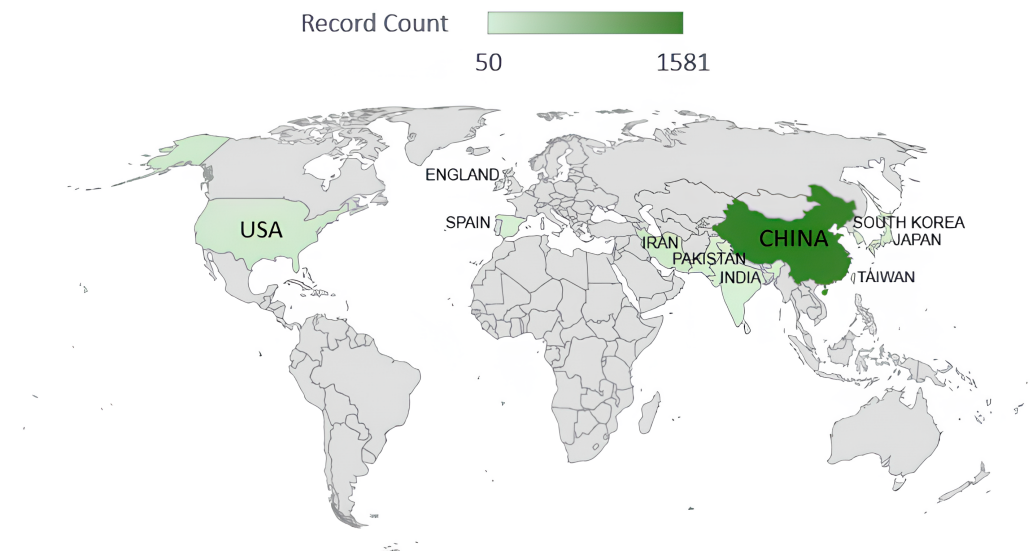


Figure 2. Leading countries.

In comparison, Taiwan (221 publications) and the United States (146 publications) rank second and third, respectively. Although their publication volumes are considerably lower than China's, both countries exhibit distinctive and meaningful research trajectories. Taiwan's output is particularly noteworthy given its relatively small population and limited resource base. Thematically, Taiwanese studies often emphasize renewable energy productivity, technological innovation, and efficiency benchmarking—reflecting a focused and efficient scientific community. Meanwhile, the United States maintains a strong presence in the field, frequently contributing to hybrid sustainability frameworks and interdisciplinary approaches that integrate DEA with environmental assessment tools. Despite its smaller output compared with China, the U.S. research remains conceptually influential, particularly in advancing methodological diversification and policy-oriented applications.

A second tier of contributors comprises Iran (127 publications), England (100), and Japan (76), each demonstrating moderate yet consistent research activity. Iran's position is particularly noteworthy given the constraints imposed by economic sanctions and limited opportunities for international collaboration, which typically hinder research productivity. England and Japan, both equipped with highly developed academic systems, continue to contribute steadily to the field, although their publication volumes appear relatively modest compared with their broader global standing in scientific research.

The third tier includes Pakistan (67 publications), South Korea (64), Spain (54), and India (50). Although their publication volumes remain relatively modest, these countries demonstrate an increasing engagement in the global research landscape. Notably, Pakistan and India reflect the rising contribution of emerging economies to international knowledge production. South Korea's comparatively lower output is somewhat unexpected, given its strong scientific and technological reputation, which may suggest either a thematic concentration of the dataset or underrepresentation within this specific research domain.

In summary, the global distribution of publications reveals China's overwhelming dominance, followed by a small group of notable but less prolific contributors. The substantial gap between China and other countries underscores the pronounced imbalance in global research capacity. Nevertheless, the growing participation of countries such as Iran, Pakistan, and India points to a gradual diversification of contributors, indicating that

research in this field is extending beyond traditional academic powerhouses to include a broader range of emerging and developing economies.

Table 3 presents the leading institutions contributing to the research field, providing insight into potential research centers and the distribution of academic activity. The Chinese Academy of Sciences (CAS) leads with 117 records, underscoring its role as the driving force in China’s academic research. As the nation’s premier research institution, CAS’s dominance reflects its broad disciplinary scope and substantial government support, enabling significant contributions across multiple domains.

Table 3. Active institutions and collaborations.

Affiliations	Record Count
Chinese Academy of Sciences	117
Soochow University	89
Nanjing University of Aeronautics Astronautics	73
Beijing Institute of Technology	69
North China Electric Power University	59
Xiamen University	56
University of Science Technology of China Cas	55
Hefei University of Technology	52
Southeast University China	48
Hohai University	45

Following CAS, Soochow University (89 publications) and Nanjing University of Aeronautics and Astronautics (73) emerge as the next most active contributors. Soochow University’s strong output underscores the growing influence of regional universities beyond China’s traditional elite, while Nanjing University of Aeronautics and Astronautics highlights the pivotal role of applied science and engineering institutions in advancing research on technology, sustainability, and governance.

Other notable contributors include Beijing Institute of Technology (69), North China Electric Power University (59), and Xiamen University (56), reflecting broad participation across both technical and comprehensive universities. North China Electric Power University exemplifies the intersection of energy and sustainability research, closely aligned with ESG-related themes.

The University of Science and Technology of China (55) and Hefei University of Technology (52) maintain a strong presence, emphasizing interdisciplinary research and applied innovation. Similarly, Southeast University (48) and Hohai University (45) further diversify the institutional landscape, with Hohai’s contributions linked to water management and environmental sustainability.

Overall, this distribution indicates that China’s research output is not only concentrated in top-tier institutions but also distributed across specialized universities, particularly those with technical, environmental, and governance orientations. The pattern suggests a coordinated national effort in which universities leverage their disciplinary strengths, reinforcing China’s leading role in this research field.

4.3. Key Contributors to DEA Research on Renewable Energy and Carbon Efficiency

Table 4 presents the most prolific and influential authors contributing to DEA research on renewable energy and carbon efficiency. The H-index is a widely used bibliometric indicator that combines productivity and citation impact, but it has well-known limitations (e.g., sensitivity to career length, field differences, and inability to account for highly cited single works). For discussion of the H-index and alternative metrics [49–51]. Therefore, we present H-indices here to help readers contextualize author influence in combination

with other indicators (total citations, recent activity), rather than as a sole evaluative metric. The data show that Chiu Yung-Ho (Soochow University, Taiwan) stands out as the most productive scholar with 71 publications and an H-index of 33, reflecting both consistent output and recognition within the academic community. Following him is Li Y. (Nanjing University of Finance & Economics, China) with 62 publications and an H-index of 17, highlighting the strong research engagement from China in this field.

Table 4. Most prolific and influential authors.

Authors	Institutes	Country	Research ID	H-Index	Records
Chiu, Yung-Ho	Soochow University	Taiwan	H-5231-2019	33	71
Li Y	Nanjing University of Finance & Economics	China	FJK-9617-2022	17	62
Cui, Qiang	Southeast University	Bangladesh	KLC-0358-2024	22	37
Lin, Boqiang	Xiamen University	Taiwan	G-3960-2010	107	34
Lin, Tai-Yu	National Cheng Kung University	Taiwan	AAP-1501-2021	11	32
Feng, Chao	Chongqing University	China	A-6705-2019	48	28
Wang, Chia-Nan	National Kaohsiung University of Science & Technology	Taiwan	JZW-4462-2024	31	28
Sueyoshi, Toshiyuki	Tokyo Institute of Technology	Japan	GDM-5048-2022	53	27
Zhang, Ning	East China University of Science & Technology	China	HCI-7860-2022	57	27
Zhou, Peng	China University of Petroleum	China	A-6527-2012	73	27

Another significant contributor is Cui Qiang (Southeast University, Bangladesh) with 37 publications, demonstrating regional diversification of scholarship beyond the dominant hubs of China and Taiwan. In terms of influence, Lin Boqiang (Xiamen University, Taiwan) emerges as a leading figure, with an impressive H-index of 107 despite having 34 publications, indicating exceptionally high citation impact and scholarly visibility. Similarly, Zhou Peng (China University of Petroleum, China) shows a strong balance of productivity and influence with 27 publications and a high H-index of 73.

Other prominent contributors include Feng Chao (Chongqing University, China) and Wang Chia-Nan (National Kaohsiung University of Science & Technology, Taiwan), each with 28 publications and H-indices of 48 and 31, respectively. Meanwhile, Sueyoshi Toshiyuki (Tokyo Institute of Technology, Japan) and Zhang Ning (East China University of Science & Technology, China) demonstrate that even with fewer publications (27 each), their H-indices of 53 and 57 signify considerable academic impact. Lastly, Lin Tai-Yu (National Cheng Kung University, Taiwan), with 32 publications and an H-index of 11, adds further evidence of Taiwan's strong presence in this research domain.

Taken together, these findings highlight that the field is dominated by Asian scholars, particularly from China and Taiwan, who contribute both high productivity and strong citation influence. This regional concentration suggests that Asia, driven by rapid industrialization and energy challenges, is at the forefront of advancing DEA research applied to energy and environmental issues.

4.4. Citation Analysis

An examination of the most highly cited works reveals the intellectual foundations and evolving priorities in the application of data envelopment analysis (DEA) to renewable energy and carbon emission efficiency (Table 5). Early contributions were particularly influential in establishing methodological and empirical benchmarks. For instance, Hu and Wang (2006) pioneered the assessment of total-factor energy efficiency across Chinese regions, producing one of the most widely cited studies (1182 citations) with lasting annual influence (59.1 citations/year) [27]. Similarly, Zhou et al. (2008, 2010, 2012) advanced methodological innovations in environmental DEA, particularly through the introduction of the directional distance function and Malmquist index analysis [24,52,53]. These works,

published in *Energy Economics* and *European Journal of Operational Research*, provided a solid theoretical basis for measuring carbon performance and abatement costs, each attracting more than 400 citations, thereby anchoring subsequent research in rigorous econometric and operational research frameworks.

Table 5. Highly cited papers shaping the field.

Title	1st Authors	Journal Title	Year	Total Citations	Average per Year
Total-factor energy efficiency of regions in China	Hu, Jin-Li	Energy Policy	2006	1182	59.1
Energy and CO ₂ emission performance in electricity generation: A non-radial directional distance function approach	Zhou, P.	European Journal of Operational Research	2012	735	52.5
Total factor carbon emission performance: A Malmquist index analysis	Zhou, P.	Energy Economics	2010	615	38.44
The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China	Ren, Shenggang	Journal of Cleaner Production	2018	580	72.5
Public spending and green economic growth in BRI region: Mediating role of green finance	Zhang, Dongyang	Energy Policy	2021	554	110.8
Efficiency and abatement costs of energy-related CO ₂ emissions in China: A slacks-based efficiency measure	Choi, Yongrok	Applied Energy	2012	504	36
A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency	Mardani, Abbas	Renewable & Sustainable Energy Reviews	2017	486	54
Low-carbon city pilot and carbon emission efficiency: Quasi-experimental evidence from China	Yu, Yantuan	Energy Economics	2021	454	90.8
Measuring environmental performance under different environmental DEA technologies	Zhou, P.	Energy Economics	2008	414	23
Energy efficiency and sustainable development goals (SDGs)	Zakari, A.	Energy	2022	406	81.2

A second thematic cluster highlights the intersection of policy design and eco-efficiency outcomes. Ren et al. (2014) explored the effects of three types of environmental regulation on eco-efficiency across Chinese regions, amassing 580 citations with a high citation rate (72.5 per year), underscoring the growing academic and policy interest in regulation-driven performance [28]. Similarly, Yu et al. (2021) investigated low-carbon city pilot policies, offering quasi-experimental evidence that attracted 454 citations at an exceptionally high rate of 90.8 per year, reflecting the surge in empirical policy evaluations [54]. These contributions demonstrate the increasing role of institutional and regulatory frameworks in shaping carbon efficiency research.

A third set of studies emphasizes the link between economic development, finance, and sustainability goals. Zhang et al. (2021) examined the mediating role of green finance in promoting green economic growth in the Belt and Road Initiative (BRI) region, securing 554 citations with the highest average citation rate (110.8 per year) [55]. This illustrates the rising prominence of finance-driven sustainability mechanisms. In parallel, Zakari et al. (2022) explicitly connected energy efficiency to the Sustainable Development Goals (SDGs), a study already cited 406 times with a strong yearly average of 81.2, highlighting the global policy relevance of DEA applications [56].

Finally, review studies have played a vital role in consolidating knowledge and directing scholarly attention. Mardani et al. (2017) provided a comprehensive review of DEA applications in energy efficiency, which has since been cited 486 times, averaging 54 citations per year [57]. This review functions as a cornerstone, synthesizing fragmented studies and guiding new research trajectories. Collectively, these highly cited papers illustrate how DEA scholarship has evolved from methodological refinement and regional applications to encompass broader themes of policy, finance, and global sustainability.

4.5. Keyword and Thematic Analysis

The co-occurrence network in Figure 3 maps the intellectual and thematic landscape of Data Envelopment Analysis (DEA) applications in renewable energy and carbon emission efficiency. For reproducibility, the following settings were applied: minimum keyword occurrence = 5, counting method = full counting, resolution parameter (cluster resolution) = default, and label size scaling increased to improve readability. The map was exported as a PNG at 300 dpi and embedded in the manuscript. These settings improved label visibility while preserving cluster structure; raw data and VOSviewer project files are available upon request. Six major clusters emerged from the analysis, reflecting interconnected yet distinct research trajectories that collectively shape the field. The size of the nodes represents the frequency of keyword occurrence, while their proximity illustrates thematic overlap. These clusters demonstrate how DEA has evolved from a tool for measuring energy efficiency into a comprehensive framework for addressing global sustainability challenges.

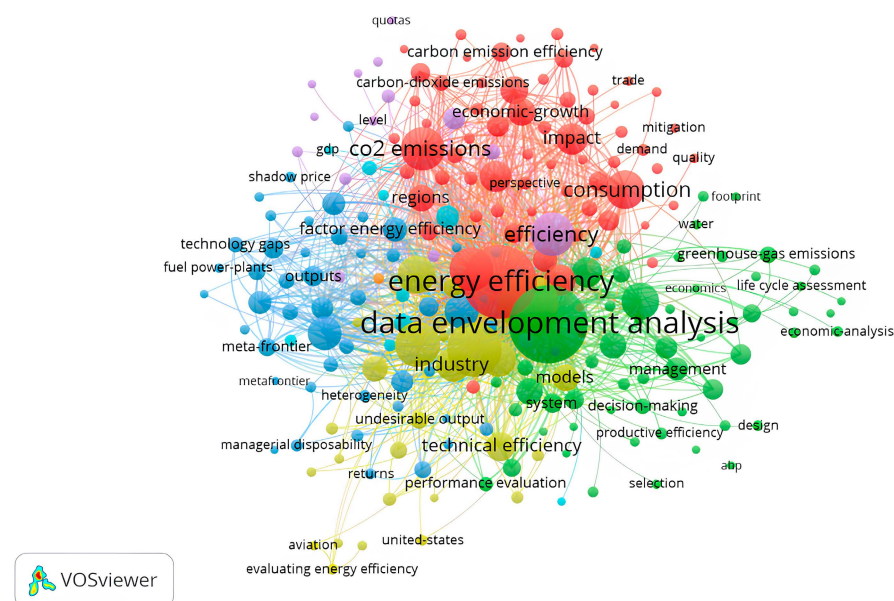


Figure 3. Keyword co-occurrence analysis.

Cluster 1 (Red): Carbon Emission and Climate Change Nexus

Cluster 1 is the largest and most central cluster, capturing essential themes such as carbon emissions, CO₂ emissions, carbon neutrality, climate change, and economic growth. This thematic core reflects the increasing deployment of DEA to evaluate environmental and carbon-reduction performance under tightening global climate commitments. Most studies quantify carbon-emission efficiency at national, regional, industrial, or urban levels, with China contributing a dominant share of outputs due to its active carbon-transition policymaking.

DEA findings are often integrated with macroeconomic indicators—such as economic growth, energy consumption, and industrial structure—to explore trade-offs between environmental responsibility and economic development [58,59]. Over time, the thematic

focus within this cluster has evolved from assessing isolated production systems toward broader evaluations of national- and regional-level carbon-neutrality pathways, especially in the context of global climate governance frameworks [60].

Cluster 2 (Green): Efficiency Benchmarking and Decision-Making Models

Cluster 2 centers on DEA's function as a benchmarking and managerial decision-support tool in energy systems, agriculture, and industrial production. Key terms—benchmarking, cross-efficiency, AHP, conservation, and economic analysis—illustrate the integration of DEA within multi-criteria decision-making (MCDM) frameworks to capture economic, technological, and environmental trade-offs [41,61].

The integration of Analytic Hierarchy Process (AHP) and cross-efficiency approaches highlights methodological hybridization, enabling comparative rankings of decision-making units (DMUs) and facilitating strategic prioritization across firms, sectors, and energy segments. These hybrid models offer nuanced assessment capabilities for regulators, managers, and policymakers engaged in sustainable energy planning [62].

Cluster 3 (Blue): Methodological Innovations and Eco-Efficiency

Cluster 3 captures the methodological evolution of DEA in response to increasing environmental and temporal complexity. Frequently co-occurring terms—directional distance function, eco-efficiency, Malmquist productivity, environmental assessment, and window analysis—highlight advances that allow DEA to incorporate undesirable outputs and dynamic-period analyses [63].

This cluster includes the development of non-radial, dynamic, and hybrid DEA models that better account for pollutants, multi-stage production processes, and technological change [64]. The use of Malmquist productivity indices has been particularly influential in tracking eco-efficiency growth over time, revealing whether improvements result from technological innovation or resource-use optimization [65].

Cluster 4 (Yellow): Industrial and Sectoral Applications

Cluster 4 captures the sector-specific implementation of DEA, particularly in *aviation*, *manufacturing*, and *heavy industries*. Keywords such as *two-stage DEA*, *bootstrap*, *decomposition*, *inefficiency*, and *environmental efficiency* reflect empirical studies that assess performance under real-world industrial constraints.

In the *aviation* sector, DEA has been widely employed to evaluate fuel efficiency, environmental impacts, and airline competitiveness [66]. In *industrial* applications, two-stage and dynamic DEA models have been used to identify inefficiency drivers, compare plant-level energy performance, and assess the outcomes of green innovation policies [67]. The frequent appearance of *bootstrap* indicates an interest in improving the robustness of DEA results by accounting for statistical uncertainty. Cluster 4's emphasis on applied modeling underscores the translation of theoretical advancements into practical tools that support sustainable industrial transformation.

Cluster 5 (Purple): Carbon Abatement, Circular Economy, and Equity Dimensions

Cluster 5 introduces a policy-oriented and normative dimension to the DEA literature. Key terms—including carbon-emission reduction, circular economy, equity, cost, and regional allocation—reflect the growing emphasis on evaluating fairness, resource distribution, and socio-environmental governance within efficiency-oriented frameworks. This thematic direction signals a shift from purely technical performance assessment toward broader policy and societal impact analysis.

Studies in this cluster increasingly use DEA to analyze how carbon-reduction responsibilities, emission quotas, and abatement costs can be allocated across regions or industries in ways that balance efficiency and equity considerations [68]. These investigations highlight the trade-offs inherent in climate-policy implementation, emphasizing that the pursuit of efficiency must be accompanied by attention to distributive justice and social inclusiveness.

The presence of the circular-economy keyword underscores an emerging research frontier in which DEA is applied to evaluate waste-reduction strategies, recycling efficiency, and resource-recovery practices [69]. This aligns with global sustainability agendas that encourage industrial upgrading and closed-loop systems to support low-carbon transitions.

Cluster 6 (Cyan): Productivity, Growth, and International Comparisons

Cluster 6 comprises macroeconomic and comparative themes, with key terms such as *Malmquist productivity*, *OECD*, *GDP*, *technical progress*, and *total factor productivity*. This cluster represents global-scale analyses that benchmark *energy and carbon efficiency* across countries, regions, or economic blocs such as the *European Union*.

Studies in this stream often employ the *Malmquist productivity index* to measure dynamic efficiency changes, distinguishing between technological progress and efficiency catch-up [70]. The focus on *OECD* and *EU economies* indicates increasing cross-national comparisons and policy evaluations under shared sustainability targets [71]. This cluster demonstrates DEA's capacity to link *micro-level efficiency analyses* with *macro-level productivity assessments*, contributing valuable insights for international energy governance and low-carbon growth strategies [72].

Overall, these six clusters reveal an integrated research landscape. The field has evolved from early studies on energy and carbon efficiency measurement toward sophisticated methodological innovations and policy applications. DEA has become an essential analytical framework for understanding how renewable energy systems contribute to emission mitigation, economic performance, and sustainable development goals.

5. Discussion

Insights from Results

The analysis reveals that Data Envelopment Analysis (DEA) has become a dominant methodological approach for evaluating efficiency in renewable energy systems and environmental performance. DEA's non-parametric nature enables it to handle multiple inputs and outputs without requiring a specific functional form, making it particularly suitable for assessing the efficiency of renewable energy plants such as wind, solar, and biomass facilities [57]. For example, studies like Hu and Jin-Li (2006) and Zhou et al. (2010) demonstrate the applicability of DEA in measuring regional and sectoral energy efficiency, offering policymakers and managers empirical insights into the allocation of resources and technological improvement paths [27,52]. These applications emphasize DEA's role in identifying best-performing renewable energy plants and benchmarking underperforming ones against efficient frontiers.

DEA has also emerged as a vital tool in carbon emission reduction and environmental benchmarking. It allows researchers to simultaneously measure economic performance and environmental impacts, enabling an integrated evaluation of eco-efficiency. The works of Ren et al. (2018) and Zhang et al. (2021) extend DEA's application by examining the mediating roles of environmental regulations and green finance in promoting carbon reduction [55,73]. Similarly, studies like Zhou et al. (2024) and Kou et al. (2022) apply DEA to investigate the effectiveness of policy interventions such as low-carbon city pilots and the contribution of energy efficiency to the Sustainable Development Goals (SDGs) [74,75]. These findings underscore DEA's versatility in addressing multidimensional sustainability targets, bridging the gap between energy economics and environmental management.

Methodologically, the evolution of DEA in this field reflects a clear trend toward more sophisticated analytical models. While classical DEA models focus on static efficiency assessment, contemporary studies increasingly employ network DEA, dynamic DEA, and DEA-Malmquist indices to capture intertemporal and inter-process efficiencies [24]. The DEA-Malmquist approach, as used in Zhou et al. (2010), facilitates the evaluation of pro-

ductivity changes over time, accounting for technological progress and efficiency shifts [52]. Additionally, hybrid models integrating DEA with machine learning (ML) techniques have emerged, enhancing predictive accuracy and enabling real-time performance monitoring. Such methodological advancements demonstrate a shift from traditional frontier analysis to more adaptive, data-driven efficiency frameworks.

Beyond these thematic advances, our synthesis identifies several methodological and contextual gaps that present opportunities for future inquiry. While DEA has been widely applied to benchmark renewable energy performance and carbon-emission reduction, relatively few studies incorporate dynamic systems perspectives that capture ecological complexity—for example, the role of biodiversity, land-use change, and ecosystem services in shaping clean-energy transitions [76]. Likewise, hybrid DEA–machine learning models remain in their infancy despite their strong potential to improve prediction accuracy, uncover nonlinear relationships, and enhance decision-support for energy planning [77,78]. Cross-country comparative analyses also remain limited; integrating policy–efficiency linkages across institutional contexts could generate deeper insights into how regulatory design influences environmental performance [79]. Addressing these gaps would significantly strengthen DEA’s role in guiding evidence-based energy and climate policymaking.

Comparison with Related Efficiency Methods

When compared with other efficiency measurement methods such as Stochastic Frontier Analysis (SFA), DEA presents distinct advantages and limitations. DEA’s key strength lies in its non-parametric flexibility and ability to handle multiple performance dimensions without requiring prior assumptions about production functions or error terms. This is particularly advantageous in environmental and renewable energy studies where data heterogeneity and measurement complexity are prevalent. In contrast, SFA, being a parametric approach, accounts for statistical noise and distinguishes inefficiency from random error, offering more robust results when measurement errors are significant.

However, DEA’s deterministic nature can lead to potential sensitivity to outliers and measurement errors, which may distort efficiency scores. Furthermore, while SFA provides confidence intervals and hypothesis testing, DEA results are largely relative and rely heavily on sample composition. Despite these limitations, the non-parametric flexibility of DEA makes it more adaptable to multidimensional sustainability contexts than SFA, particularly in integrating energy, environmental, and economic indicators. Recent literature increasingly combines both methods or incorporates hybrid DEA–SFA frameworks to leverage the respective strengths of each.

The findings underscore DEA’s central role in renewable energy and environmental efficiency research. Its evolution from classical models to hybrid and dynamic frameworks signifies a methodological maturity that aligns with the growing complexity of sustainability challenges. The integration of DEA with other analytical techniques holds promise for future research, particularly in refining carbon performance metrics and supporting data-driven environmental policy design.

6. Conclusions

This study provides a comprehensive mapping of the intellectual structure and research dynamics surrounding the application of Data Envelopment Analysis (DEA) in renewable energy and carbon emission efficiency. By synthesizing 2389 articles indexed in the Web of Science core collection, the findings illuminate the rapid expansion and diversification of DEA applications in the context of energy transition and environmental sustainability. The analysis reveals a strong concentration of research in Asia—particularly in China and Taiwan—where scholars such as Chiu Yung-Ho, Li Y., and Lin Boqiang have significantly advanced methodological innovation and empirical exploration in the field.

The review highlights three major thematic directions. First, DEA has evolved as a robust tool for benchmarking the operational and environmental efficiency of renewable energy systems, ranging from wind and solar power plants to national energy sectors. Second, DEA-based models have been instrumental in evaluating carbon emission efficiency and guiding low-carbon policy design, supporting governments and industries in their decarbonization efforts. Third, the methodological evolution from traditional DEA models toward network DEA, dynamic DEA, DEA–Malmquist index, and hybrid DEA–machine learning models demonstrates the field’s commitment to addressing complex, multi-dimensional energy systems with higher analytical precision.

Comparative insights also indicate that while Stochastic Frontier Analysis (SFA) remains valuable for parametric efficiency estimation, DEA provides greater flexibility in handling multi-input–multi-output structures and non-parametric datasets common in energy and environmental studies. Nonetheless, future research should consider integrating DEA with other frontier methods to enhance robustness and interpretability, particularly under uncertainty and heterogeneity in energy systems.

This study contributes to the ongoing discourse on sustainable energy management by charting the intellectual landscape, identifying influential contributors, and uncovering methodological trends that shape the efficiency measurement paradigm. The results provide a valuable reference for researchers, policymakers, and practitioners seeking to optimize renewable energy systems and advance carbon neutrality goals through data-driven efficiency assessment.

A promising avenue for future research is the integration of DEA with Environmental–Social–Governance (ESG) indicators and Life-Cycle Sustainability Assessment (LCSA) frameworks. While DEA has effectively measured eco-efficiency and carbon reduction, current applications rarely capture broader social and governance aspects. Incorporating ESG metrics, such as governance quality, labor practices, and community impact—would enable more holistic benchmarking and strengthen relevance for sustainability-driven decision-making and investment analysis.

Similarly, combining DEA with LCSA would allow assessment of cradle-to-grave environmental and cost burdens, enabling comparison of renewable technologies beyond operational performance. Such hybrid DEA–ESG–LCSA models could support cross-country benchmarking, policy scenario evaluation, and dynamic tracking of sustainability progress using extensions like Malmquist indices. Although challenges exist—such as inconsistent ESG disclosure and LCSA data availability—developing standardized indicator sets and hybrid DEA structures (e.g., multi-stage or network DEA) would enhance analytical rigor.

Although this study provides a comprehensive overview of DEA applications in renewable energy and carbon emission efficiency, it is important to acknowledge that the analysis relied exclusively on the Web of Science (WoS) Core Collection. As a result, relevant studies indexed only in other major databases—such as Scopus or IEEE Xplore—may not have been captured. Future integration of multiple databases could improve coverage and reduce potential database-specific selection bias. WoS was chosen due to its high metadata consistency, strong representation of energy-efficiency and DEA-related journals, and standardized citation formats, which support methodological rigor and replicability. Nonetheless, the absence of Scopus indexing constitutes a limitation that should be considered when interpreting the findings.

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