Applied Energy 413 (2026) 127744

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

India's rural energy transition: Evidence from village-level survey aggregates of clean energy adoption across states

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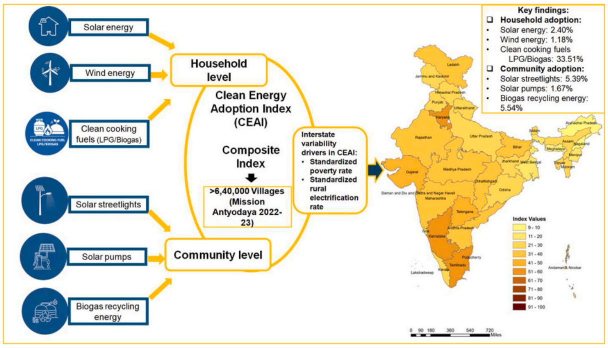
HIGHLIGHTS

- Develops a composite Clean Energy Adoption Index of energy transition in rural India.
- Integrates household-level and village-scale renewable infrastructure indicators.
- Identifies installation–utilization gaps in decentralized rural energy systems.
- Quantifies spatial disparities and structural determinants of interstate variation.
- Informs decentralized, demand-responsive energy planning and policy prioritization.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Clean energy
Composite energy index
Community energy infrastructure
Decentralized renewable energy
Energy policy
Rural energy transition

ABSTRACT

Energy transition in villages underpins sustainable development and net-zero goals, but nationally comparable metrics that distinguish between adoption of clean energy at the household level and community infrastructure are rare. To bridge this gap, the present study offers a new measure, namely the Clean Energy Adoption Index (CEAI), using village-level data from a survey conducted in 2022/23 by the Government of India as part of its 'Mission Antyodaya', which has the village as its focus. The survey spanned 641,357 villages and 244.17 million rural households. The proposed index, using normalized indicators, distinguishes between adoption at the household level of measures that contribute to sustainable development and village-level infrastructure built for the same end. The adoption of one such measure, namely decentralized supply of electricity to households, is low: 2.40% of 5.86 million households use solar systems and 1.18% (2.89 million) use wind power. Using clean fuels for cooking, another such measure, fares better, with 33.5% (81.83 million) households relying on liquefied petroleum gas or biogas. Community metrics show, for every 1000 villages, 55.5 biogas or waste-recycling units, 5399 installations of solar streetlights (totaling 3.46 million), and 1671 solar-powered pump-sets for irrigation (1.07 million units of electricity). Systematic normalization and aggregation allowed us to calculate the CEAI,

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https://doi.org/10.1016/j.apenergy.2026.127744
Received 31 December 2025; Received in revised form 9 March 2026; Accepted 15 March 2026

which was validated through robustness checks under varied scaling and weighting. Regression explained 65% of the variation between different Indian states ($R^2 = 0.65$), with rural electrification as the primary driver. A significant positive interaction between electrification, poverty alleviation, and literacy amplifies the level of adoption, signaled by the coming together of infrastructure, targeting the right beneficiaries, and human capital. India's national CEAI of approximately 31 suggests progress skewed toward infrastructure rather than toward adoption at the household level, with decentralized supply of electricity making a poor showing in terms of deployment at community level. Regional disparities underscore structural barriers. The index provides a scalable tool for prioritizing policies aligned with the UN Sustainable Development Goals in rural energy systems and can also be applied to other developing economies.

1. Introduction

Rural areas are central to global energy transition. They provide critical natural resources and host much of the infrastructure underpinning the transition, with far-reaching implications for both physical landscapes and rural social systems [1,2]. Despite the central position, explicit integration of rural development with energy-transition scholarship remains limited, and the concept of a distinct “rural energy transition” continues to remain inadequately explored in social science research [3]. This gap underscores the need for more grounded analyses that account for the interaction between material conditions, spatial structures, and social dynamics shaping rural energy pathways. Rural areas play a substantial although often under recognized role in advancing sustainable energy systems. Endowments of natural resources and agricultural base make villages particularly suited for deploying renewable energy including bioenergy [4]. Systems based on renewable energy not only generate clean energy but also put crop residues to productive use while contributing to mitigating the adverse effects of climate change [5]. Solar energy, wind energy, and biomass resources are widely available in rural areas and can be effectively harnessed for decentralized energy production [6,7]. However, technological potential alone does not ensure successful transition: social acceptance, institutional capacity, availability of finance, and spatial differences continue to lead to uneven levels of transition, highlighting the importance of location-specific and empirically grounded inquiry.

Energy transitions in rural areas are closely linked to sustainable and inclusive development. Improved access to modern and clean sources of energy enhances material living conditions, supports well-being, and expands opportunities for women. Empirical evidence shows that adoption of clean cooking fuels improves objective indicators of welfare [8–10], enhances subjective well-being and life satisfaction [11–13], and contributes to empowerment of women by reducing their drudgery and expanding their participation in economic and social spheres [14,15]. Despite these benefits, access to energy across many rural areas in developing economies remains unreliable and unaffordable. Expansion of the conventional electricity grid, although effective in urban settings, often proves expensive and technically challenging in remote or sparsely populated areas [16]. Addressing energy poverty, climate imperatives, and rural inequalities therefore requires efficient, equitable, and decentralized deployment of clean energy. Location-specific solutions based on renewable energy are particularly critical to reaching underserved communities and ensuring that the benefits of energy transition are inclusive.

India presents a particularly significant case. Rapid population growth and sustained economic expansion have sharply increased energy demand. As the world's most populous country, India accounts for nearly a third of Asia's population, and the country's energy consumption is projected to exceed that of any other major economy by 2040. Per capita energy use rose by approximately 25% over the past decade, increasing from 14,682 MJ per person in 2014/15 to 18,410 MJ per person in 2023/24 [17]. The *World Energy Outlook 2024* reports that total energy demand reached 1074 Mtoe (million tonnes of oil equivalent) in 2023 and is projected to grow to 1921Mtoe by 2040 [18]. India thus faces the dual challenge of meeting the rising demand while reducing carbon intensity in line with the country's global climate commitments [19]. Rural India occupies a pivotal position in this transformation, encompassing over 94% of the country's land area, housing nearly 65% of its population, and supporting close to half of its people who depend on agriculture for their livelihoods [20,21]. Clean energy for productive rural applications such as cold storage, rice mills, textile looms, and irrigation represents an estimated market of USD 53 billion. High-growth segments include solar-powered hydroponic systems to grow fodder, distributed solar refrigeration, and solar-based textile production [22]. Strengthening the adoption of clean energy in rural areas can enhance local energy self-sufficiency, generate employment, and address rural out-migration. Socioeconomic indicators reflect notable rural progress. Multidimensional poverty declined substantially between 2015/16 and 2020/21, lifting millions out of deprivation [23]. Penetration of the internet in rural areas has expanded rapidly, inequality in incomes is now narrower, and investments in infrastructure related to roads, education, and water have strengthened economic resilience [23,24]. However, these gains have also led to mounting environmental pressures. Rapid economic expansion has increased the country's dependence fossil fuels, resulting in larger emissions of greenhouse gases, worsening air pollution, and resource depletion [25–27]. The resulting impacts, including more frequent extreme weather events, retreating glaciers, and stressed ecosystems, underscore the urgency of accelerating the adoption of clean energy and greater energy efficiency [28–30]. Financial development further complicates this landscape: although improved capital allocation supports growth [31], fossil-fuel-intensive investment can hasten environmental degradation [32].

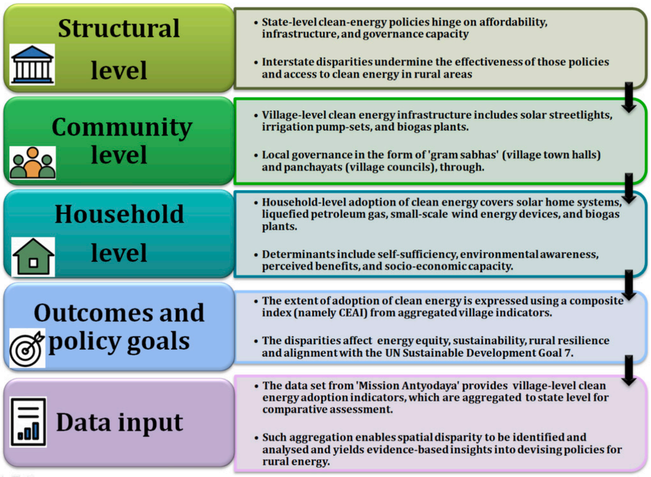
Aligning growth with expansion of clean energy is therefore central to India's long-term development trajectory. The ‘Panchamrit’ commitments require accelerated transformation in rural energy. Panchamrit refers to the five-point climate action plan announced by India at the COP26 summit in Glasgow in 2021 to fight climate change. The plan comprises 500 GW of installed capacity based on fuels other than fossil fuels (solar, wind, nuclear, hydro) by 2030, a 50% share of renewable energy in total installed capacity by 2030, a 45% reduction in emissions intensity (from its level in 2005), a reduction in emissions by 1 billion tonnes, and net zero by 2070 [33]. Given their demographic share and rising demand, rural areas are indispensable to achieving these targets. India's policy framework reflects an infrastructure-led transition model. National programs such as PM KUSUM (the Hindi acronym for Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyaan, which translates to the prime minister's program to ensure energy security and development for farmers, to be achieved through solar-powered pumpsets and decentralized energy supply), the Rooftop Solar program, the National Biogas and Manure Management program, and the ‘Pradhan Mantri Ujjwala Yojana’ (prime minister's scheme to make available clean cooking fuels in rural areas) have expanded renewable assets and access to clean cooking fuels. These initiatives emphasize supply-side infrastructure, often preceding sustained behavioral shifts in household energy use. Although infrastructure has expanded substantially, the outcomes of this energy transition remain spatially uneven.

Systematic spatial assessment of both the potential and deployment of clean energy is therefore essential. Mapping adoption at the household level, use of bioenergy on community scale, and decentralized supply of electricity based on renewable energy makes it possible to identify the patterns of diffusion of improvements, gaps in infrastructure, and regions to be prioritized for targeted intervention. Aligning technological deployment with such local resources as solar-rich or biomass-intensive zones can improve planning efficiency and policy coherence. Although lifecycle analyses and governance-focused studies have advanced the debate on an equitable distribution of energy [34,35], comprehensive state-level comparisons capturing inter-regional differences remain limited. Ultimately, energy transitions materialize at the levels of households and communities. Beyond infrastructure, meaningful transformation is reflected in shifts in energy-use patterns, demand behaviour, and the everyday socioeconomic routines that shape household and livelihood activities [36,37]. Assessing the progress toward energy transition in villages therefore requires that both access and adoption dynamics are measured.

Building on this perspective, the present study provides the first national-scale spatial assessment of India's progress toward energy transition in rural areas covering more than 640,000 villages. The transition is conceptualized as a recognized, strategically planned, and actively implemented process, measured through statistical evidence on energy-use types, structural configurations, functional characteristics, and spatial distribution [37]. The analysis quantifies the extent of adoption of solar-based electrification, wind-based supplementary power, community-scale biogas plants and waste-to-energy systems, and clean cooking fuels such as LPG (liquefied petroleum gas) and biogas at the level of households. The analysis also evaluates community-level infrastructure related to renewable sources of energy, including solar street lighting and solar-powered pump-sets for agricultural and public-service applications. Through a composite index framework, the study (1) systematically evaluates the extent of variation between different Indian states, (2) identifies leaders as well as laggards in energy transition, and (3) offers policy-relevant insights for advancing equitable and spatially balanced rural decarbonization.

1.1. Conceptual framework

The transition to clean energy in rural India unfolds across interconnected structural, institutional, and household domains. To capture these multi scalar dynamics, we adopted a three-tier analytical framework comprising macro (structural), *meso* (community), and micro (household) levels that situates observed adoption patterns within broader socio technical processes (Fig. 1). Drawing on the scholarship in the fields of energy access, institutional economics, and sustainability transitions [38,39], the framework conceptualizes technology diffusion not as a purely technical process but as one shaped by policy design, governance capacity, market structures, and user practices operating simultaneously across scales.



Structural level

- State-level clean-energy policies hinge on affordability, infrastructure, and governance capacity
- Interstate disparities undermine the effectiveness of those policies and access to clean energy in rural areas

Community level

- Village-level clean energy infrastructure includes solar streetlights, irrigation pump-sets, and biogas plants.
- Local governance in the form of 'gram sabhas' (village town halls) and panchayats (village councils), through.

Household level

- Household-level adoption of clean energy covers solar home systems, liquefied petroleum gas, small-scale wind energy devices, and biogas plants.
- Determinants include self-sufficiency, environmental awareness, perceived benefits, and socio-economic capacity.

Outcomes and policy goals

- The extent of adoption of clean energy is expressed using a composite index (namely CEAI) from aggregated village indicators.
- The disparities affect energy equity, sustainability, rural resilience and alignment with the UN Sustainable Development Goal 7.

Data input

- The data set from 'Mission Antyodaya' provides village-level clean energy adoption indicators, which are aggregated to state level for comparative assessment.
- Such aggregation enables spatial disparity to be identified and analysed and yields evidence-based insights into devising policies for rural energy.

Fig. 1. Multilevel framework for assessing the transition to clean energy in Indian villages.

1.1.1. *Macro, or structural, level*

At the macro, or structural, level, national policies, affordability, and infrastructure shape the trajectories of access to renewable energy. Large-scale public programs including PM-KUSUM, the Rooftop Solar program, and the National Biogas and Manure Management program expand the capacity of decentralized supply of renewable energy through subsidies on capital investments, support to bridge the viability gap, and performance incentives. Complementary schemes such as the Pradhan Mantri Ujjwala Yojana have accelerated the diffusion of clean cooking fuels among rural and low-income households. Despite these initiatives, disparities among different states in India remain pronounced. Variations in governance quality, fiscal capacity, institutional effectiveness, market maturity, and implementation efficiency generate uneven outcomes of the transition across states. The macro-structural layer therefore establishes the enabling—or constraining—environment within which subnational transitions in rural energy unfold.

1.1.2. *Meso, or community, level*

The *meso*, or community, level captures community-scale infrastructure and local institutional arrangements. Decentralized assets including solar streetlighting, solar-powered pump-sets for irrigation, community biogas plants, and waste-to-energy or recycling units depend heavily on local coordination, capacity to undertake routine maintenance and repairs, and collective governance structures. Weak institutional oversight, limited financing, or unclear ownership arrangements frequently undermine long-term functionality. Conversely, robust monitoring systems, community participation, and accountable management enhance reliability, equity, and socioeconomic benefits [40,41]. This intermediate layer functions as a critical transmission mechanism between national policy objectives and household-level outcomes, translating macro-level programs into tangible service delivery within rural settlements.

1.1.3. *Micro, or household, level*

At the micro, or household, level, decisions on adoption are shaped by affordability, reliability, perceived benefits, ease of operation, maintenance requirements, and sociocultural compatibility. Household investments in solar home systems, decentralized electrification, biogas digesters, or clean cooking fuels are embedded within broader institutional and market environments. These decisions reflect not only income and access constraints but also behavioral norms, gender roles, and expectations regarding service quality [42,43]. The household layer thus captures the demand-side dynamics of the transition, highlighting how infrastructure availability translates—or fails to translate—into sustained usage and behavioral change.

1.1.4. *Operationalization through the clean energy adoption index*

The framework described above is operationalized through a composite index, namely the Clean Energy Adoption Index (CEAI), which aggregates indicators across household and community domains while treating macro-structural drivers as contextual explanatory factors. Household-level indicators include the extent of adoption of decentralized electricity systems and clean cooking fuels (LPG and biogas). Community-level indicators capture densities of infrastructure related to renewable energy on a village scale, including public and productive-use assets. Using Mission Antyodaya data covering more than 640,000 villages, the CEAI enables systematic state-level benchmarking of the extent to which clean energy has been adopted in Indian villages. By integrating infrastructure provision and household uptake within a unified composite structure, the index advances beyond earlier electrification-focused or small-sample analyses and provides a comprehensive measure of performance related to energy transition in rural areas. Robustness and sensitivity analyses validate the selection of indicators, normalization procedures, and aggregation methods, ensuring that the method is both stable and replicable.

1.1.5. Research objectives and policy relevance

The study pursues three core objectives: (1) to identify the structural and institutional correlates underlying the disparity among Indian states in terms of the extent to which their rural areas have adopted clean energy, (2) to benchmark state-level performance and quantify spatial disparities, and (3) to serve as a basis for prioritizing those infrastructural, financial, and governance interventions that enhance both efficiency and equity in transitioning to clean energy in rural areas.

The proposed index, namely CEAI, facilitates cross-state comparison, gap analysis, and progress tracking toward adoption of clean energy in India and its climate commitments, including the United Nations Sustainable Development Goal 7 (SDG 7) and related global targets [44–47]. As a transparent and scalable tool based on publicly accessible survey indicators and replicable aggregation techniques, the framework is transferable to other data-constrained developing-country contexts. By bridging infrastructure metrics and household adoption dynamics, the index contributes to evidence-based rural energy planning and strengthens analytical capacity for monitoring sustainable energy transitions in low- and middle-income economies.

2. Data and methods

2.1. Conceptual framing and data source

The present study constructs a state-level composite indicator, using data from more than 640,000 villages in India, of the extent to which clean energy has been adopted in rural India. The data were part of the Mission Antyodaya 2022/23 survey, which spanned all the states and union territories in India (MoRD, 2025) [48]. The analysis is based on the premise that widespread uptake of a new energy source signals the onset of energy transition [36]. Clean energy in this context encompasses electricity from renewable sources of energy (solar and wind), decentralized bioenergy (biogas), and LPG for cooking. Although LPG is a fossil fuel, it is included due to its substantially lower particulate emissions and proven role in mitigating household air pollution in rural areas. The survey offered standardized, self-reported data on infrastructure and household amenities, capturing technology adoption and infrastructure rather than generation or consumption of energy and there liability, affordability, or service quality [49]. Village-level data were aggregated as the mean values for the respective states or union territories before constructing the index. The resulting CEAI thus provides a state-level measure derived from village-level data.

2.2. Selection of indicators

Six indicators were selected to capture both household-level adoption and community-level infrastructure within the CEAI framework. At the household level, adoption was measured as the percentage of rural households using solar energy for electrification (SEEI), wind energy for electrification (WEEI), and clean cooking fuels (specifically LPG and/or biogas) captured under the Clean Cooking Fuel Index (CCFI). At the community level, infrastructure was assessed as the proportion of villages equipped with solar street lighting (SSLI), solar-powered irrigation pump-sets (SPI), and community biogas and waste-recycling systems (CBG&WRI). Together, these indicators provide a multidimensional representation of decentralized access to clean energy, distinguishing between end-user adoption and shared infrastructure for renewable energy. These indicators capture observable dimensions of the diffusion of clean energy in rural systems. The index excludes reliability, affordability, service quality, mini-grid performance, or productive energy uses, positioning it as an adoption- and infrastructure-focused composite rather than a comprehensive index of the performance of energy services in rural India.

2.3. Normalization and aggregation

All indicators were standardized using min–max normalization to a 0–100 scale:

$$I_{ij} = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}}$$

where Iij denotes the normalized value of indicator *i* for the state or union territory *j*. This transformation preserves interstate variation while ensuring comparability across heterogeneous units.

Outliers were assessed using inter quartile range (IQR) thresholds and absolute standardized score criteria ($|z| > 3$). Extreme observations were retained, as they reflect structural interstate disparities rather than measurement errors. To evaluate sensitivity to extreme values, a 5% Winsorized min–max normalization (5th–95th percentile trimming) was additionally implemented and compared against the baseline specification. (The lowest 5% of data points were replaced by the value at the 5th percentile, and the highest 5% of data points were replaced by the value at the 95th percentile.)

The composite CEAI was computed as the arithmetic mean of six component indices:

$$\mathrm{CEAI}j = \frac{1}{n} + \ldots \sum_{i=1}^{n} \mathrm{I}ij$$

where nj $\leq$ 6 represents the number of available indicators. Equal weights were applied to ensure transparency and balanced representation of household and community dimensions. States with substantial missing data were excluded from analysis.

2.4. Robustness and sensitivity analysis

To address the concerns related to normalization sensitivity and weighting choice, four categories of robustness checks were undertaken. Spearman rank correlations between the baseline equal-weighted CEAI and alternative scaling specifications ranged from 0.991 to 0.997 (z-score, 5% Winsorized min–max, and percentile rank transformation), whereas correlations under alternative weighting schemes ranged from 0.982 to 0.989 (Appendix 1, Table A1), confirming very high ordinal robustness. Kendall's τ coefficients ranged from 0.841 to 0.955, reinforcing strong rank consistency across specifications. Mean rank differences varied between 0.38 and 1.47, and the maximum observed rank shift did not exceed the four positions under any alternative specification.

The index was recomputed using two data-driven weighting schemes derived from principal component analysis (PCA) and entropy-based methods. The weights derived from PCA ranged from 0.13 to 0.21, whereas entropy-based weights ranged from 0.15 to 0.19 across the six component indices (Appendix 1, Table A2). Both approaches yielded near-uniform weight distributions, and no single indicator dominated structurally. Rank correlations relative to the equal-weight baseline remained very high (Spearman $\rho = 0.989$ for PCA; 0.982 for entropy).

Bootstrap resampling (2000 iterations) further confirmed the stability of the rankings (Appendix 1, Table A3). The highest-ranked state remained invariant (rank width = 0), whereas most states showed rank intervals of four positions or fewer. The widest interval was of five positions, occurring among closely clustered mid-tier states. At the lower end, the bottom-ranked state showed a rank width of one position, indicating very high stability. These results demonstrate that CEAI rankings are not driven by sampling variability in index construction.

Quintile stability analysis (Appendix 1, Table A4) indicated that all baseline top- and bottom-quintile states retained their quintile classification across the six specifications tested. The gap in terms of the CEAI between quintiles exceeded30 index points, making cross-quintile movement highly unlikely under reasonable changes in normalization or weighting. Collectively, these robustness checks confirm that the observed ranking patterns are structurally stable and methodologically resilient.

2.5. Spatial analysis and regionalization

Spatial patterns were analyzed using ArcGIS (ArcMap v10.8.1). Choropleth maps were classified using the Jenks natural breaks optimization method with ten classes (0–10, 10–20, …, 90–100), minimizing within-class variance and maximizing between-class variance.

For comparative analysis, states and union territories were grouped into five macro regions: North, South, East, West, and North-East. Alternative regional aggregations did not change the state-level rankings (Spearman $\rho = 1.000$), confirming complete robustness of the regional grouping.

2.6. Explanatory model

To complement the descriptive and spatial analysis of the CEAI, an explanatory cross-sectional regression framework was developed to identify the structural correlates of interstate variation across 34 Indian states and union territories. Whereasthe CEAI provides relative performance rankings, the regression model enables a systematic evaluation of whether socioeconomic and infrastructural conditions account for observed differences in the extent to which renewable energy had been adopted.

2.6.1. Variable standardization and model selection

All continuous explanatory variables were standardized into zero-mean, unit-variance z-scores to ensure scale comparability and to mitigate artificial multicollinearity arising from multiplicative interaction terms. Standardization reduced the maximum variance inflation factor (VIF) to 2.73, well below the conventional threshold of 5.

A systematic all-subsets selection procedure was implemented, evaluating ten two-way interactions, three quadratic terms, and four three-way interactions (over 150 candidate specifications). Models were ranked by Adjusted R^2, conditional on simultaneously satisfying (1) residual normality (Shapiro–Wilk test, $p > 0.05$), (2) homoscedasticity (Breusch–Pagan test, $p > 0.05$), and (3) acceptable multicollinearity (maximum VIF < 5). The preferred specification maximizes adjusted R^2 while meeting all diagnostic criteria and minimizing the Akaike Information Criterion (AIC), consistent with the principle of parsimony.

2.6.2. Final log-linear specification

The dependent variable is the natural logarithm of CEAI, $\ln(\mathrm{CEAI}\_j)$. Log-transformation was adopted to (1) correct residual non-normality observed in the linear specification, (2) reflect theoretical diminishing returns in technology diffusion, and (3) reduce moderate right-skewness in the distribution of CEAI. Post-transformation diagnostics confirmed that the residuals were normally distributed and improved the fit of the model.

Ordinary least squares (OLS) estimation yieldedthe following specification:

$$\ln\left(\mathrm{CEAI}\_j\right) = \beta_0 + \beta_1 zX_2\_j + \beta_2 zX_3\_j + \beta_3\left(zX_2\_j \cdot zX_3\_j \cdot zX_4\_j\right) + \beta_4 zX_4\_j + \varepsilon\_j$$

where zX_2, zX_3, and zX_4 denote the standardized poverty rate, rural electrification rate, and literacy rate, respectively. The model includes a theoretically motivated triple interaction term capturing the joint moderating effects of poverty, electrification, and literacy.

Per capita income (X_1) and an agroecological zone dummy (X_5) were evaluated but excluded from the final model. Per capita income was statistically insignificant across specifications and did not improve AIC, whereas the agroclimatic dummy lacked explanatory contribution. The retained specification therefore balances theoretical relevance and statistical robustness.

2.6.3. The triple interaction term

The inclusion of the three-way interaction extends the additive framework to capture conditional and synergistic effects among infrastructure, human capital, and socioeconomic targeting. Electrification provides physical access; literacy proxies absorptive capacity; and poverty reflects both deprivation and eligibility for subsidy-based programs.

The marginal effect of electrification is conditional:

$$\partial \ln(\mathrm{CEAI}) / \partial (zX_3) = \beta_2 + \beta_3 (zX_2 \cdot zX_4)$$

Thus, the electrification effect was stronger in states in which poverty and literacy were simultaneously above average, indicating a convergence premium when infrastructure readiness, human capital, and the potential to target appropriate beneficiaries co-exist. This specification enhances the model's policy-diagnostic relevance by identifying state profiles most responsive to investment in electrification.

2.6.4. Data sources

All the explanatory variables were sourced from official publications of the Government of India pertaining to the reference period 2022/23. Poverty rates were obtained from NITI Aayog (Multidimensional Poverty Index, 2021); rural electrification data, from the Ministry of Power; literacy rates, from the Census of India (2011), and adjusted for intercensal trends and per capita income from the Ministry of Statistics and Programme Implementation's State Domestic Product series. Agroecological classification followed the zones as delimited by the Indian Council of Agricultural Research. State-level harmonization ensured temporal consistency across sources.

2.6.5. Diagnostic testing and validation

The final model was subjected to comprehensive OLS diagnostics, including Shapiro–Wilk and Jarque–Bera tests for residual normality, Breusch–Pagan and White tests for heteroscedasticity, VIF for multicollinearity, Durbin–Watson statistics for error independence, and Cook's Distance and Studentized residuals for influential observations. Back-transformed fitted values ($\exp[\ln(\mathrm{CEA}\hat{\mathrm{I}})]$) remained within the theoretical [0,100] range for all states, confirming internal consistency despite the bounded dependent variable.

2.6.6. Interpretation strategy

The analysis was associative rather than causal. With $n = 34$ cross-sectional observations, coefficients on standardized predictors represent semi-elasticities in standard deviation units: a one-standard-deviation increase in X_i corresponds to a β_i change in ln (CEAI), equivalent to $(\exp(\beta\_i) - 1) \times 100\%$ change in CEAI, ceteris paribus.

Sensitivity analyses across alternative predictor subsets, dependent-variable normalizations, and sub-index specifications confirmed the directional stability of the main effects, suggesting that the reported structural associations were robust.

2.7. Reproducibility

All indicators were derived from the public Mission Antyodaya 2022/23 dataset. Village-level data were aggregated as mean values for the state or union territory using population-weighted averages (household indicators) and proportional village coverage (infrastructure indicators). The full workflow, comprising aggregation, normalization, indexing, robustness tests, and ranking, is fully reproducible from the source data.

3. Results

Fig. 2 presents the results for Indices 1 and 2, which assess the

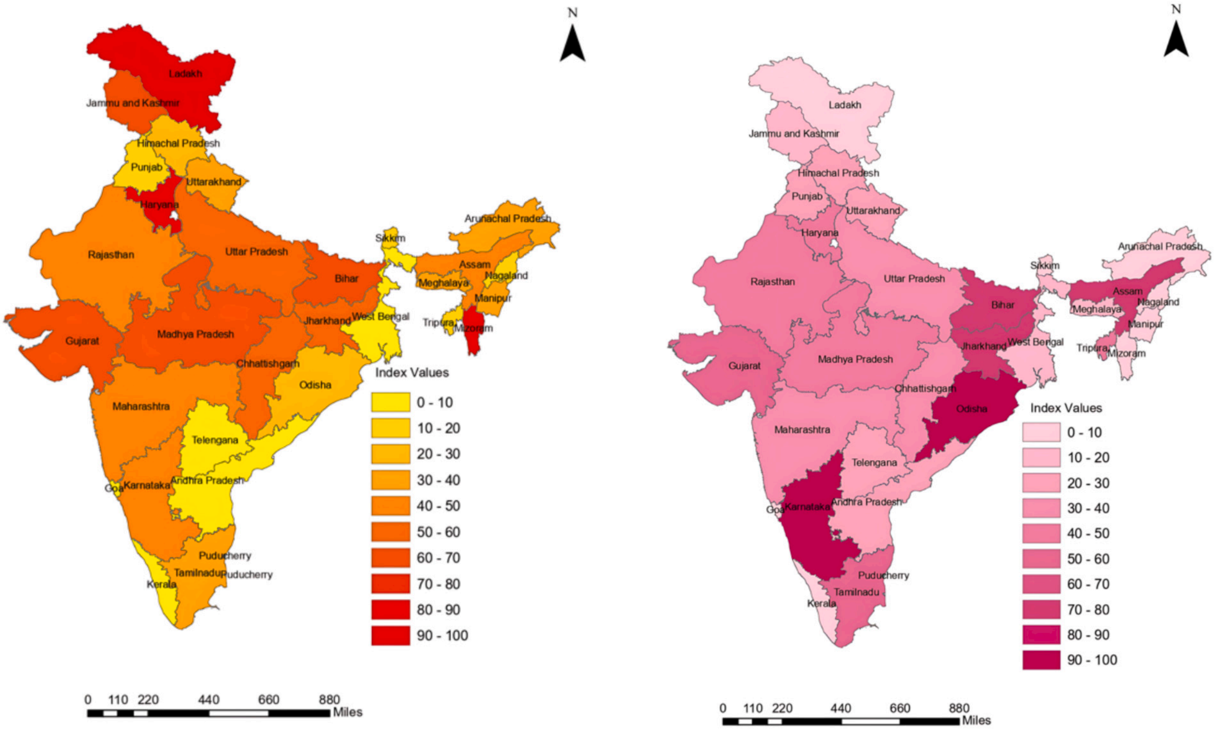


Fig. 2. (a) Index of solar energy for electrification, by state (0–100; household adoption percentage normalized using min–max scaling; denominator: total rural households). Choropleth classification: equal-interval (10-unit classes). (b) Index of wind energy for electrification, by state (0–100; household adoption percentage normalized using min–max scaling; denominator: total rural households). Choropleth classification: equal-interval (10-unit classes).

adoption at households (HHDs) level of solar energy (Fig. 2a) and of wind energy (Fig. 2b), respectively. The figures highlight spatial variations in adoption and the degree to which these technologies were embedded in everyday use of energy in rural areas.

3.1. Indices 1 and2: Adoption of clean energy (solar and wind) at household level

Fig. 2a is a choropleth map of Indian states showing the values of the household-level solar electrification index (SEEI; 0–100 scale) in their rural areas. Ladakh shows the highest value (dark red, within a range of 90–100), followed by Haryana (70–80), Mizoram, Gujarat, and Madhya Pradesh (progressively 60–70 and 50–60). Bihar shows moderate values (30–40), whereas Uttar Pradesh and Jharkhand show the lowest values among major states (10–20 and 0–10, respectively). These spatial distributions demonstrate the efficacy of decentralized solar systems in remote, grid-constrained regions such as Ladakh, complemented by effective policy outreach in states such as Haryana and Mizoram. Conversely, persistent low SEEI in populous states highlights barriers including high upfront costs and limited adoption mechanisms. As Sharma et al. (2021) [50] note, awareness of solar home systems and solar-powered pump-sets was greater in energy-poor villages of Bihar, Jharkhand, and Uttar Pradesh, although constraints remain—reinforcing the need for targeted subsidies, financing, and institutional support to ensure equitable rural electrification.

Fig. 2b does for the household-level wind electrification index (WEEI; 0–100 scale) what Fig. 2a did for solar power. Karnataka shows the highest values (70–100), followed by Odisha and Bihar (progressively 50–70), with relatively strong performance also by Assam and Jharkhand (40–60). In contrast, several northern and northeastern states, along with union territories, record very low values (0−20), indicating minimal household-level penetration of wind energy. This geographic concentration underscores wind energy's dependence on favorable wind regimes and technical feasibility, unlike the more universally deployable solar systems. The uneven distribution highlights the need for region-specific strategies for deploying renewable energy that align the choice of technology with local resources, infrastructure, and viability to optimize rural electrification.

3.2. Index 3: adoption of clean cooking fuels at household level

Fig. 3 is a choropleth map of Indian states showing the use of clean cooking fuels at the household level (0–100 scale) in their rural areas. Kerala, Lakshadweep, and Andaman and Nicobar Islands show the highest values (80–100), followed by Telangana, Sikkim, Goa, and the union territory comprising Dadra, Nagar Haveli, Daman, and Diu (70–90). Several northern and central states show intermediate values (40–60), whereas Jharkhand, Chhattisgarh, Rajasthan, and Arunachal Pradesh show the lowest values (0−30), reflecting persistent reliance on biomass, a messy fuel at best. This heterogeneous distribution—skewed in favor southern states and smaller union territories—highlights the role of strong administrative outreach, scheme implementation, and last-mile delivery in driving adoption beyond simple regional gradients. Lower-performing regions underscore barriers such as affordability, the ease of exchanging a full cylinder of LPG for an exhausted one, and infrastructure gaps, necessitating targeted interventions for sustained supply chains and behavioral consolidation and a focus on long-term use in the case of high performers.

3.3. Indices 4 and 5: adoption of renewable energy (solar streetlights and pump-sets) at community level

Fig. 4 shows the distribution of adoption of community-level solar streetlights (Index 4) and solar-powered pump-sets (Index 5).

Fig. 4a shows that village- and community-level adoption of solar streetlights in rural India remains largely low to moderate, with only a few states showing high levels of adoption. The highest levels are seen in Lakshadweep, followed by Kerala, Karnataka, Tripura, and Haryana, reflecting more active deployment through local institutions and targeted rural infrastructure initiatives. Overall, the erratic distribution

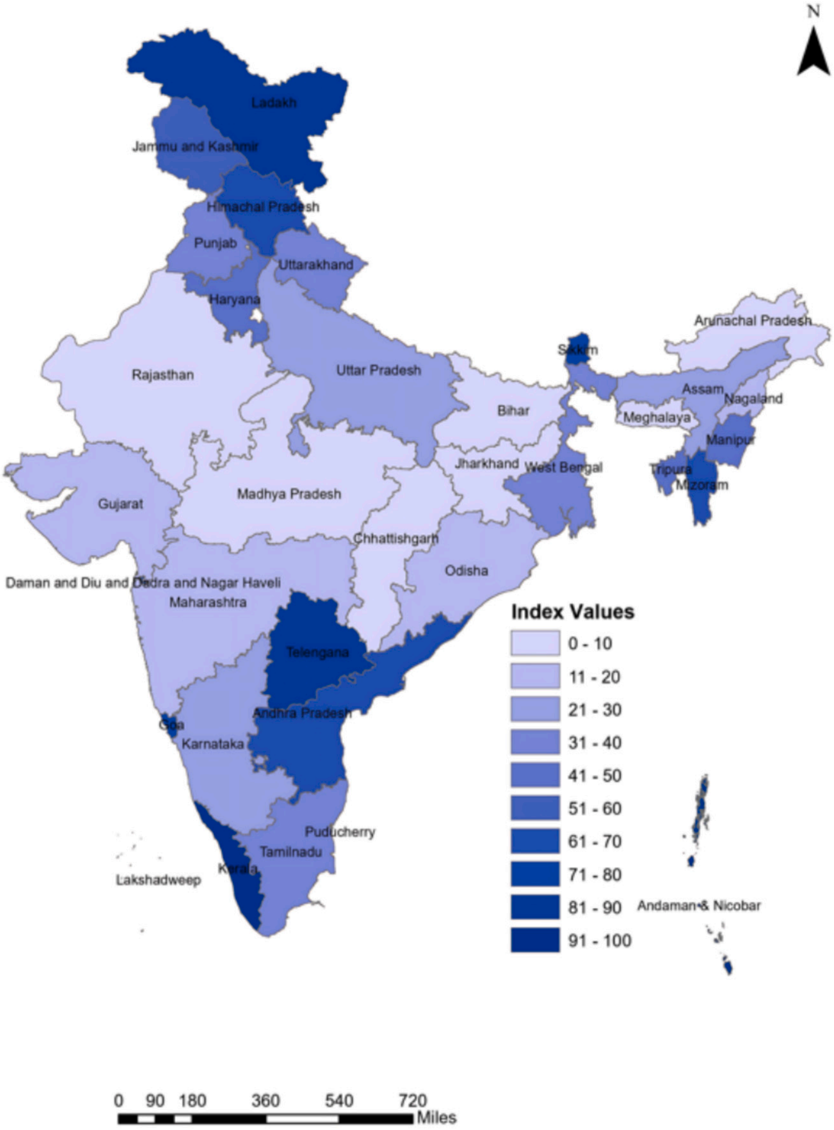


Fig. 3. Index of the use of clean cooking fuels, by state (0–100; household adoption percentage normalized using min–max scaling; denominator: total rural households). Choropleth classification: equal-interval (10-unit classes).

indicates that community-level solar streetlighting is unevenly institutionalized, shaped by differences in local governance capacity, financing arrangements, and availability of long-term maintenance services.

Fig. 4b shows a pronounced spatial variation in adoption levels of solar-powered pump-sets. The highest level is seen in Tamil Nadu and Haryana, followed by Karnataka, Maharashtra, and Rajasthan, reflecting a strong alignment between agricultural demand, groundwater dependence, and targeted initiatives such as the PM-KUSUM scheme. In contrast, many of the eastern and northeastern states show low uptake, highlighting the influence of state-level policy, institutional capacity, and agroecological suitability on the diffusion of the technology. The review by Gupta and Singh (2025) [51] showed similar patterns across South Asia and identified capital subsidies, low operating costs, reliable availability of water, and durability of systems as key drivers. The authors also noted that differences among countries in adoption rates are largely shaped by variations in government policy, geographic conditions, and the degree of international support.

3.4. Index 6: community biogas plants and waste-recycling systems

Fig. 5 shows the level of adoption of community-level biogas plants and waste-recycling systems.

Fig. 5 shows that the use of community-level biogas and waste-recycling systems in rural India is growing, but unevenly. Adoption is noticeably higher in states such as Karnataka, Telangana, Madhya Pradesh, Rajasthan, and Gujarat, in which supportive institutions, abundant livestock resources, and closer links with rural waste-management and energy programs have helped these systems take root. By contrast, much of the eastern and northeastern India continues to see limited uptake, reflecting ongoing challenges related to financing, technical know-how, and sustained community involvement. These regional patterns mirror global experience. A recent systematic review by Biró et al. (2025) [52] highlights local acceptance as a critical driver of biogas deployment and shows that social factors such as trust, fairness in decision-making, and meaningful community participation explain a larger share of adoption outcomes (45%) than that explained by financial considerations alone (31%).

3.5. Adoption of clean energy across states and union territories in rural India

Fig. 6 presents the overall picture of the adoption of clean energy

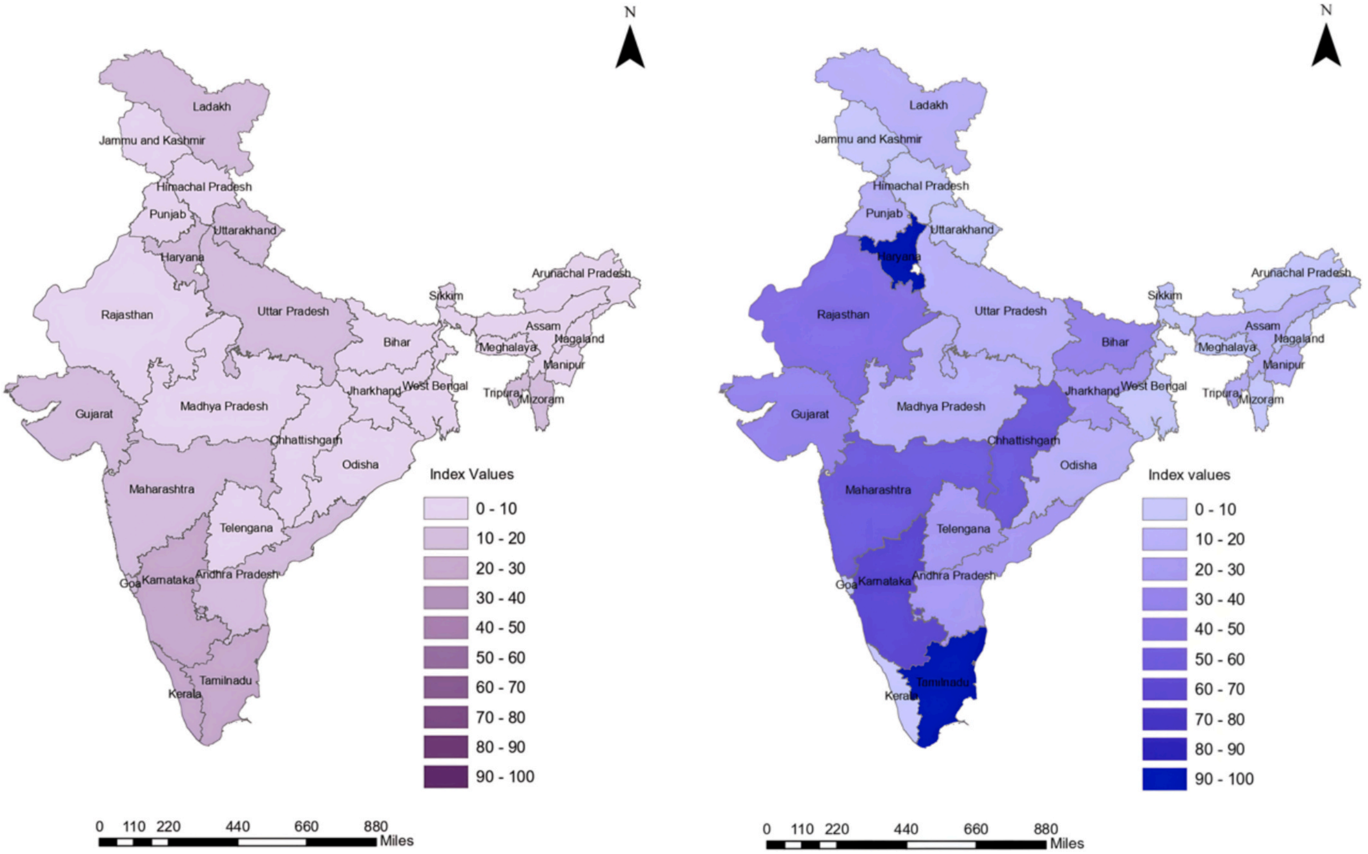


Fig. 4. (a) Index of adoption of solar streetlighting, by state (0–100; average installations per village normalized using min–max scaling; denominator: total surveyed villages). Choropleth classification: equal-interval (10-unit classes). (b) Index of adoption of solar-powered pump-sets for irrigation, by state (0–100; average installations per village normalized using min–max scaling; denominator: total surveyed villages). Choropleth classification: equal-interval (10-unit classes).

across states and union territories in their rural areas by combining the six indices discussed earlier into a single index, namely CEAI, the clean energy adoption index, which highlights the combined impact of household- and community-level renewable energy technologies on the ongoing energy transition in rural India.

Fig. 6 shows pronounced regional disparities in adoption levels of technologies based on renewable energy across rural India, consistent with the data given in Table 1. The darker shades, which represent higher levels of adoption, are concentrated in the southern and northwestern states, whereas the lighter shades, which represent low levels of adoption, dominate the eastern and northeastern states and hilly areas and island territories. Southern leaders such as Karnataka (ranked first), Tamil Nadu, and Telangana demonstrate strong and diversified renewable portfolios [53]. In the northwest, Haryana and Gujarat also record high performance, supported by the deployment of solar pump-sets, expansion of wind energy, and sustained policy backing. A transitional belt across central India, including Madhya Pradesh and Maharashtra, shows moderate progress, largely shaped by selective, technology-specific interventions. By contrast, northeastern and Himalayan states such as Arunachal Pradesh, Nagaland, and Meghalaya lag behind, reflecting infrastructural constraints, dispersed settlements, and weaker system integration. Overall, the heat map reinforces a clear south–north and core–periphery gradient, driven by differences in infrastructure capacity, policy continuity, and the embedding of sources of renewable energy within rural development pathways.

Table 1 shows marked heterogeneity among Indian states and union territories in terms of the extent to which they have adopted different technologies related to the transition to clean energy in their villages, the value of the composite CEAI ranging from 57.48 for Karnataka to below 11.00 in the northeastern states and 0.34 in Goa. The leading performers—Karnataka, Haryana, and Tamil Nadu—owe their progress more to distinct technological configurations than to any uniform strength across all dimensions. Karnataka benefits from its high potential for wind energy together with greater penetration of solar streetlighting and community biogas plants and waste-recycling systems; Haryana's strength lies in solar electrification and near-universal biogas–waste recycling infrastructure; and Tamil Nadu scores due to a relatively balanced portfolio spanning wind, solar streetlighting, and community-scale systems. The mid-tier states, on the other hand, follow more specialized pathways: Gujarat is well above the national average in solar and wind electrification, and Telangana scores high in adoption of clean cooking fuels and widespread solar streetlighting. The states that make a poor showing do so across all the six component indices that makes up the composite index.

At the aggregate level, the pan-India value of the CEAI (30.75) indicates moderate progress. Among the technologies, India is stronger in wind electrification and solar-powered pump-sets but weaker in solar streetlighting and decentralized biogas–waste systems, as is evident from the gaps of 15–20 index points that separate the top-performing states from the rest. These disparities underscore substantial policy, infrastructural, and investment differentials [54], with high-performing (in terms of renewable energy) states such as Karnataka reflecting significantly higher shares in energy sources other than fossil fuels than the national average.

3.6. *Adoption of clean energy*

The values of the composite index must be viewed alongside national percentages and absolute counts because the indices capture relative changes independent of scale whereas percentages provide insights into

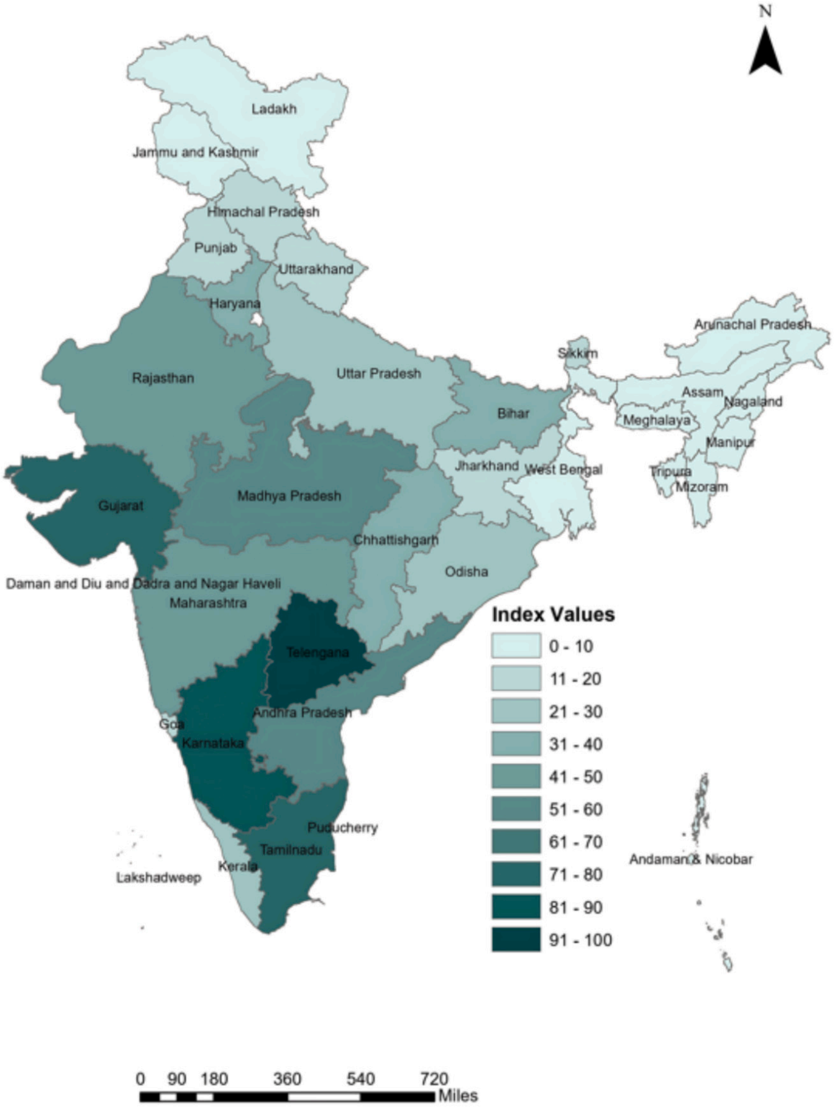


Fig. 5. Index of adoption of community-level biogas plants and waste-recycling plants, by state (0–100; average installations per village normalized using min–max scaling; denominator: total surveyed villages). Choropleth classification: equal-interval (10-unit classes).

proportions, and counts reveal the true magnitude—preventing misinterpretation from small bases inflating the indices and enabling robust cross-regional and temporal comparisons [55]. Table 2 therefore presents absolute counts and percentages showing the extent of adoption of clean energy by rural households and communities at the aggregate, or pan India, level.

Table 2 highlights the finding that the transition to clean energy in rural India has been structurally uneven, the progress being greater in clean fuels for cooking than that in decentralized supply of electricity based on renewable energy. Deployment of solar and wind energy at the household level remains limited, and community-level infrastructure is unevenly distributed across villages, indicating that the transition is being driven primarily by clean cooking fuels and not so much by broad-based diffusion of distributed electricity systems. This analysis is consistent with recent evidence [56], which links the switching to cleaner fuels by households to policy support while emphasizing continuing affordability and infrastructure constraints, particularly in states such as Rajasthan and Odisha. Overall, the findings point to a transition that remains largely supply- and infrastructure-oriented, underscoring the need for policies that move beyond installation targets toward improving access, enabling productive energy use, and strengthening local institutional and technical capacity for sustained adoption.

3.7. Priority states and regions for advancing rural energy transition in India

Differences in performance among states are consistent with the diffusion and adoption theory [57], reflecting uneven progress across social systems, a result of institutional capacity, availability of infrastructure, socioeconomic conditions, policy efficacy, and receptivity to innovation. The progress denotes evolutionary stages, not mere gaps—particularly among the five most populous rural states (Uttar Pradesh, Bihar, West Bengal, Maharashtra, and Madhya Pradesh), which represent nearly half of rural households [48]. Priorities change with the stage. For example, West Bengal and Uttar Pradesh require integrated interventions: West Bengal excels in clean fuels for cooking but lags in decentralized sources of power based on renewable energy, solar-powered pump-sets for irrigation, and community infrastructure; Uttar Pradesh shows moderate electrification and is slower to put waste to productive uses and adopt community-level solutions (Fig. 7a). The demographic and agrarian scale of both the states demands coordinated strategies to strengthen supply, institutions, and demand. Bihar and Madhya Pradesh need sector-specific acceleration, which can be

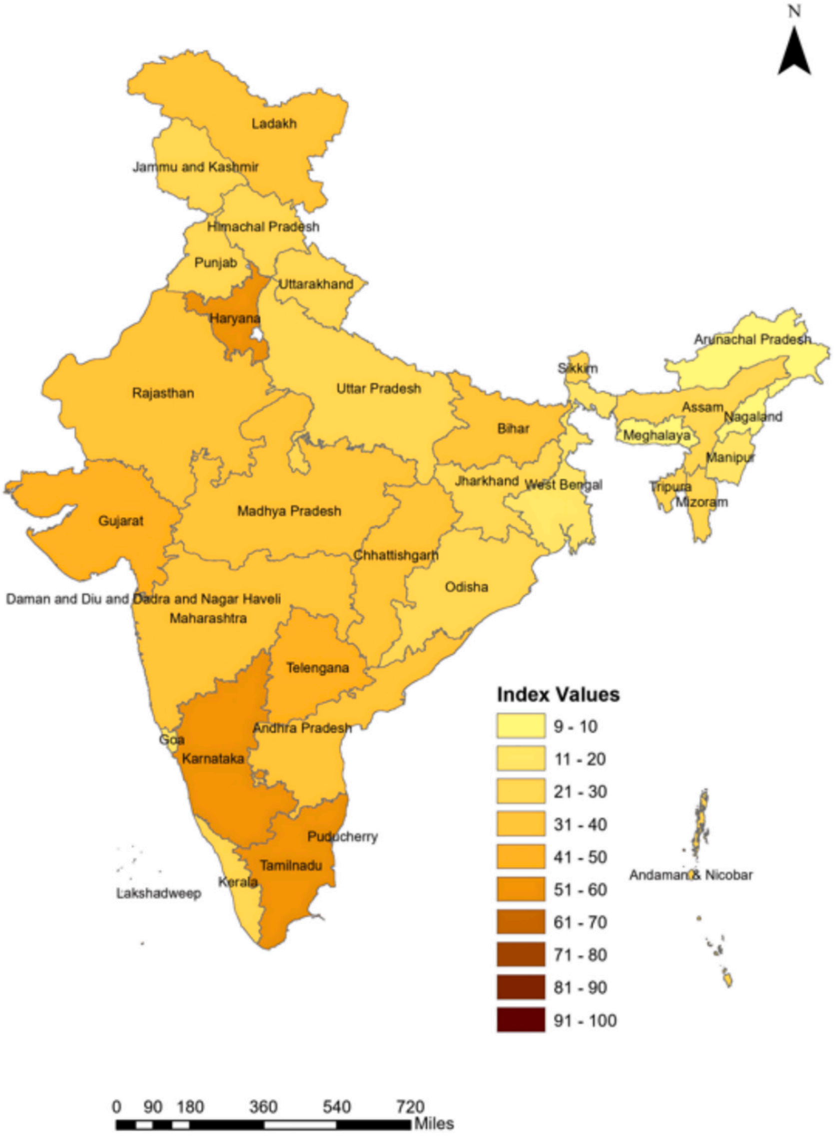


Fig. 6. Clean energy adoption index, by state (0–100; arithmetic mean of six min–max normalized sub-indices derived from household adoption percentages and average installations per village). Choropleth classification: equal-interval (10-unit classes).

achieved by leveraging household electrification, augmenting the availability of clean cooking fuels, and promoting productive use of waste and of biogas plants. Maharashtra, with moderate multidimensional progress, warrants consolidation of all the technologies through scaling, sectoral integration, and reliability optimization (Fig. 7a). Ultimately, rural energy transitions are phased, context-embedded processes, spreading over time from innovators to late adopters. Stage-sensitive policies—introducing technologies, giving them momentum, and integrating established access—align with diffusion principles. Linking them to Panchamrit commitments mentioned earlier could support reduction in emissions, alleviation of poverty, and co-benefits of sustainability.

The Clean Energy Adoption Index (CEAI) reveals the progress of five macro regions within India in transitioning to clean energy (Fig. 7b). The southern region shows the most progress, an index value of 37.69, reflecting robust uptake of clean fuels. Fig. 7b illustrates limited regional dispersion, with four of the five regions exhibiting broadly similar index values, while the Northeast remains noticeably lower, recording an index value of 18.66. Inter-regional variation remains moderate (CV = 23.3%), though not statistically significant (ANOVA F = 1.77, df = 4.29; $p > 0.05$), suggesting that the differences were due primarily to heterogeneity *within* a region and factors at the level of individual states rather than those *between* regions. At the state level, the CEAI ranged from9.14 to 57.48 (Table 1; Q1: 20.39; median: 26.99; Q3: 32.80), with four of eight northeastern states in the bottom quartile, none in the top quartile, and all below the national mean (30.75), confirming the northeastern region's structurally disadvantaged position.

This relative under performance is due to persistent structural constraints: rugged terrain, dispersed settlements, weak grid penetration, and uneven policy implementation—despite considerable potential to deploy renewable energy [58]. The pattern therefore reflects the spatial concentration of energy transition in India's countryside, with systemic challenges primarily concentrated in the northeast. In the context of the Panchamrit commitments, particularly the goal of achieving 500 GW of installed capacity from sources other than fossil fuels and lowering the carbon intensity of the country's GDP by 45% by 2030, this regional gap underscores substantial untapped potential for development and for mitigation of the adverse impacts of climate change. Expanding decentralized, community-oriented systems based on renewable energy in the northeastern region could yield substantial gains from modest investments by lowering emissions, supporting livelihoods, and strengthening energy security, thereby narrowing spatial disparities and

Table 1

Extent of adoption of six technologies promoting energy transition in rural India, by state or union territory, in descending order of a composite index, namely the Clean Energy Adoption Index (CEAI), based on the six indices, one for each technology (SEEI, Solar Energy for Electrification Index; WEEI, Wind Energy for Electrification Index; CCFI, Clean Cooking Fuels Index; SSLI, Solar Street Light Index; SPI, Solar Pump Set Index; CBG&WRI, Community Biogas and Waste Recycling Index).

State or Union Territory (*)	CEAI	SEEI	WEEI	CCFI	SSLI	SPI	CBG&WRI
Karnataka	57.48	40.11	100.00	28.73	85.70	20.60	69.75
Haryana	55.37	88.88	40.41	49.66	36.97	17.92	98.36
Tamil Nadu	53.10	32.63	51.27	31.29	78.14	25.25	100.00
Gujarat	43.61	67.22	54.53	18.48	70.55	12.18	38.67
Telangana	41.95	8.23	29.62	88.33	100.00	5.46	20.04
Bihar	36.41	60.47	75.27	4.59	33.88	6.65	37.59
Ladakh*	35.78	100.00	5.53	81.67	0.00	10.90	16.58
Maharashtra	33.32	42.10	36.12	11.94	45.21	10.96	53.60
Lakshadweep*	32.80	0.00	0.00	96.80	0.00	100.00	0.00
Madhya Pradesh	32.33	66.51	48.41	5.81	54.37	2.30	16.57
Rajasthan	31.82	43.75	45.45	5.20	48.39	3.90	44.25
Chhattisgarh	31.41	54.10	39.62	2.75	30.67	7.97	53.36
Andhra Pradesh	31.40	7.00	29.83	61.42	54.85	11.35	23.97
Mizoram	29.99	88.51	3.67	69.51	2.93	11.22	4.11
Jharkhand	29.04	59.58	71.93	0.00	13.70	6.13	22.93
Odisha	28.48	26.34	90.08	19.49	20.88	2.39	11.71
Assam	27.10	42.49	70.98	21.96	9.07	2.21	15.92
Kerala	26.88	6.47	0.11	100.00	27.74	20.84	6.12
Uttar Pradesh	25.98	50.08	31.96	21.09	21.38	11.82	19.57
Jammu and Kashmir	25.29	64.88	10.64	53.59	8.80	8.03	5.80
Tripura	23.47	13.51	46.42	40.90	6.66	18.16	15.17
Dadra, Nagar Haveli, Daman, Diu*	22.45	16.12	9.10	73.87	24.44	8.45	2.70
Himachal Pradesh	22.37	21.75	28.95	61.96	10.38	5.08	6.08
Uttarakhand	21.94	37.64	22.08	35.95	13.93	14.44	7.62
Sikkim	20.92	14.24	4.46	78.56	13.97	4.64	9.62
Andaman and Nicobar Islands*	20.39	10.38	2.20	96.14	3.39	3.98	6.28
Punjab	20.05	19.00	26.00	36.39	16.17	8.56	14.17
Goa	19.19	5.77	0.66	76.95	17.05	14.35	0.34
Manipur	17.18	33.12	3.29	48.23	3.38	4.27	10.79
Puducherry*	15.38	4.22	11.84	59.76	13.45	3.00	0.00
West Bengal	10.99	3.41	13.08	36.28	5.82	2.16	5.21
Arunachal Pradesh	9.45	36.36	5.54	5.74	4.35	0.48	4.24
Nagaland	9.24	17.42	6.26	17.29	8.30	4.68	1.47
Meghalaya	9.14	31.97	11.51	8.18	1.74	0.00	1.46
Pan India	**30.75**	**41.22**	**46.67**	**25.13**	**8.10**	**28.79**	**34.58**

Table 2

Extent of adoption of clean energy by households and communities in rural India.

Category	Indicator	Unit	All-India total	Numbers per 1000 villages (%)
Survey coverage	Villages surveyed	Number	641,357	–
	Rural households	Number	244,165,578	–
Household level	Adoption of solar electrification	Households	5,864,689	2.40
	Adoption of wind electrification	Households	2,886,261	1.18
	Adoption of clean cooking fuels (liquefied petroleum gas or biogas)	Households	81,830,605	33.51
Community level (village infrastructure)[1]	Villages with community biogas/waste-recycling systems	Villages	35,594	55.5
	Solar-powered streetlights	Number	3,462,318	5399
	Solar-powered irrigation pump-sets	Number	1,071,243	1671

[1] Community-level indicators standardized per 1000 surveyed villages.

accelerating national progress to honor the country's commitments toward climate change [59].

3.8. Determinants of the composite index

To examine the structural correlates of variation among Indian states in transitioning to clean energy in their rural areas, a log-linear OLS regression model with interaction terms was estimated following a systematic selection of model using more than150 candidate specifications (see Section 2.6 for full details of the specification procedure). The progression toward selecting a regression model (baseline OLS to final specification) is presented in Appendix 2 (Table A05). The final model regresses the natural logarithm of CEAI on two main-effect predictors, namely standardized poverty rate (zX_2) and standardized rural electrification rate (zX_3),alongside a triple interaction term ($zX_2 \cdot zX_3 \cdot zX_4$) and standardized literacy rate (zX_4) as a conditioning control. All continuous predictors were standardized to z-scores before estimating to eliminate the multicollinearity induced by interaction term construction, following established econometric practice [60].

Rural electrification rate (zX_3) emerged as the dominant structural determinant of the composite index of clean energy adoption, shoring the largest coefficient among all predictors ($\beta_2 = 0.587$, $p < 0.001$). In the log-linear specification, a one-standard-deviation improvement in rural electrification was associated with a 79.9% increase in CEAI [$\exp(0.587) - 1 = 0.799$], holding all other variables constant. Poverty rate (zX_2) carries a positive and statistically significant coefficient ($\beta_1 = 0.238$, $p = 0.009$). This finding is consistent with the supply-side and policy-targeting architecture of India's rural energy programs.

The triple interaction term ($zX_2 \cdot zX_3 \cdot zX_4$) constitutes the central novel finding of this analysis. It is positive and statistically significant ($\beta_3 = 0.211$, $p = 0.005$), indicating that the effect of rural electrification on CEAI was not uniform across states but amplified when poverty and literacy co-occurred simultaneously at above-average levels. This convergence premium reflects a synergistic adoption dynamic: when

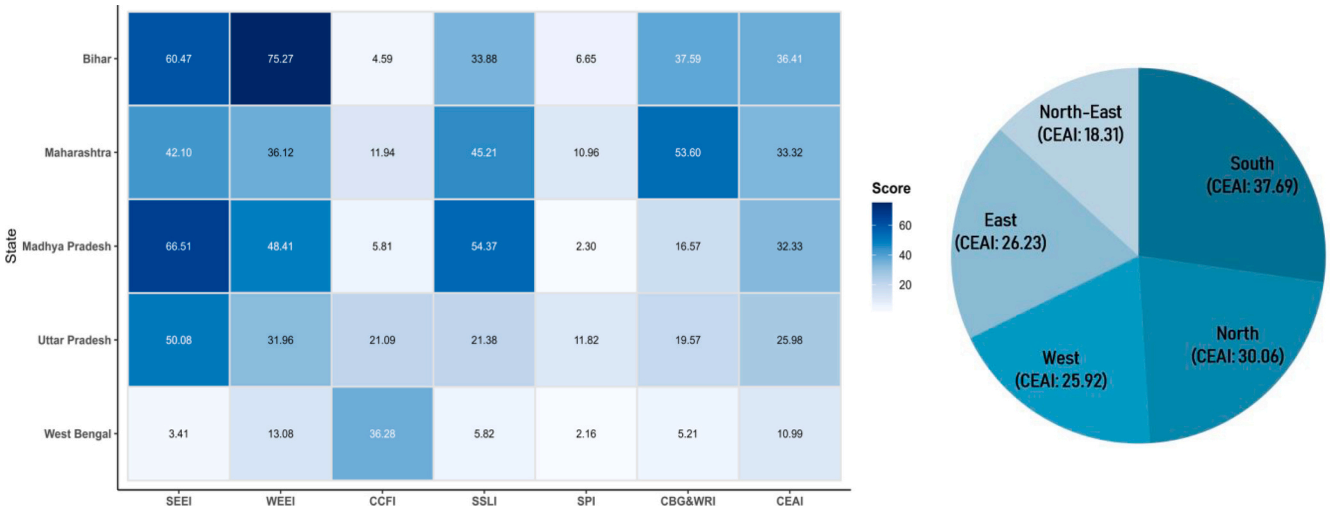


Fig. 7. (a) Performance of selected Indian states in transitioning to clean energy in their rural areas, expressed in terms of six indices and a composite index (CEAI) based on them. (b) Regional levels of India's composite Clean Energy Adoption Index for rural areas.

infrastructure readiness (X_3), program-targeting eligibility (X_2), and human capital-mediated absorptive capacity (X_4) align concurrently within a state, the predicted CEAI receives a further multiplicative boost of approximately 23.5% [$\exp(0.211) - 1 = 0.235$] beyond what could be predicted from individual factors. The conditional marginal effect of electrification on ln(CEAI) is given by $\partial \ln(\mathrm{CEAI})/\partial(zX_3) = 0.587 + 0.211\cdot(zX_2\cdot zX_4)$, confirming that the adoption benefit of electrification investment is maximum in states that simultaneously show above-average poverty and above-average literacy.

Literacy rate (zX_4) did not attain individual statistical significance ($\beta_4 = 0.066$, $p = 0.415$). This does not imply that literacy is unimportant but that at the state level of aggregation and with $n = 34$, it operates primarily through interaction rather than as an independent additive driver. The partial insignificance of zX_4 is expected when its effect is largely absorbed by a well-specified interaction, a pattern common in moderated regression analyses. Per capita income (X_1) and the agro-ecological zone dummy (X_5) were evaluated across all candidate models but not retained in the final specification: X_1 was statistically insignificant across all sub-models ($p > 0.18$), and its inclusion raised the AIC; similarly, X_5 contributed no statistically meaningful improvement to any specification. The preferred model was selected on the basis of maximum Adjusted R^2 subject to all diagnostic criteria being satisfied simultaneously.

State-level predicted versus actual comparisons are presented in Appendix 2 (Table A6). Only three states, namely Haryana, Tamil Nadu, and West Bengal, exhibit Studentized residuals exceeding 2.0. All 34 back-transformed predicted values fell within the theoretical range $[0-100]$, confirming no boundary violations. These three outliers were substantively informative rather than erroneous: Haryana and Tamil Nadu were consistent over performers, their actual CEAI exceeding model predictions, probably reflecting unmeasured quality of program implementation, whereas West Bengal was an under performer despite a relatively favorable X-profile.

Collectively, these results indicate that adoption of technologies related to clean energy in rural India is embedded within, and shaped by, the broader structure of state-level development and that the relationship is non-linear and interactive rather than simply additive. The states in which electrification infrastructure, human capital, and policy-eligible poverty converge are likely to reap disproportionate dividends in the form of high adoption levels from continued investment in infrastructure.

4. Discussion

The transition to clean energy in India's rural areas can be interpreted as the outcome of interacting technological, economic, institutional, and sociocultural dynamics. With a national average CEAI of approximately 31, measurable progress toward SDG 7 and SDG 13 is evident; however, the pace and spread of the transition remain moderate (Table 1) and uneven (Fig. 7b). Progress depends not only on expanding the capacity to supply clean energy but also on how technologies are deployed, accessed, and functionally integrated into rural production systems and household energy practices. Interstate disparities arise not so much from differences in resource endowments alone as from differences in institutional effectiveness, infrastructure readiness, and broader socioeconomic conditions. This systems-oriented interpretation aligns with scholarship on governance capacity, policy coherence, and localized implementation contexts. For instance, Mbasso et al. (2025) demonstrate that whereas policy-driven expansion of renewable energy in Cameroon accelerated its deployment, sustainability gains and cross-sectoral benefits remained uneven due to institutional, infrastructural, and implementation constraints [37,61–63]. A recent National-level assessments indicate that India's energy transition between 2010 and 2025 was rapid and policy-driven, with total installed capacity based on sources other than fossil fuels increasing from 17 GW to 190 GW, led primarily by solar energy and closely associated with GDP growth [54]. Nevertheless, constraints on grid integration and financing, and risks of intermittent supply of electricity, continue to limit system-wide efficiency. Achieving 500 GW capacity from sources other than fossil fuels, a target set for 2030, will therefore require sustained mobilization of capital, harmonization of regulations across states, and accelerated digital optimization of energy systems. Overall, the transition trajectory is structurally promising but spatially differentiated, with long-term resilience contingent on institutional alignment, financial innovation, and inclusive integration within rural development frameworks [54]. Within this broader structural context, the roles of technology, innovation, and resource endowments warrant closer examination.

4.1. *Technology, innovation, and resource endowments*

Technological innovation constitutes a necessary but not sufficient condition for accelerating the transition to clean energy in rural areas. High-performing states such as Karnataka, Tamil Nadu, Haryana, and Gujarat (Table 1and Fig. 6) enjoy diversified portfolios of renewable energy, early adoption, falling technology costs, and cumulative learning effects [37,64]. Advances in hybrid optimization techniques further demonstrate how algorithmic innovation can strengthen decentralized renewable systems. A Gauss–Seidel–Particle Swarm Optimization (GS–PSO) framework, for example, led to faster convergence, lower computational burden, and more favorable trade-offs between reliability, costs, and emissions in rural microgrids in northern Cameroon. By integrating deterministic and metaheuristic approaches, the model reduced energy shortages while lowering operational costs and emissions, underscoring the value of computational efficiency and multi-objective optimization in designing resilient configurations involving renewable energy in rural areas. However, such system-level optimization remains largely case-specific and has rarely been extended to comparative, subnational assessments of the extent to which renewable energy has been adopted [65].

Karnataka's performance shows the effective coupling of mature wind technologies, biogas systems, favorable resource endowments, and institutional capacity. At the same time, several resource-rich states remain mid-ranked in terms of the CEAI, indicating that natural potential does not automatically translate into effective adoption or system integration. These findings reinforce the view that technology diffusion must be embedded within enabling infrastructure, coherent governance frameworks, and local demand structures to deliver sustained energy services and meaningful climate mitigation outcomes under SDG 13 [66,67].

4.2. Market dynamics and livelihood linkages

Market dynamics critically shape which renewable technologies achieve scale in rural contexts. Higher values of the index of solar-powered pump-sets in agriculturally intensive states such as Haryana and Tamil Nadu (Table 1) show how adoption accelerates if technologies are tightly aligned with livelihood needs, supported by targeted subsidies, and justified by favorable economic returns [68–70]. On the other hand, the comparatively limited diffusion of solar streetlighting and other community-based systems reflects weak revenue models, financial constraints, and challenges in aggregating dispersed demand. As a result, energy transition remains skewed toward agricultural applications, whereas household- and community-level services expand more slowly, constraining inclusive energy access and utilization under SDG 7 [71,72]. From the perspective of applied energy, this imbalance underscores the importance of designing market instruments that incentivize productive and shared energy uses beyond irrigation-centric applications.

4.3. Policy coherence and institutional capacity

Policy coherence and institutional capacity are central to translating national ambitions related to renewable energy into effective local outcomes. States with higher CEAI scores typically show clearer policy signals, stronger intersectoral coordination, and more robust implementation mechanisms. Evidence from solar-powered pump-sets and biogas programs indicates that well-designed policies can reduce investment risk, improve uptake, and enable decentralized participation in rural energy systems [53,73]. Conversely, states that lag behind in the transition to clean energy in their rural areas do so not because of they have limited natural resources but because of administrative bottlenecks and fragmented governance structures, highlighting the importance of institutional capacity in advancing both SDG 7 and SDG 13 [74,75]. These findings reinforce the finding that policy effectiveness depends on cross-sectoral alignments across energy, agriculture, and rural development domains.

4.4. Socioeconomic and infrastructural drivers

Consistent with the explanatory model—particularly the positive roles of literacy and poverty-targeted electrification—sociocultural factors mediate clean energy adoption and system performance (Table 3a). Variations in uptake of technologies like biogas plants and waste-recycling systems reflect differences in education, household structure, livestock ownership, cooking practices, and local knowledge [76–78]. Higher literacy and economic capacity enhance awareness, risk absorption, and sustained use, reinforcing the link between human capital and CEAI. Technologies aligned with everyday livelihood practices (e.g., cooking and farming) show greater stability, while low adoption signals mismatches in design, local norms, gender roles, affordability, or maintenance. These dynamics intersect with poverty-related structural barriers from the regression analysis, emphasizing that rural clean energy transitions require shifts in social practices, behavioral norms, and institutions beyond mere technological substitution [37,71].

Recent research underscores infrastructure expansion—especially electrification—as key to these transitions, enabling shifts in household energy practices and technology uptake [79], though adoption remains shaped by education, information access, and household capabilities [80,81]. Developmental benefits peak when technology availability aligns with favorable socioeconomic conditions and institutions [82]. Thus, the observed interaction between electrification, poverty, and literacy reflects a synergistic dynamic where infrastructure, policy inclusion, and human capital jointly drive rural clean energy adoption.

4.5. Implications for rural energy systems aligned with UN sustainable development goals

Overall, the composite index, namely CEAI, indicates that India's transition to clean energy in its rural areas remains uneven (Fig. 6) and is closely associated with underlying development conditions (Tables 3a and 3b). The explanatory model demonstrates that the level of adoption is significantly influenced by income, literacy and level of education, and baseline electrification, with a positive interaction effect indicating amplified returns if the required infrastructure is available, the program correctly targets people who are eligible for its benefits, and the required human capital exists. High-performing states reflect the gains from aligning technological innovation with coherent policy and supportive institutional environments, whereas states with poor performance reveal constraints arising from inadequate infrastructure and ineffective governance.

Advancing SDG 7 and SDG 13 will therefore require a transition toward decentralized and demand-responsive systems that integrate clean energy with agriculture, livelihoods other than farming, and essential community services. Evidence from comparable regions in Asia, Africa, and Latin America similarly highlights the importance of

Table 3a

Regression at the level of state in India: determinants of interstate variation in the composite index.

Variable	Exp. Sign	Coefficient (β)	Std. Error	*t*-value	*P* value	Level of significance
Constant (β_0)	–	3.190	0.053	60.02	< 0.001	***
zX_2: Poverty rate (standardized)	+†	0.238	0.085	2.812	0.009	***
zX_3: Rural electrification rate (standardized)	+	0.587	0.082	7.152	< 0.001	***
$zX_2 \times zX_3 \times zX_4$[Triple interaction term]	+	0.211	0.069	3.046	0.005	***
zX_4: Literacy rate (standardized)	+	0.066	0.080	0.828	0.415	ns
Model fit statistics	$R^2 = 0.651$	Adjusted $R^2 = 0.603$	F(4, 29) = 13.53 | $p < 0.001$			

Table 3b
Diagnostic test results for the final OLS specification.

Diagnostic test	Statistic	p value	Conclusion
Residual normality: Shapiro–Wilk	W = 0.979	0.735	Normally distributed
Residual normality: Jarque–Bera	JB = 0.264	0.876	Normally distributed
Homoscedasticity: Breusch–Pagan	LM = 2.079	0.721	Homoscedastic
Homoscedasticity: White's General Test	LM = 11.222	0.669	Homoscedastic
Multicollinearity: Maximum VIF	2.73	–	Below threshold of 5
Model condition number	4.16	–	Well below 30; numerically stable
Out-of-bound predictions [0,100]	0 violations	–	All back-transformed predictions valid
AIC	19.037	–	Lowest AIC across all 150+ specifications evaluated
BIC	26.670	–	Lowest BIC across all specifications evaluated

Notes. Dependent variable: ln(CEAI); n = 34 states and union territories; Estimation: OLS with standardized predictors.*** $p < 0.01$; ns = not significant. † Positive coefficient on poverty reflects a subsidy-driven program targeting in economically disadvantaged states (see interpretation below). All predictors standardized: $zX_i = (X_i - \bar{X}_i)/s_i$. Interaction term constructed as the product of standardized variables. Back-transformed predictions: exp.(fitted ln(CEAI)). VIF computed on standardized predictors. Baseline linear OLS (untransformed CEAI, five predictors): $R^2 = 0.64$, Adj.$R^2 = 0.58$ reported for comparison only; residual normality violated (Shapiro–Wilk $p = 0.009$).

coordinated governance, inclusive financing mechanisms, and equity-oriented system design in translating the gains from deploying technologies into sustained development and favorable outcomes related to climate change [83].

5. Conclusion

The present study developed and operationalized a composite index (CEAI) of the extent of adoption of clean energy as a scalable benchmarking framework for assessing the extent of penetration of sources of clean energy in rural India. The study offers the first nationally comprehensive evaluation that systematically differentiates household-level adoption from community-scale renewable infrastructure across more than 640,000 villages. By integrating six core indicators spanning decentralized electricity, clean fuels for cooking, and village-level systems based on renewable energy, the analysis delivers a consolidated national overview of differing patterns of adoption of clean energy at both household and community levels. The study (1) identifies structural and institutional determinants of the unevenness between different states in India in terms of the transition to clean energy in their rural areas, (2) benchmarks state-level performance to quantify spatial disparities, and (3) derives policy-relevant insights for prioritizing interventions related to infrastructure, financing, and governance that enhance efficiency and equity. The findings indicate that rural India remains at an early and spatially heterogeneous stage of the transition to clean energy. Although the deployment of infrastructure related to renewable energy has progressed, adoption intensity, especially that of decentralized supply of electricity, remains limited, suggesting a transition that is led predominantly by available infrastructure and not by use or productivity. Benchmarking of performance using the CEAI shows moderate yet persistent disparities among states, with systematically lower performance by the northeastern states, reflecting their geographic isolation and structural barriers to the diffusion of technologies.

Econometric results demonstrate that the outcomes of transition are structurally embedded and non-linear. Rural electrification is the dominant determinant of variation in the CEAI among states, and its effect is significantly reinforced through a positive interaction with income and literacy. This convergence dynamic implies that investments in electrification generate higher returns from the adoption of technology so long as three critical elements converge: availability of infrastructure, correct targeting of beneficiaries, and human capital. In contrast, per capita income and agroecological conditions cease to be significant once structural variables are controlled for, underscoring the importance of institutional coherence and absorptive capacity over income alone. From the perspective of applied energy systems, the analysis highlights a persistent gap between infrastructure and effective end-use. Expanding access by itself is insufficient to stimulate sustained, livelihood-oriented use of energy. Strengthening the transition to clean energy in the countryside will require demand-responsive and decentralized systems that integrate investments in renewable energy with agriculture, irrigation, rural enterprises, and essential services, supported by coherent governance and financing. By shifting the focus of analysis from merely counting the number of installations to assessing effective adoption and system performance, the CEAI offers a transparent, transferable, and policy-relevant tool for advancing inclusive and low-carbon rural transformation in India and comparable developing economies.

6. Limitations and future research

The present study relies on self-reported survey data, which may be affected by measurement error, reporting bias, and inconsistent recognition of technologies at the village level. Informal, hybrid, or non-functional systems could be underreported, and aggregation to higher administrative levels may obscure intraregional variation, reliability, usage intensity, and user experience. Equal weighting, although transparent, may not fully reflect region-specific priorities or the relative importance of different technologies. Future research should employ district- or village-level indices, longitudinal and behavioral data, and mixed-methods approaches to better capture the evolution of decentralized systems based on renewable energy and their contribution to outcomes pertinent to energy and climate change that are aligned with the UN SDGs.

CRediT authorship contribution statement

Dileep Kumar Pandey: Writing – original draft, Formal analysis, Conceptualization. **Souvik Ghosh:** Writing – review & editing, Validation, Supervision, Resources, Methodology. **Usha Das:** Writing – review & editing, Validation, Software, Resources. **Bitan Mondal:** Writing – review & editing, Visualization, Software. **Anil Datt Upadhyay:** Writing – review & editing, Validation, Supervision.

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.

Acknowledgements

The first author gratefully acknowledges the valuable guidance and support provided by the Director of Research, Central Agricultural University, Imphal, Manipur, throughout the course of this study. Their encouragement and facilitation significantly contributed to the successful completion of this research.

Appendix 1: Robustness and Sensitivity Analysis of CEAI

Table A1

Sensitivity of CEAI Rankings to Alternative Normalization and Weighting Specifications.

Specification	Type	Mean Rank Difference	Max Rank Shift	Spearman ρ	Kendall τ	Top Quintile Stable?	Bottom Quintile Stable?
Baseline: Equal-weighted min–max (CEAI)	Scaling	–	–	**1.000**	1.000	Yes	Yes
Z-score standardization	Scaling	0.61	2	0.997	0.941	Yes	Yes
Winsorised min–max (5% trim)	Scaling	0.38	1	0.997	0.955	Yes	Yes
Percentile rank transformation	Scaling	0.94	3	0.991	0.882	Yes	Yes
PCA-derived weights (PC1 loadings)	Weighting	1.47	4	0.989	0.863	Yes	Yes
Entropy-based weights	Weighting	1.23	3	0.982	0.841	Yes	Yes

Cross-referenced in Section 2.4 of the main text. Spearman rank correlations and rank-shift statistics relative to baseline equal-weighted min–max CEAI. $n = 34$ States and Union Territories.

Table A2

PCA- and Entropy-Based Weighting Schemes Compared with Equal Weights.

Weighting Scheme	SEEI	WEEI	CCFI	CBG&WRI	SSLI	SPI	Spearman ρ vs Equal	Kendall τ
Equal weights (Baseline CEAI)	**0.167**	**0.167**	**0.167**	**0.167**	**0.167**	**0.167**	–	–
PCA (PC1-based loadings)	0.21	0.17	0.19	0.16	0.14	0.13	0.989	0.863
Entropy-based weights	0.18	0.16	0.17	0.15	0.19	0.15	0.982	0.841

PCA weights derived from first principal component loadings of the correlation matrix of the six normalized sub-indices (n = 34). Entropy weights computed using the Shannon entropy method applied to the normalized sub-index matrix.

Table A3

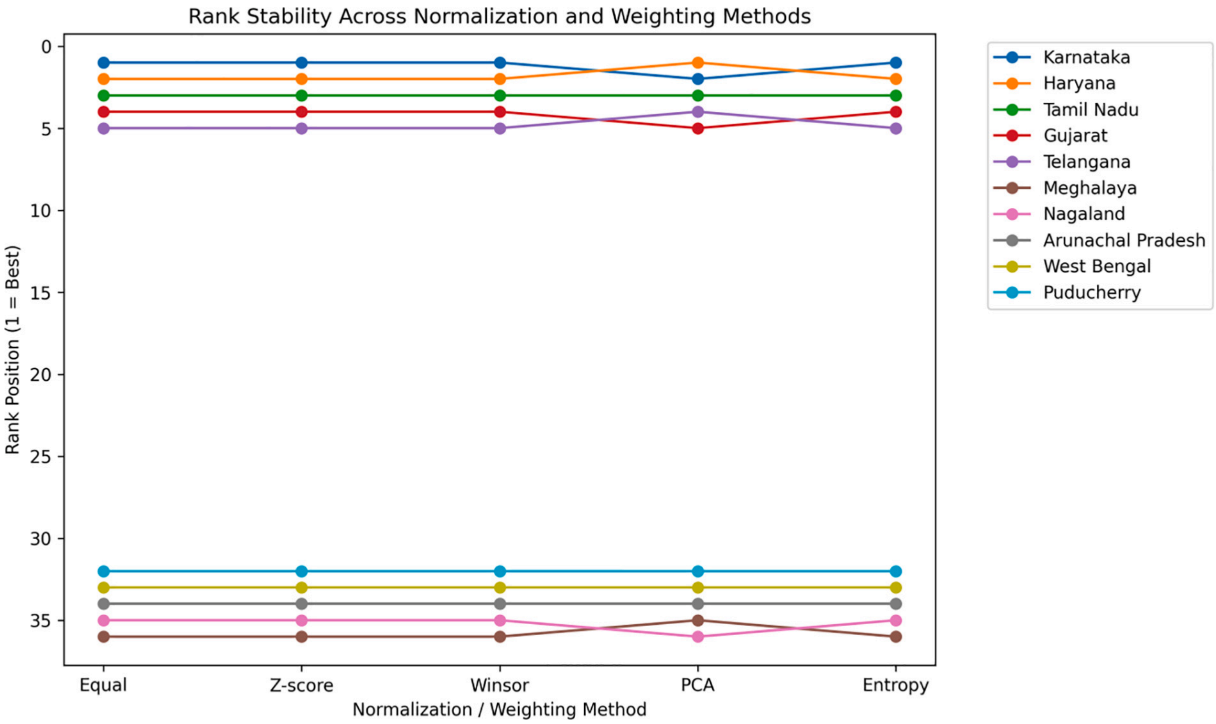
Bootstrap-Based Rank Uncertainty Analysis — 95% Rank Confidence Intervals.

State/Union Territory	CEAI Score	Baseline Rank	95% CI Lower (2.5th pctile)	95% CI Upper (97.5th pctile)	Rank Width	Stability
Karnataka	57.48	1	1	1	0	Fixed — rank invariant across all simulations
Haryana	55.37	2	1	3	2	Very high stability
Tamil Nadu	53.10	3	2	4	2	Very high stability
Gujarat	43.61	4	3	5	2	Very high stability
Telangana	41.95	5	4	6	2	Very high stability
Bihar	36.41	6	5	8	3	High stability
Ladakh	35.78	7	5	9	4	High stability
Maharashtra	33.32	8	8	11	3	High stability
Lakshadweep	32.80	9	7	12	5	High stability
Madhya Pradesh	32.33	10	8	12	4	High stability
Rajasthan	31.82	11	9	13	4	High stability
Chhattisgarh	31.41	12	10	14	4	High stability
Andhra Pradesh	31.40	13	11	15	4	High stability
Mizoram	29.99	14	12	16	4	High stability
Jharkhand	29.04	15	13	17	4	High stability
Odisha	28.48	16	14	18	4	High stability
Assam	27.10	17	14	15	1	Very high stability (Assam: 14–15)
Kerala	26.88	18	16	20	4	High stability
Uttar Pradesh	25.98	19	17	21	4	High stability
Jammu & Kashmir	25.29	20	18	22	4	High stability
Tripura	23.47	21	19	23	4	High stability
Dadra & Nagar Haveli	22.45	22	20	24	4	High stability
Himachal Pradesh	22.37	23	21	25	4	High stability
Uttarakhand	21.94	24	22	26	4	High stability
Sikkim	20.92	25	23	27	4	High stability
Andaman & Nicobar Islands	20.39	26	24	28	4	High stability
Punjab	20.05	27	25	29	4	High stability
Goa	19.19	28	26	30	4	High stability
Manipur	17.18	29	27	31	4	High stability
Puducherry	15.38	30	28	32	4	High stability
West Bengal	10.99	31	29	32	3	High stability
Arunachal Pradesh	9.45	32	30	33	3	High stability
Nagaland	9.24	33	31	34	3	High stability
Meghalaya	9.14	34	33	34	1	Very high stability

Bootstrap resampling with B = 2000 iterations. In each iteration, CEAI was re-computed by drawing sub-indices with replacement and re-ranking all 34 states/UTs. The 2.5th and 97.5th percentiles of the rank distribution define the 95% confidence interval. Point estimate = baseline rank from Table 1.

Table A4
Top and Bottom Quintile Membership Across All Specifications.

State/Union Territory	Quintile (Baseline)	Quintile Retained Across All Specs?	Baseline CEAI Score	Baseline Rank	Rank Range	Remark
CONSISTENTLY TOP PERFORMERS						
Karnataka	**Top**	**Yes**	57.48	1	1–1	Highest CEAI; rank invariant
Haryana	**Top**	**Yes**	55.37	2	1–3	Narrow range; consistently top 3
Tamil Nadu	**Top**	**Yes**	53.10	3	2–4	Narrow range; consistently top 4
Gujarat	**Top**	**Yes**	43.61	4	3–5	Stable top-5 performer
Telangana	**Top**	**Yes**	41.95	5	4–6	Stable top-6 performer
Bihar	**Top**	**Yes**	36.41	6	5–8	Top quintile across all specs
Ladakh	**Top**	**Yes**	35.78	7	5–9	Top quintile in 5 of 6 specs
CONSISTENTLY BOTTOM PERFORMERS						
Meghalaya	**Bottom**	**Yes**	9.14	34	33–34	Bottom quintile invariant across all specs
Nagaland	**Bottom**	**Yes**	9.24	33	31–34	Bottom quintile across all specs
Arunachal Pradesh	**Bottom**	**Yes**	9.45	32	30–33	Consistently bottom quintile
West Bengal	**Bottom**	**Yes**	10.99	31	29–32	Consistently bottom quintile
Puducherry	**Bottom**	**Yes**	15.38	30	28–32	Bottom quintile across all specs



Top quintile = Ranks 1–7; Bottom quintile = Ranks 28–34. Assessed across 6 specifications: baseline equal-weighted CEAI, z-score, winsorised min–max, percentile rank, PCA weights, and entropy weights.

Appendix 2. Regression Model Diagnostics and Predicted Values

Table A5
Regression Model Selection Progression: Baseline OLS to Final Specification.

Model	Specification	k	R^2	Adj. R^2	AIC	BIC	SW p	BP p	Assessment
M0	CEAI ~ X2 + X3 (Linear OLS, original baseline)	2	0.351	0.309	257.0	262.0	0.009*	0.769	Normality violated; limited explanatory power. Reported for historical comparison only.
M1	ln(CEAI) ~ X2 + X3 (Log-linear, baseline)	2	0.527	0.496	25.43	30.15	0.317	0.770	All assumptions met. Reference specification for incremental gains.
M2	ln(CEAI) ~ X1 + X2 + X3	3	0.553	0.509	25.44	31.53	0.273	0.829	Marginal Adj.R^2 gain over M1; X1 individually insignificant ($p > 0.18$).
M3	ln(CEAI) ~ zX2 + zX3 + zX2·zX3	3	0.553	0.508	25.45	31.54	0.832	0.439	Two-way interaction non-significant alone; standardization reduces MaxVIF from 2452 to 2.48.
M4	ln(CEAI) ~ zX2 + zX3 + zX2·zX3·zX4 + zX4 [FINAL MODEL]	4	0.651	0.603	19.04	26.67	0.735	0.721	Largest Adj.R^2 gain (+9.4 pp. over M2); lowest AIC/BIC; all assumptions satisfied; MaxVIF = 2.73.

Dependent variable: ln(CEAI) for Models M1–M4; untransformed CEAI for M0. k = number of predictors (excluding constant). SW p = Shapiro-Wilk p-value for residual normality (accept H_0 at $p > 0.05$). BP p = Breusch-Pagan *p*-value for homoscedasticity (accept H_0 at $p > 0.05$). MaxVIF = maximum Variance Inflation Factor (acceptable <5). All continuous predictors standardized to z-scores before interaction term construction.

Table A6

Predicted versus Actual CEAI Values — Final Model [M4].

State/Union Territory	Actual CEAI	Fitted ln(CEAI)	Predicted CEAI	Residual	Studentized Residual
Karnataka	57.48	3.641	38.12	+19.36	1.42
Haryana	55.37	3.411	30.30	+25.07	2.14
Tamil Nadu	53.10	3.310	27.38	+25.72	2.27
Gujarat	43.61	3.589	36.20	+7.41	0.64
Telangana	41.95	3.573	35.62	+6.33	0.63
Bihar	36.41	3.809	45.08	−8.67	−0.87
Ladakh	35.78	3.530	34.11	+1.67	0.17
Maharashtra	33.32	3.475	32.29	+1.03	0.11
Lakshadweep	32.80	3.595	36.43	−3.63	−0.40
Madhya Pradesh	32.33	3.370	29.07	+3.26	0.38
Rajasthan	31.82	3.417	30.49	+1.33	0.16
Chhattisgarh	31.41	3.467	32.02	−0.61	−0.07
Andhra Pradesh	31.40	3.415	30.42	+0.98	0.12
Mizoram	29.99	3.133	22.95	+7.04	0.97
Jharkhand	29.04	3.311	27.41	+1.63	0.27
Odisha	28.48	3.286	26.74	+1.74	0.22
Assam	27.10	3.024	20.58	+6.52	0.99
Kerala	26.88	3.085	21.88	+5.00	0.75
Uttar Pradesh	25.98	3.271	26.34	−0.36	−0.05
Jammu & Kashmir	25.29	3.261	26.07	−0.78	−0.10
Tripura	23.47	3.178	23.99	−0.52	−0.08
Dadra & Nagar Haveli	22.45	3.500	33.11	−10.66	−1.35
Himachal Pradesh	22.37	3.403	30.05	−7.68	−1.01
Uttarakhand	21.94	3.375	29.22	−7.28	−0.98
Sikkim	20.92	3.297	27.03	−6.11	−0.89
Andaman & Nicobar Islands	20.39	3.253	25.86	−5.47	−0.83
Punjab	20.05	3.335	28.06	−8.01	−1.19
Goa	19.19	3.002	20.13	−0.94	−0.17
Manipur	17.18	2.554	12.86	+4.32	1.08
Puducherry	15.38	3.187	24.23	−8.85	−1.59
West Bengal	10.99	3.049	21.10	−10.11	−2.24
Arunachal Pradesh	9.45	2.280	9.77	−0.32	−0.15
Nagaland	9.24	2.162	8.69	+0.55	0.24
Meghalaya	9.14	2.326	10.24	−1.10	−0.43
Summary statistics	Mean = 26.88	–	Mean = 26.02	RMSE = 8.12	Skew = 0.146

Model: ln(CEAI) ~ zX2 + zX3 + (zX2·zX3·zX4) + zX4. Predicted CEAI = exp.(fitted ln(CEAI)). Residual = Actual − Predicted. Studentized residuals exceeding |2.0| flag potential influential observations. All 34 back-transformed predictions fall within [0, 100], confirming no boundary violations.

Data availability

The data used in this study are publicly available. The repository can be accessed at https://missionantyodaya.dord.gov.in/pre-loginNationalConventionalNonConventionalEnergyReport.htm.

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