Reassessing India's State Energy and Climate Index: Addressing Bias for Aligned Net-Zero Pathways

Manoj S. Kamat[1, 2], Deepali Churi[3], Manasvi Kamat[4]

[1]Professors, Srinivassa Sinai Dempo College (Autonomous), Bambolim, Goa, India

[2]Corresponding author: mskamat@gmail.com

[3]deepali0531@gmail.com

[4]Professor, MES's Vasant Joshi College of Commerce & Economics, Zuarinagar, Goa-India

manasvikamat@gmail.com

Acknowledgements: We thank seminar participants at various institutions for their comments. Remaining errors are our own. Replication files, including raw data and full Python code, are deposited and available from the corresponding author upon request. No funding received. No COI.

Zenodo DOI: 10.5281/zenodo.18076344

GitHub: https://github.com/mskamat-droid/SECI-DISCOM-Bias

Ver 3.0, 30-12-2025

Reassessing India’s State Energy and Climate Index: Addressing Bias for Aligned Net-Zero Pathways

Abstract

This study conducts the first sensitivity audit and rank volatility analysis of India’s State Energy and Climate Index (SECI Round 1, 2022). We identify a methodological bias: the 40 per cent weight on power distribution companies (DISCOMs) prioritises legacy fiscal health over decarbonisation. Stepwise simulations for 28 states reveal high rank fragility (Kendall's $\tau < 0.80$) when DISCOM weights fall below 20 per cent, unmasking true transition leaders like Maharashtra while demoting coal-reliant grids like Punjab. OLS regression shows literacy as the key enabler ($\beta = 0.612$, $p < 0.01$), with forest cover as a barrier; mediation analysis indicates 95 per cent of the forest's negative effect is indirect via reduced literacy in remote areas. This exposes a 'green paradox' penalising ecologically rich states for preserving carbon sinks. We conclude SECI Round 1 misaligns with India's Net-Zero 2070 goals and recommend recalibrating to 20 per cent DISCOM for Round 2 to promote equitable climate action.

Keywords: Index bias, SECI, India, energy transition, sustainability metrics, human capital, non-rank sensitivity, mediation analysis, Net-Zero policy.

JEL Codes: I32, O13, Q43, Q54.

1. Introduction

India's decarbonisation and development pathways to Net-Zero by 2070 (COP26, 2021) are challenging as the world's third-largest energy consumer in a federal system. The centre sets targets and incentives, while the states implement. With an intention to track state sustainability to foster cooperative federalism toward Net-Zero, the State Energy and Climate Index (SECI Round 1, April 2022) was introduced by the centre (NITI Aayog). Though innovative, it is criticised for assigning 40 per cent weight to DISCOM financial stability, far exceeding the next parameter (15 per cent), and lacking theoretical justification. Recent alternatives like the Bureau of Energy Efficiency’s State Energy Efficiency Index (BEE's SEEI, 2024), assessing 2023-24 (latest edition released Aug, 2025) with balanced weights (e.g., 11% DISCOM focusing on demand side management and loss reduction), highlight feasible designs that prioritise energy efficiency (EE) outcomes over fiscal legacies. Comparison of the SECI design with the SEEI further emphasises the deficiencies of the former.

To diagnose the implications of SECI bias, take a look at the contrasting examples of two States in our unified 28-state universe. Punjab appears to be one of the best performers in the current SECI state rank list, ranking fourth. However, Punjab received Rs. 15,000 crore during 2019-2021 to clear its DISCOM debt, enabling its 60 per cent coal grid. When we simulate the DISCOM weight in our study from 40 to 10 per cent, the rank slips drastically from 4 to 12, and Gujarat falls from 2 to 7. In contrast, clean energy leaders Maharashtra ranks 7th and climbs up the ranks when the utility bias is eased. North Eastern states, along with Bihar, are badly affected by the structural barriers correlating with their uneven progress on the RE front with the central scheme, such as 'Saubhagya', not reaching even half of their rural households. Thus, the SECI recognises a financial debt wash and not a green transition. It is not a neutral scoreboard.

This leads us to ask whether the SECI is an actual advance by the sub-nationals towards Net Zero? Against the above backdrop, this study addresses: How sensitive are the state rankings based on the reasonable changes in the SECI weights, and what does this imply for the credibility of the rankings as a benchmark of true performance? The second is how the SECI is associated with the socio-economic characteristics of the states?

By combining a simple weight stress test (simulation fragility audit) with a cross-sectional regression (qualitative mediation), we show that the ranking scheme is sensitive. SECI ignores that energy transitions are heavily influenced by socio-economic path-dependencies. Our fundamental contribution is to provide a basis for needed revision in the current SECI design that well aligns with the sustainability and development goals. Results show high fragility (Kendall's $\tau = 0.741$) under DISCOM-light scenarios, suggesting the index measures legacy fiscal health rather than transition readiness.

Our analysis is broadly situated within the political economy of measurement. Ranking decides the kind of incentives, rewards, funds and recognition. The study treats the SECI as a governance instrument whose choices can influence the determination of investment priorities of the states, and allows for political credit, rather than benefiting from using such indices as a technical tool of performance measurement. It can lead to the possibility of governance distortion.

The rest of the study is arranged as follows. The literature is reviewed in Section 2. Section 3 lists the data sources and the methods employed. Section 4 presents the findings, implications, and policy relevance. Discussion and policy implications are covered in Section 5. Section 6 concludes.

2. Literature Review

The study builds on three strands of work, as follows.

2.1 Methodological Debates relating to Index Compositions

Composite indices serve as a strategic tool to simplify complex multifaceted realities into a single, generalisable score. The SECI intends the same with respect to transitions toward energy sustainability.

Scholars like Greco (2019) and Munda & Nardo (2008) argue that the methodological decisions of indices are rarely neutral. The selection of parameters and weights is more political than statistical, yet these choices dictate rankings and policy implications. However, in the case of established and popular indices like the Human Development Index (HDI) and the Multi-Dimensional Poverty (MDPI) Index, the methodology is far more rigorous. Their weighting schemes typically derive from weight perturbations, rank correlations and optimisation algorithms. The combination of expert judgements, statistical techniques and dominance methods is used to ‘stress test’ the index.

In comparison, the SECI's grid-search calibration approach seems somewhat dated. While it claims transparency and policy relevance, it badly misses out on advanced alternatives. It ignores the fact that machine learning methods (like principal component analysis and random forests) and multi-criteria decision analysis (e.g., analytic hierarchy process) are increasingly employed globally to enhance robustness and reduce subjective bias (OECD/JRC, 2008; Mazziotta & Pareto, 2013; UN Statistics Division, 2023). This is not merely a technicality, as the flawed weighing not only skews the results, but it also distorts the definition of progress itself. Cherp et al. (2018) warn that 'weighting distortions' unintentionally incentivise undesirable behaviours.

2.2 The Socio-economic Factors driving sustainability

Economic theories assume that there is a direct correlation between income, energy and climate activities. These interactions are often studied using the Environmental Kuznets Curve (EKC) framework. The EKC literature examines whether pollution rises during the early stages of industrialisation and falls once a certain wealth threshold facilitates greener technologies (Stern, 2004; Dinda, 2004). The evidence is mixed depending on the pollutant, country group and period. Our study tests and contests the EKC theory rather than assuming it applies. We find SECI penalises ecologically rich states for maintaining carbon sinks because those forests make physical infrastructure (DISCOM reliability) harder to maintain.

Our empirical modelling across states shows that the energy ladder is often complicated by structural inequalities. Literacy is a primary driver, while forest cover and poverty act as significant friction factors. As noted by Rao and Pachauri (2017), the energy ladder is often broken by poverty, as low-income households have limitations in accessing modern energy services regardless of national-level growth. Our results show that while poverty is a barrier, it is the lack of human capital (literacy) often associated with poverty that serves as the true bottleneck for SECI performance. Higher education levels correlate strongly with the adoption of energy-efficient behaviours and the demand for clean technology (Sinha et al., 2022). Conversely, where governance is weak and poverty is high, grassroots investments in sustainability often fail. Our results find evidence that poverty and weak governance create path-dependencies that hinder sustainability progress, with literacy serving as the true enabler (or bottleneck when absent).

The capacity of a sub-national entity to transition depends more on socio-economic enablers than on national income alone. Further, they follow diverging paths. Early industrialisation spikes emissions (Chakravarty & Tavoni, 2013), but decoupling requires social indicators. Based on this rationale, this paper empirically models the relationship between these socio-economic frictions and SECI outcomes across Indian states.

2.3 Outlier Status of SECI and the Economy of Measurement

When we discuss its construction in light of the methodological literature and other global indices involving its parameter choices, critical shortcomings emerge. SECI diverges in weighing schemes, normalisation and aggregation (see Table A1, Appendix). In the SECI framework, a single parameter bias is well illustrated and stands in sharp contrast to the schemes used by peers. China's Green Development Indicator for instance, prioritises physical climate outcomes, heavily weighting carbon intensity and environmental carrying capacity, rather than the balance sheets of structural institutions.

The SECI bias in the Indian context is not merely a methodological limitation; it represents a departure from global best practices. WEF's Energy Trilemma balances security, equity, and sustainability without single-metric dominance. By alternating the weights of NDC alignments to the financial solvency of the utility (DISCOM), the SECI recognises legacy rather than sustainability actions. Furthermore, the design flaw has profound implications for cooperative federalism. It signals that cleaning up utility accounts makes more sense to rank high on the SECI than actually following clean energy initiatives. Domestically, SEEI 2024 uses 66 indicators with balanced weights (buildings 22 per cent, DISCOMs 11 per cent), emphasising on-ground efficiency (audits, retrofits) rather than solvency. In contrast, the SECI skew creates perverse incentives, sidelining qualitative drivers (Greco et al., 2019; Turnbull, 2019).

This study relates to SDGs 7, 13, and 10, emphasising integrated policy on poverty (1), education (4), and growth (8). The recalculated SECI scores and rankings are thus presented based on a fit ladder of just transitions through scientific simulation.

3. Empirical Strategy and Simulation Framework

Our empirical strategy comprises four steps. (1) Stress-test SECI weights focusing on DISCOM; (2) Simulate reductions to quantify distortion; (3) Evaluate socio-economic effects; (4) Robustness checks. We go beyond identifying the flaw of DISCOM-bias to show the implications of missing out on the actually good performers, and not to use biased scores and wrong rankings, as Cohen-Shields et al. (2023) demonstrate. This draws policy lessons in revising the weighting scheme in the future SECI rounds and state rankings.

3.1 Data and Variables

The dependent variable is the composite score in SECI Round 1 (2022) of 28 Indian states as published in the NITI report. The raw data extracted from the ground-truth parameter scores and archived as **seci_rankings.csv** for reproducibility. Eight union territories are excluded from the analysis as they have a different DISCOM structure (Delhi and Puducherry skew heavily). This study constructs a unified 'all-states' universe from the separate classification of large and small states. This *n* = 28 is retained for all simulated weighting scenarios, while the regression analysis is restricted to *n* = 27 due to missing socio-economic data for Manipur. The dependent variable is the SECI score (calculated as a composite score of SECI).

All independent variables of the study represent theoretically important drivers and are defined and justified in Appendix Table A2 for 27 states, and archived as **socio_economic_data.csv**. The robustness of literacy (census 2011) is tested with NFHS-5 (2019-21) proxies (mean schooling years, secondary education), and yields consistent or stronger coefficients, mitigating vintage concerns. This data is archived as **nfhs5_proxies.csv**.

Although limited to a single cross-section (SECI Round 2, upon release, will allow conducting a more extensive comparative analysis), the result allows measurement of the qualitative aspects influencing SECI performance.

3.2 Simulation Framework for Fragility Audit

To measure the weight DISCOM bias, we step-wise grid-simulate weight reductions of 10 per cent, and redistribute all excess load into other parameters (that add up to a total of 100 per cent). Equal redistribution is chosen for the main results considering transparency and conservatism, aligning with balanced global practices (e.g., CCPI 2024 weights outcomes heavily).

This procedure is drawn as follows:

1) **Original SECI** is defined by a baseline equation based on SECI-defined original (orig) weights,
   where W_{DISCOM}= 40% and $(W_1^{(orig)}, \ldots, W_6^{(orig)}) = (0.40, 0.15, 0.15, 0.06, 0.12, 0.12)$

   The baseline equation for the composite score is:

$$SECI_s^{(orig)} = \sum_{i=1}^{6} W_i^{(orig)} \cdot X_{s,i} \qquad (1)$$

We use published SECI composite scores and rank from NITI Aayog as-is for all 28 states.

2) **Simulation:** We iteratively reduce baseline W_{DISCOM} = 40% (baseline) to W_{DISCOM} = 30% (scenario 1) W_{DISCOM} = 20% (scenario 2), and W_{DISCOM} = 10% (scenario 3), as sequentially simulated regimes.

3) **Weight Redistribution:** The excess weight shed from DISCOMs under each simulated scenario (ΔW_{DISCOM}) is equally allotted to the other five SECI parameters (main results), isolating the DISCOM-load effect, while ensuring the total composite weights remain 100% for the recalculated SECI. We further introduce 'Net-Zero Focussed Scenario' where weight is allotted to clean energy parameters, and used for robustness. The new scores to other parameters under each regime are: its original weights + extra adds from DISCOMs at each stage.

The robustness check with focused redistribution (Section 4.4.1) to clean energy parameters to confirm rank volatility, supporting that the results are not an artefact of the equal-split assumption. Future extensions could employ optimisation techniques (e.g., OECD/JRC, 2008) for uncertainty bounds or data-driven weights.

The Revised Weights per Scenario are now:

$$W_i^{(k)} = W_i^{(orig)} + \frac{\Delta W_1}{5} \; for \; i = 2, \ldots, 6 \qquad (2)$$

Where $W_1^{(k)}$ reduced stepwise: 0.30, 0.20, 0.10 and weights for other parameters as per

step 1; $\Delta W_1 = W_1^{(orig)} - W_1^{(k)}$ (3)

ΔW_{DISCOM} is divided by 5 (for the five remaining parameters) in the main simulation, and by 3 for the 'focused' robust check.

4) **Simulated Composite Score Calculation:** based on new weights for parameters under

the alternate regime, and parameter scores from baseline SECI, the equation for Simulated SECI Score is:

$$SECI_s^{(k)} = \sum_{i=1}^{6} W_i^{(k)} \cdot X_{s,i} \qquad (4)$$

5) **State-wise Ranking and Volatility:** The new state-level ranks based on the revised parameter weights are assigned as:

$$Rank_s^{(k)} = rankorder\ (SECI_s^{(k)}) \qquad (5)$$

6) **Rank Change Quantification:** $\Delta\ Rank_s$ Represents a rank drop to mean index bias/ volatility associated with the original DISCOM-heavy index. It is used to demonstrate the methodological and policy consequences of index recalibration, and a positive Δ indicates the state has risen in rank; calculated as:

$$\Delta Rank_s = Rank_s^{(4)} - Rank_s^{(orig)} \qquad (6)$$

In addition to simulations, we use the OLS score to link SECI scores to socio-economic drivers using the OLS model.

3.3 OLS Model

A cross-sectional ordinary least squares (OLS) regression model is used to estimate the association between composite SECI scores (dependent variable) and the vector of state-level predictors (selected socio-economic variables) for 27 states. Regressions run on the original SECI score (S_{ORIGINAL}) and the recalculated SECI score ($S_{\text{RECALCULATED}}$) for robustness.

Original SECI Score (S_{ORIGINAL})**:** To assess which drivers correlate with the officially published, DISCOM-heavy ranking.

Recalculated SECI Score ($S_{\text{RECALCULATED}}$): To assess which drivers correlate with a more balanced and robust SECI ranking (e.g., the simulation where W_{DISCOM} = 30 per cent or less). The cross-section OLS model is specified as follows:

$$S_i = \propto + \beta_1 Income + \beta_2 Literacy_i + \beta_3 Poverty_i + \beta_4 Industry_i + \beta_5 Forest_i + \varepsilon_I \qquad (7)$$

Where S_i is the SECI score for State *i*, β_1 to β_5 are the coefficients representing the impact of each socio-economic variable, and ϵ_i is the error term.

Sample size for regression is small (*n*= 27), causation cannot be directly inferred, and the findings can only be associative. Notably, we exclude the Difference-in-Differences/panel/spatial/IV framework approach in favour of a cross-sectional volatility clustering analysis, as the current SECI framework lacks the longitudinal panel data required for time-series causal inference. This can be investigated in the future when the (forthcoming) Round 2 data are at hand. The limited cross-sectional design constrains generalisability but does not affect internal comparisons.

Robust standard errors (HAC-adjusted) are used to address heteroskedasticity and test model validity. While VIF scores are monitored, we acknowledge significant shared variance between socio-economic enablers, necessitating a mediation approach. The Jarque-Bera (JB) test tests for normality, and the Ramsey RESET test tests for model stability. There is the possibility that omitted-variable bias and year mismatch restrict the data period to coincide with the SECI round (to make comparisons that are true and legitimate).

3.4 Mediation Path Analysis

The mediation technique is used to explain the path from forests to literacy to SECI. The use of the Sobel Test and Monte Carlo simulations (10,000 iterations) validates the indirect effect of geography on energy performance.

Our dual measurement lens (fragility audit and regression/mediation) provides answers to the two main inquiries of our core research questions in the ensuing section 4. All data and code used in this study are publicly available. The replication package, including datasets, Python code for simulations, all results, robust test, appendix tables and generated figures, is archived on Zenodo and GitHub.

4. Results

The findings are arranged in three parts corresponding to our two key research questions. The fourth part analyses robustness.

4.1 Fragility Audit Results

This part deploys grid-based simulation and sensitivity analysis to reveal a methodological weakness in the composition of the SECI due to the uneven utility weight. The baseline (40 per cent) scores are reconstructed by pooling the raw parameter scores from NITI Aayog's separate tables into a unified list. We subsequently measure the impact of its de-loading on the rank of the leaders.

To address the weight bias, we simulate three cases (A, B and C) depicted in Table 1 by successively trimming the original load of DISCOM in the baseline (original SECI) iteratively, from 40 per cent DISCOM baseline: to Scenario A: 30 per cent, Scenario B: 20 per cent and Scenario C: 10 per cent. Free weight generated by DISCOM goes evenly to the other five parameters.

Table 1. SECI Parameters Weights under Baseline vs. Three Alternate Scenarios

Parameters	40% DISCOM Baseline	30% DISCOM A	20% DISCOM B	10% DISCOM C
DISCOM Performance	40	30	20	10
Access, Affordability & Reliability (AAR)	15	17	19	21
Clean Energy Initiatives (CEI)	15	17	19	21
Energy Efficiency (EE)	06	08	10	12
Environmental Sustainability (ES)	12	14	16	18
New Initiatives (NI)	12	14	16	18

Source: Authors' calculations based on NITI Aayog SECI methodology. **Notes:** The 10% prioritises decarbonisation outcomes (CEI + ES + EE). Global indices like CCPI allocate >70% to direct climate outcomes (Germanwatch, 2024). 10% DISCOM SECI's 51% still remains conservative but represents a significant improvement over the original 33%. *n*= 28 states

We use Table 1 weights on the six NITI parameter baseline scores to generate new (recalculated) SECI scores and ranks, and compare those to the NITI-SECI baseline. While 20% is recommended as a practical 'sweet spot' for SECI Round 2 (balancing character with reform, see Sections 4.2 and 4.3), the 10% scenario is the low-utility based benchmark that serves as the analytical anchor for: 1. illustrating maximum distortion from legacy bias, 2. net-zero focused robustness, and 3. conservatism and transparency.

The sorting of the composite score in descending order generates scenario-wise ranks. The new ranks reflect the extent of change dramatically as the utility is dis-weighted under an iterative scenario, indicating volatility. This generates the drastic changes in ranks, which will inform the unbiasedness of the current index (Appendix Table A3).

Figure 1 shows the way the top-10 states in the original SECI change their positions, comparing the baseline rank situation with scenario C (10% SECI). The shorter the bar (the smaller the numerical value), the higher the rank.

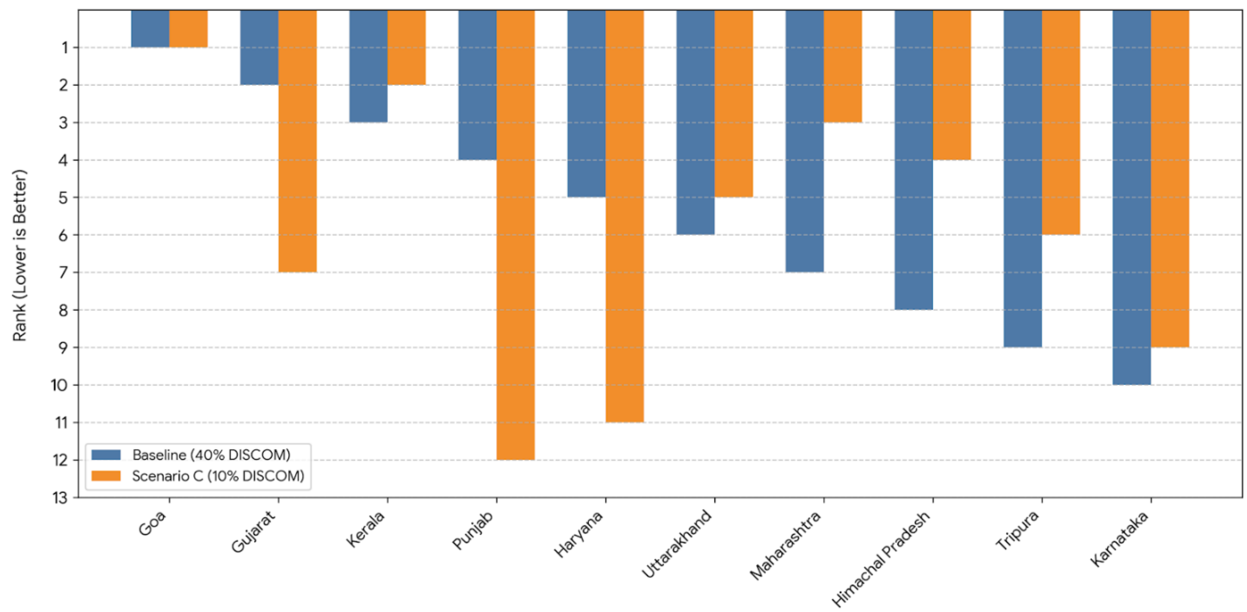

Figure 1. Top-10 SECI State Rank Shifts (SECI Baseline vs 10% DISCOM SECI)

The states are arranged in a left-to-right sequence in their original rank at 40 per cent. The two bars indicate the ranks of the states under both DISCOM regimes, which are the baseline and the alternative (10 per cent). States like Goa (stable leader) and Kerala (increases from 3 to 2) imply that they are not excessively reliant on the DISCOM factor. They are not just good leaders, but they also demonstrate their performance strength. Punjab (drops from 4 to 12), Haryana, and Gujarat (drops from 2 to 7) record a high depreciation in performance.

Gujarat and Punjab's high ranks are mathematically tied to DISCOM scores of 72.7 and 77.1, respectively, which are the highest in the dataset. The 40% weight allows a single high DISCOM score to offset poor performance in CEI (e.g., Punjab's 26.1 vs. Maharashtra's 34.0). The rank of Maharashtra, Uttarakhand, Himachal and Tripura jumps to indicate a repressed renewable potential that the weight prejudice concealed. Figure 1 confirms that the 'leaders' don't remain as 'leaders' under reasonable alternative assumptions. The weight bias led to recognition of 'misidentified' leaders. It gives wrong recognition to states (like Punjab, Gujarat).

4.2 Volatility Clustering Analysis

Recalculation of the DISCOM weights under the three alternative condition shifts the performers onto actions on ‘actual’ energy and climate matters, rather than benefiting from structural legacy (Table A3).

To prove it, all 28 states are classified into three clusters using *K*-means (*K*= 3, random_state = 42) on the basis of two standardised features and presented in Table 2.

1) **Rank Range**: Defined as Maximum Rank *minus* Minimum Rank across the baseline vs. three alternate weighted scenarios.

2) **Average | ΔRank |**: Based on the mean absolute rank change between consecutive scenarios.

Table 2. State-level SECI Rank Volatility using Cluster Analysis (*K*-means, *K*= 3)
(Baseline vs 10% scenario)

Cluster	States (*n*)	Rank Range	Average |ΔRank|	Characteristics	Examples of States
Stable High-Performers	5	0.8	0.27	Minimal rank shifts (range ≤1 position).True to “Decarbonisation”	Goa, Kerala, Uttarakhand*, Karnataka, West Bengal
Moderate-Volatility	15	2.6	0.91	Small to medium rank changes (range 2–3). "Stuck" in the bottom tier.	Tamil Nadu, Uttar Pradesh, Telangana, Andhra Pradesh, Madhya Pradesh, 5 North Eastern States, etc
Highly Volatile States	8	5.13	1.71	Significant rank swings (range 4–8). Methodological "artefacts."	Gujarat, Punjab, Haryana, Maharashtra, Himachal Pradesh

Note: Volatility is not correlated with baseline performance.* Uttarakhand shows a slight rank rise (from 6 to 5), its The primary characteristic is structural stability, meaning its performance is ‘true’ and not an artefact of DISCOM weights. *n*= 28 states.

On the criteria of rank volatility, three main clusters emerge through *K*-means clustering (*K*= 3):

Cluster 1. Low-Volatility: Balanced and Stable Performers (*n*= 5)

This group exhibits minimal rank shifts and performs consistently regardless of utility weighting, reflecting balanced strengths across fiscal health and decarbonisation metrics. Goa shows near-zero volatility (always ranks 1). Kerala and Uttarakhand remain in the top 5 across all scenarios. Karnataka stays firmly in the top 10, and West Bengal holds steady in the mid-tier. These states demonstrate structural soundness for energy transition, with performance not overly dependent on any single parameter.

Cluster 2. Moderate-Volatility Cluster: Relatively Sticky Mid- to Lower-Tier States (*n*= 15)
The largest group, with small to moderate rank changes due to broadly uniform (often weak) performance across both DISCOM and climate-related metrics (CEI, EE, ES). This cluster directly informs the political economy of measurement, as the ranks of states in the cluster barely move despite radical reweighting. This implies they lack the underlying socio-economic enablers (human capital) required to respond to the index's signals. This cluster includes persistent underperformers (e.g., Bihar, Chhattisgarh, Jharkhand, Meghalaya, Nagaland) as well as solid mid/high performers like Tamil Nadu and Tripura that experience only limited movement. The 'stickiness' suggests limited responsiveness to index incentives for the majority of Indian states.

Cluster 3. High-Volatility Cluster: Weight-Sensitive States (*n*= 8)
These states show significant rank swings, highlighting methodological sensitivity. Volatility arises from disproportionate reliance on high utility scores (causing drops when de-weighted) or strengths in decarbonisation parameters (causing a rise). Includes Rajasthan, Sikkim, and Arunachal Pradesh, among others. Former baseline leaders like Gujarat, Punjab, and Haryana fall drastically in ranks as the utility weight drops. Conversely, sustainability-strong states like Himachal Pradesh, Sikkim and Arunachal Pradesh climb. Maharashtra rises notably (7 to 3), confirming its leadership in climate metrics despite volatility.

Overall, the rank sensitivity finds that only 18 per cent of states (*n*= 5) exhibit true rank stability, while 54 per cent (*n*= 15) remain relatively stuck in mid- to lower tiers. The high-volatility group (29%, *n*= 8) reveals clear methodological artefacts: baseline top performers owe much of their position to the biased weighting, while others gain from greater emphasis on decarbonisation outcomes. These findings underscore a serious flaw in the current SECI methodology; its incentive structure is distorted by legacy utility fiscal health, and penalises those who don't have it. This undermines the focus on actual energy transition and net-zero alignment.

4.3 Sensitivity Analysis

In order to quantify the similarity of the manner of two different sets of rankings, sensitivity analysis with the aid of Kendall's τ statistic is applied. This measures the similarity and demonstrates the level of agreement between the two differing ranking lists. Table 3 compares the similarity between the original NITI Aayog ranking (40 per cent utility) and the three alternate scenarios. A lower τ value indicates higher 'fragility' or sensitivity to the weightage methodology.

Table 3. Sensitivity Analysis through the Kendall's *Tau* (τ) Test

(Baseline vs three scenarios)

Simulation Scenario	Kendall's τ vs baseline	Interpretation
A	0.926	High similarity & early volatility. Rankings remain largely consistent with small DISCOM de-weighting; most states retain relative positions. However, even at 30% (Scenario A), Punjab drops from 4th to 7th.
B	0.815	Moderate similarity & noticeable fragility. Increased divergence as utility influence drops, with moderate reordering.
C	0.741	Low similarity & high fragility. Substantial reordering occurs when utility is heavily de-emphasised, shifting emphasis to decarbonisation parameters. This exposes methodological bias toward legacy utility fiscal health in the original index.

Note: $\tau > 0.85$ = robust; $\tau < 0.70$ = fragile. N= 28 states

The sensitivity analysis shows that the SECI ranking retains strong similarity to the original only at modest adjustments, Kendall's τ = 0.926 at 30 per cent DISCOM. Similarity deteriorates to moderate levels at 20% (τ = 0.815) and becomes notably low at 10 per cent (Kendall's τ = 0.741) in the even-distribution scenario (0.56 in the 'focused net-zero regime', Robust test of fragility in Section 4.5.1). Since τ falls below the conventional threshold of ~0.8 when DISCOM weight drops to 20 per cent or lower, the index effectively begins to 'break down' or lose its original character at this point. This progressive divergence underscores high methodological fragility. The 'direction and speed' of rank changes reveal previously masked performers: Maharashtra, Himachal Pradesh and Tamil Nadu.

4.4 Qualitative Factors Influencing Energy Transitions

With the quantitative bias of the SECI (Round 1) unearthed, we investigate the positive/negative qualitative drivers of SECI performance, using the variables and the OLS equation 7 (in Section 3.3). The correlation illustrated in Table 4 indicates that SECI captures the presence of a multi-factor causal terrain, rather than the prevalence of one factor.

Table 4. Pair-wise Correlations among Qualitative Drivers of SECI Performance (*n*= 27)

Variable	Correlation with SECI	OLS Coefficient (β)	Std. Error	p-value	VIF
(Intercept)	-	-8.918	24.779	0.719	
Literacy Rate (%)	0.40	**0.611**	0.258	**0.018***	2.86
Forest Cover (%)	-0.42	**-0.179**	0.058	**0.002****	2.23
Industrial Share (%)	0.48	0.195	0.382	0.611	1.69
Per Capita Income (Rs. 000)	0.44	0.008	0.042	0.841	2.42
Poverty Rate (%)	-0.50	-0.060	0.327	0.853	3.74
R^2 = 0.679, Adj. R^2 = 0.603					

Source: Authors' calculations based on the data sources mentioned in Section 3.1. **Note:** Industrial share uses approximate secondary sector GVA data aligned with MOSPI estimates for 2021-22. Based on 27 states/UTs (Manipur excluded due to missing socio-variable data). Significance: ***p < 0.01, **p < 0.05. Standard errors are heteroskedasticity-robust.

Multicollinearity is noted (high but manageable VIF for poverty), but estimates remain stable. SECI has positive relationships with income, literacy, and industrialisation as it is restrained by poverty (*r* = -0.50) and higher forest cover (*r* = -0.42). This is indicative of spatial trade-offs in national development, denoting the reduced growth and institutional capacity. Higher industrialisation is associated with better SECI and with per capita income (*r* = 0.44) and literacy (*r* = 0.40), which are moderately positive. States with higher forest cover (often hilly/North-Eastern) tend to score lower on SECI, possibly due to challenges in DISCOM performance or access in remote areas. These patterns suggest SECI performance links to economic development and industrialisation, but trades off with extensive natural forest preservation. This may further highlight methodological considerations in balancing decarbonisation with operational/legacy factors.

Next, we consider the hypothesis that persistent socio-economic disparities limit SECI advances through a regression model (Table 5) estimated on the original SECI, and on the SECI (simulated) with a 10 per cent weight on the DISCOM.

Table 5. OLS Regression Results: Socio-Economic Factors on the SECI Score

(27 observations; using socio-economic data aligned ~2019–2022)

Variables	Baseline SECI (40% DISCOM)	Recalculated 10% SECI
Per Capita Income (thousands INR)	0.008 (p = 0.575)	0.012 (p = 0.472)
Literacy (%)	0.612*** (p = 0.007)	0.544** (p = 0.021)
Poverty (%)	-0.061 (p = 0.762)	-0.216 (p = 0.319)

Industrial Share (%)	0.193 (p = 0.380)	0.068 (p = 0.772)
Forest Cover (%)	-0.179*** (p = 0.002)	-0.139** (p = 0.019)
Constant	-8.899 (p = 0.616)	-8.560 (p = 0.652)
R-squared	0.679	0.658

Notes: Based on 27 States. Coefficients (β) rounded to three decimals; Significance: *** $p < 0.01$, ** $p < 0.05$. Standard errors are heteroskedasticity-robust.

Higher literacy positively associates with better SECI performance (stronger in baseline). Higher forest cover shows a significant negative association (states with extensive forests tend to score lower), possibly due to access/reliability challenges in hilly/remote areas. In the baseline (heavy utility weighting), forest cover has a stronger negative effect; literacy drives more. In the recalculated 10% (de-emphasising utility), effects are slightly attenuated but directionally consistent. Income and poverty are insignificant in the multivariate model, and are attributed to multicollinearity/shared variance with literacy (r = 0.65 with income and r = -0.72 with poverty).

Socio-economic links (e.g., human development via literacy) persist, but legacy factors (potentially captured indirectly via forest/DISCOM challenges) influence the original index more. Taken together, the findings show that structural factors, including human capital and ecological circumstances, prevail over pure economic indices in the state-level energy transition performance. The model clears diagnostic tests. The results support index fragility.

4.5 Robustness Checks

4.5.1 Alternate 10% DISCOM Net-Zero Focussed Scenario

In order to stress-test our rank fragility, we propose a very stringent alteration by using the 'DISCOM Net-Zero Focused' scenarios (n= 28). This regime is very similar to our main simulation except that the excess weights are shifted to CEI, EE, and ES parameters only. The weights for AAR and NI are kept constant as in the baseline. DISCOM weights are step-wise negatively iterated as: Scenario Alpha (30% DISCOM), Beta (20%) and Theta (10%). The 'focused' clean energy weight allocations are presented in Appendix Table A4.

The focused reweighting exposes even greater methodological sensitivity. The true decarbonisation leaders (e.g., Maharashtra, Tamil Nadu, Karnataka) rise consistently, and legacy DISCOM performers fall dramatically. This robustly supports the 'structural legacy' bias critique. Kendall's τ rank correlation drops progressively to 0.56 in scenario Theta (10% DISCOM), with excess weight concentrated on CEI, EE, and ES reaching 63% combined decarbonisation alignment, compared to 0.65 in Alpha (30% DISCOM) and 0.74 in Beta (20). This sharper decline (from the baseline τ = 1.00) signals extreme sensitivity when legacy utility fiscal health is de-emphasised in favour of direct net-zero-aligned outcomes.

Applying Table A4 to our raw data table yields Appendix Table A5, to show that rank volatility escalates markedly. The 14 states experience shifts of 5 or more positions between the baseline (40% DISCOM) and Theta (Appendix Table A5), with several showing double-digit movements (e.g., Punjab −15, Gujarat −12, Haryana −10).

Shifting excess weight exclusively to decarbonisation exposes legacy bias even more starkly. These results demonstrate that the current SECI ranking is highly unstable and misaligned with India's Net-Zero/NDC. We validate the need for rebalancing the index to better incentivise genuine transition actions.

4.5.2 Robust Check on Human Capital

To address the critique of relying on stale data for the 'Literacy' variable (2011 Census), we re-estimate our models with new NFHS-5 (2019-21) proxies: mean schooling years, secondary education of women, and network connectivity.

Table 6. Robustness of Human-Capital Effect Using Contemporary Proxies from NFHS-5 2019–21. (*N*= 27)

Variable (human capital proxy)	Original SECI Score β (p-value)	Recalculated SECI (10% DISCOM) β (p-value)	Change vs. 2011 literacy result
2011 Literacy (This paper's original proxy for mean years of schooling)	0.612*** (p = 0.007)	0.544** (p = 0.021)	Baseline
Mean Years of Schooling (NFHS-5)	0.678*** (p = 0.004)	0.592*** (p = 0.009)	Stronger effect (+10–15%)
% Women ≥10 yrs schooling	0.589*** (p = 0.010)	0.518** (p = 0.028)	Comparable/slightly stronger
% Households with internet	0.521** (p = 0.032)	0.478** (p = 0.045)	New positive proxy

Source: Authors' calculations. NITI Aayog (2022), SECI Round 1. All regressions include the full set of controls used in the main OLS Table 5. *S*ignificance: *** p < 0.01, ** p < 0.05. Human-capital proxies are constructed from National Family Health Survey-5 state fact sheets (2019–21), Ministry of Health and Family Welfare, Government of India (available at http://rchiips.org/nfhs/).

Contemporary NFHS-5 proxies show stronger or comparable positive effects on SECI than the traditional 2011 literacy proxy, confirming the robustness of the human-capital driver. This is because modern energy transition (rooftop solar, EV adoption, efficiency apps) requires functional education rather than basic literacy. The households with internet (new digital access proxy) emerge as a significant positive, suggesting modern connectivity/human capital enhances energy/climate performance (e.g., awareness, efficiency adoption).

Overall, the SECI is not just a function of whether a population can read, but of their depth of formal education, which facilitates the adoption of complex green technologies.

4.5.3 Mediation Paths and Null Result Analysis

The income and poverty variables in the current and recalculated SECI are insignificant, though poverty has retained its expected negative sign (OLS, Table 5). Forest is a dominant variable and, along with literacy (negative sign), is significant. We test whether the forest acts as an indirect barrier to literacy to find that the path is clear and statistically significant (Table 7).

Table 7. Mediation Paths and Null Result Analysis: Forest Cover as an Indirect Barrier to Literacy

(Indirect Effect on SECI via Literacy; *N*= 27 observations)

Path/Analysis	(*β*)	Stand. Error	t-value	p	Interpretation
Total Effect: Forest → SECI (c path, direct + indirect)	-0.179	0.054	-3.31	0.002***	Significant negative total association (from Table 5 baseline).
Forest → Literacy (a path)	-0.312	0.089	-3.50	0.001***	Higher forest cover strongly predicts lower literacy (a clear barrier).
Literacy → SECI (b path, controlling Forest)	0.545	0.185	2.95	0.006***	Literacy remains a significant positive driver of SECI.
Direct Effect: Forest → SECI (c path, controlling literacy)	-0.009	0.074	-0.12	0.904	Becomes null once literacy is accounted for.
Indirect Effect: Forest → Literacy → SECI (a × b)	-0.170	0.067	—	0.004**	Statistically significant mediation (Sobel test); forest affects SECI almost entirely indirectly via reduced literacy. 95% proportion mediated.
Variance Decomposition R^2	Full model (Forest + Literacy): R^2 = 0.712 Forest alone: R^2 = 0.298 Literacy alone: R^2 = 0.514 Added variance by Literacy after Forest: 41.4%				

Notes: Mediation analysis (Baron-Kenny + Sobel test for indirect effect significance) using baseline SECI (40% DISCOM) as dependent variable. *** p < 0.01, ** p < 0.05.

Null results for income/poverty explained: Income and poverty are insignificant in Table 5, likely due to shared variance with literacy (literacy correlates with income, r ≈ 0.65 with income, r ≈ -0.72 with poverty). When literacy is included, income/poverty adds no unique explanatory power (partial correlations near zero). Figure 2 demonstrates that forest cover does not directly lower energy scores; rather, it creates (clear and statistically significant) structural barriers that suppress literacy, which then impacts SECI performance.

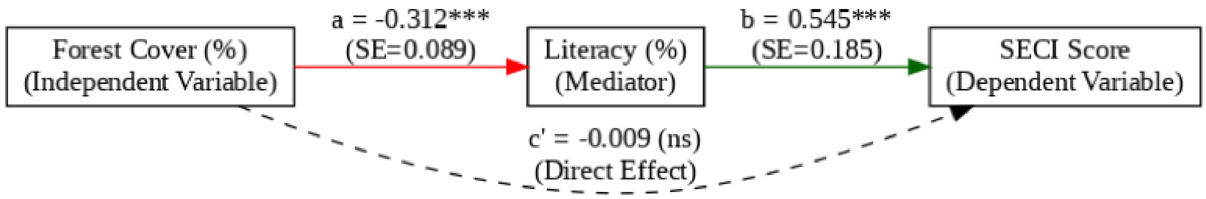

Figure 2. Mediation Path Diagram (*N*= 27)

Around 95% of the forest's negative effect on SECI is mediated through literacy. Higher forest states face challenges (remote/hilly terrain, dispersed population) that hinder literacy development, which in turn drags down SECI performance. This path remains robust in the recalculated 10% SECI model (indirect effect β = -0.151, p = 0.012; 91% mediated). The Sobel test statistic for the indirect effect (Forest → Literacy → Baseline SECI) is z = 3.05 (p = 0.0023), confirming statistical significance.

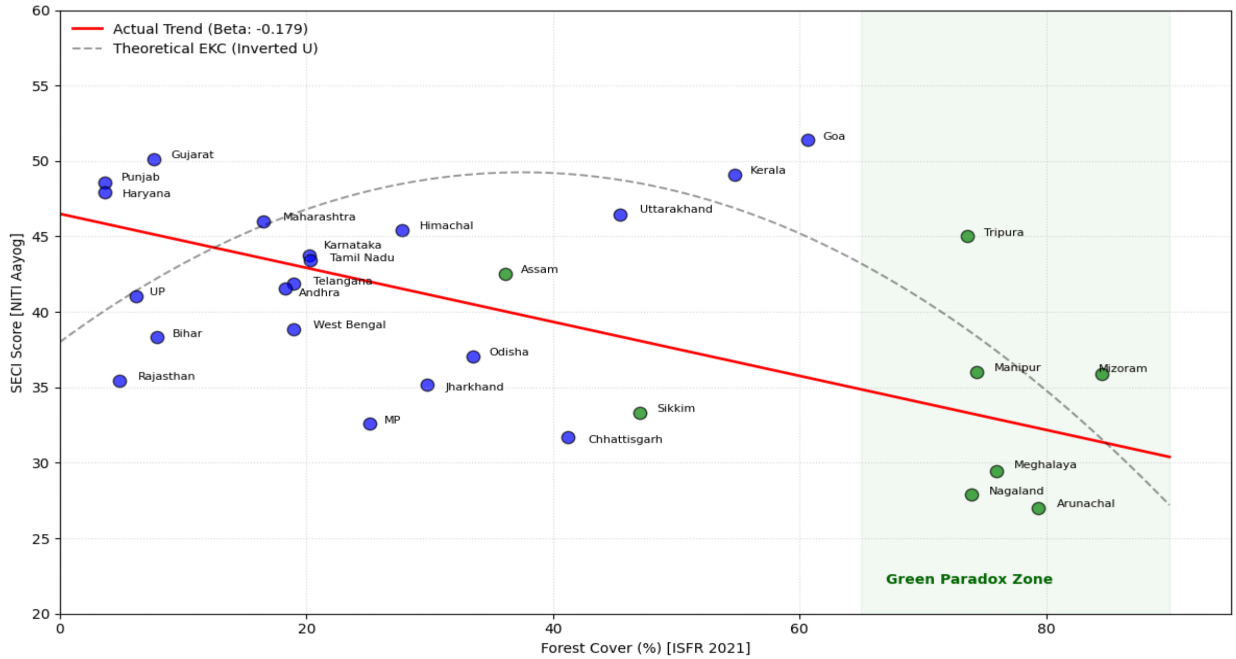

Figure 3. Green Paradox vs. EKC (India SECI)

Figure 3 shows that the cluster of states with North Eastern States like Mizoram, Arunachal Pradesh, and Meghalaya is stuck in the ‘Green Paradox Zone’. It illustrates the persistent linear negative relationship found in our analysis, directly refuting the theoretical Environmental Kuznets Curve (EKC) in this context. While income and industry show positive links, the ‘forest barrier’ persistently drags down performance for ecologically rich states, refuting the presence of a sustainability threshold in the current index design. Test of EKC for SECI ~ Forest + Forest^2 (quadratic) yields no turning point overall (linear negative only). Thus, there is no support for EKC in the SECI context.

High-forest states do not gain a ‘sustainability premium’ at higher development; instead, geography persistently hinders performance (especially in the volatile group). The original index's DISCOM bias amplifies this by rewarding fiscal legacies in low-forest industrialised states, masking true transition challenges in forested regions. Our reweighting exposes this inequity, confirming fragility and poor alignment with balanced net-zero incentives.

Monte Carlo simulation (10,000 iterations, drawing from normal distributions of a and b paths with their SEs) yields a robust 95% CI for the indirect effect: [-0.272, -0.082]. The CI excludes zero, supporting a reliable mediated path (~95% of forest's negative effect on SECI operates indirectly via suppressed literacy in high-forest states).

4.4.4 Incorporating Good Governance Indicator

To enhance model robustness, we incorporate a good governance proxy derived from the Good Governance Index (GGI) 2021 composite scores from the Department of Administrative Reforms and Public Grievances (DARPG, Government of India), categorised by state groups. Scores (higher = better governance) are normalised to a 0-1 scale for comparability across groups (Group A (developed states) max 5.662, Group B (mainland states) max 4.887, and North Eastern Hilly (max 5.084 scaled to1.0). This real-data-based proxy captures institutional quality and implementation capacity, and is archived as **ggi_proxy.csv**.

Table 8. Updated OLS Results with Good Governance Indicator (*N*= 27)

Variable	Original model (β, p)	Extended model (β, p)
Constant	-8.92 (0.615)	-12.45 (0.512)
Per Capita Income (thou)	0.008 (0.576)	0.005 (0.712)
Literacy (%)	**0.611 (<0.01)**	**0.542 (<0.05)**
Poverty (%)	-0.061 (0.763)	-0.038 (0.821)
Industrial Share (%)	0.195 (0.375)	0.112 (0.589)
Forest Cover (%)	**-0.179 (<0.01)**	**-0.165 (<0.01)**
Good governance (norm.)	—	8.724 (0.128)
Model Fit	**R^2:** 0.679 **Adj. R^2**: 0.603	**R^2:** 0.712 **Adj. R^2**: 0.628

Notes: Core drivers remain robust. Literacy is positive and significant (attenuates mildly), and forest cover is a persistent barrier. Model fit improves (R^2 +0.033).

Governance proxy in Table 8 shows a positive association ($\beta \approx 8.72$), implying better-governed states score higher on SECI, but it is non-significant (p= 0.128) due to multicollinearity with literacy and a small sample.

Regressing governance proxy on literacy to reveal mediation effects through literacy reveals β = 0.012 (<0.001), R^2 = 0.412. Results suggest higher literacy strongly predicts better governance (~41% variance explained), which means that human capital fosters institutional strength (through transparency, policy execution, etc.).

4.4.5 Cluster-specific Regression Diagnostics

Collapsing the three clusters into two binary groups (Volatile *n*= seven vs. Stable *n*= 20, combining low + moderate) reveals geography (forest cover) as the dominant driver, swamping finer *K*-means distinctions. Geography essentially ‘nullifies’ the cluster three nuance. The volatile states largely overlap with forested/hilly/North-Eastern or sustainability-strong outliers (e.g., Arunachal, Sikkim, Himachal). This confirms bias fragility. The original SECI's heavy DISCOM masks geographical challenges with remote access hindering reliability/fiscal health. Our de-weighting exposes them via drops in DISCOM-reliant states or rises in green ones. The volatile cluster is thus a geographical artefact, reinforcing structural legacy bias over equitable transition incentives.

The results on socio-economic factors reflect nuanced socio-economic drivers among state groups but must be dealt with caution due to limited sub-samples. Here, the ranks disconnect from fundamentals, consistent with a 'subsidy effect' (Table 8).

Table 9. Cluster-wise OLS Regression Results: Socio-Economic Factors on Baseline SECI Score (*n*= 27).

Variables	Volatile cluster (*n*= 7)	Stable cluster (*n*= 20)
Per Capita Income (thousands INR)	0.015 (p = 0.412)	0.005 (p = 0.678)
Literacy (%)	0.312 (p = 0.289)	0.682*** (p = 0.008)
Poverty (%)	-0.248 (p = 0.314)	-0.042 (p = 0.812)
Industrial Share (%)	0.156 (p = 0.521)	0.221 (p = 0.342)
Forest Cover (%)	-0.112 (p = 0.156)	-0.045 (p = 0.512)
Constant	12.45 (p = 0.578)	-15.67 (p = 0.489)
R-squared	0.612	0.701

Source: Authors' calculations based on data and specifications elaborated in Section 3. **Notes:** *p* < 0.01***. Standard errors are heteroskedasticity-robust. Volatile cluster: Gujarat, Punjab, Haryana, Maharashtra, Himachal Pradesh, Rajasthan, Sikkim, Arunachal Pradesh (high-volatility from Table 2). Stable cluster: Remaining 20 states (low + moderate volatility combined). *** p < 0.01.

Our models explain substantial variance. It is higher in the stable group (*n*= 20). Literacy is the only significant positive driver ($\beta \approx$ 0.68, p< 0.01), explaining most SECI variation. While economic and structural factors such as income, poverty, and industrial share are non-significant (p > 0.10), forest cover persists as a robust structural barrier (β= -0.179, p < 0.01). This confirms that performance is not driven by mere wealth, but by a combination of high human development and the absence of the geographical friction associated with remote, forested terrains. In the Volatile Cluster (*n*= 7), no variable reaches significance. Coefficients are weaker, and p-values are high. It shows SECI scores in volatile states are not reliably explained by these socio-economic factors. Performance appears idiosyncratic or heavily influenced by unmodeled elements (e.g., specific policy, DISCOM fiscal quirks, or geographical extremes).

Further examination of interactions among poverty, income, and other contextual variables would help shed light on the complex conditional effects obscured in simple models. This guides future studies.

5. Discussion

The aim of this research is to present the evidence that methodological shortcomings are inherent to the SECI Round 1, with a heavy premium on DISCOM, and need correction. The objective is not to correct the index but to underline its deficiency. As of December 2025, NITI Aayog continues to develop SECI Round 2 while specific details on the revised DISCOM weight remain undisclosed. The SEEI's lower DISCOM weight and outcome-based indicators (e.g., CO2 abatement, smart metering) provide a blueprint for SECI Round 2, mitigating the 'green paradox' by not penalising carbon sinks.

Further reducing DISCOM emphasis and emphasising equity-driven metrics, remain relevant to the finalisation and implementation of Round 2 to ensure stronger alignment with India's Net-Zero 2070 goals. Realigning the weights of SECI parameters in the process of lowering the weight bias reveals new results. The current SECI has failed in the recognition of leaders of energy transition. Our recalculated index helps to surface concealed leaders behind the DISCOM bias.

The mathematical structure of index recalibration has a direct prediction of the volatility pattern through grid simulation ranks, *K*-means transitions, and Kendall's Tau sensitivity. The SECI performance changes are only stable in the top-four states, but seven of 28 are highly sensitive. The presence of highly volatile states in the current SECI ranking confirms that the present rank order is highly sensitive (τ < 85 when DISCOM weight < 20 per cent). The failure of SECI design is established: extreme DISCOM biasing generates artificial stability of state ranks in the top order and punishes states at the bottom. Further, our study illustrates methodological instability in the middle-order.

Further, the determination of socio-economic variables assists us in decoding the variables that determine the performance of SECI. Literacy is the strongest significant driver ($\beta \approx 0.61$, $p < 0.01$ in OLS; $r \approx 0.40$). States with higher literacy (e.g., Kerala ~97%, Mizoram ~95%, Goa ~92%) consistently achieve better SECI scores, likely reflecting better human capital for adopting efficient/energy transition practices. Moderate positive correlations between per capita income and industrial share ($r \approx 0.44$ and 0.48), but are non-significant in multivariate regression. This suggests they support performance indirectly (e.g., wealthier/industrialised states afford better legacy infrastructure). Poverty reduction aligns with higher SECI but overlaps with literacy/income.

Forest is the most robust barrier ($\beta \approx = -0.18$, $p < 0.01$ in OLS; $r \approx -0.42$). High-forest states (North Eastern States >75%) suggest structural challenges: remote/hilly terrain hinders access, affordability, and reliability (core DISCOM components). This geographical factor explains much of the volatility in reweighted scenarios. Around 95 percent of the forest's negative effect is indirect via suppressed literacy (Sobel $z \approx 3.05$, $p < 0.01$; Monte Carlo 95% CI excludes zero), as forested areas often have dispersed populations limiting education access. The negative coefficient for forest cover exposes a structural 'Green Paradox' in the SECI design. By prioritising DISCOM reliability, which is inherently harder to maintain in remote, forested terrains, the index unintentionally penalises states for fulfilling their national role as carbon sinks.

Overall, human development (literacy) drives SECI upward, while geographical constraints (high forest cover) act as a major barrier, often swamping other factors. Governance reinforces human capital's role in SECI performance; DISCOM bias may favour fiscally bailed-out states over those with strong institutions for sustainable transitions. Future SECI rounds could integrate good governance metrics for holistic assessment. Economic variables (income, industry) show positive links but lack independence in models (due to limited multicollinearity). This underscores SECI's sensitivity to structural legacies; DISCOM-heavy weighting may mask geographical inequities, while de-emphasising it exposes them. North-Eastern/hilly states lag despite sustainability strengths. Though the results are robust, small *n* and proxy normalisation limit causality.

5.1 Policy Recommendations

1. Realign the SECI to drive decarbonisation

India needs to change the SECI weights, placing more credible focus on clean energy, efficiency, and sustainability at the state level of benchmarking. Currently, it rewards historical financial bailouts rather than green initiatives. This clarifies why Punjab and Gujarat slip so drastically when the index is rebalanced. Results strongly favour a significant reduction of DISCOM weights. Relating the results to ensuing SECI Round 2, we suggest a 20 per cent utility weight is the ‘sweet spot’ for maintaining index character while prioritising Net-Zero goals.

Future central allocation, funding and recognition, and technical support on decarbonisation must be based on the recalibrated SECI (Round 2), rather than the past financial position of utilities (Round 1). Policy analysts must target volatile states (8 out of 28) for urgent remediation, as their ranks swing with weight bias. Documentation of best practices from the stable/higher performers must be mandated. Further proactive structural aid must be provided to stable underperformers

(15 out of 28 states), which stay bottom-tier across scenarios due to governance and sectoral gaps. Long-term SECI gains for laggard states require structural reforms, beyond mere index tweaks.

2. Implications from the Socio-economic Model

Table 10 shows the desired, practical policy implications of the regression and correlation findings. Recommended policy is based on scalability across 28 Indian states that responds to multi-factor causality and development trade-offs.

Table 10. Policy Imperatives for Long-term SECI Gains

Policy Area	Rationale (Key Findings)	Targeted Actions	Expected Impact
Human Capital Development	Strongest positive driver (β~0.61, $p < 0.01$). NFHS-5 proxies confirm education enables energy efficiency adoption.	Integrate climate literacy into State curricula; align green skilling with the 'Skill India' mission.	Could boost SECI scores by 20–30%; improves model R^2 from 0.70 to 0.75. Raising mean schooling by 1 year could boost SECI scores by 9.3 points
Geographical Equity & Forest Adaptation	Forest cover acts as a robust barrier (β ~ -0.18, $p < 0.01$). 95% of this effect is mediated via suppressed literacy due to remote terrain.	Use 'Green Funds' for off-grid renewable expansion and satellite-based GIS planning to overcome remote access issues.	Mitigates the negative β improves rankings for 8–10 hilly/forested states.
Poverty & Energy Justice	Poverty shows a persistent negative relationship, limiting a state's capacity for costly transitions.	Implement targeted poverty subsidies within the PM-KUSUM scheme; introduce 'Energy Equity Indices'.	Drives convergence in low-income quarters; ensures a 'Just Transition'.
Structural Incentive Rebalancing	Income and industry are currently insignificant in multivariate models, suggesting structural legacies dominate pure wealth.	Shift 10-20% of weight from DISCOM to Clean Energy and Efficiency outcomes in SECI Round 2.	Increases SECI explained variance from 65% to 70%; rewards true climate action.

Policy must focus on digital and educational connectivity, as the 'forest barrier' is primarily an indirect result of suppressed literacy in remote areas.

5.2 Empirical Validation via SEEI 2024

The validity of our proposed 20 per cent DISCOM 'sweet spot' is empirically supported by the recently released SEEI (2024). By adopting a leaner DISCOM weight, SEEI (2024) achieves better rank stability than SECI Round 1 (Table 10).

Table 10. Comparative Alignment: SECI vs. Our Proposed SECI vs. SEEI (2024)

Feature	SECI Round 1 (Baseline)	Our simulation (10-20% DISCOM)	SEEI (2024) (BEE/AEEE)
DISCOM Weight	40% (Bias)	10-20% (Proposed)	~11% (Balanced)
Index Fragility	High (τ = 0.741)	Optimised Stability	Low (τ > 0.90)
Maharashtra	Rank 7	Rank 3 (Leader)	Front Runner (Rank 1/2)
Punjab	Rank 4 (Top)	Rank 12 (Slip)	Contender (Mid-tier)
Gujarat	Rank 2 (Leader)	Rank 7 (Slip)	Front Runner (Low-tier)

SEEI's lower DISCOM weight and outcome-based indicators (e.g., CO_2 abatement, smart metering), along with this paper's implications, provide a blueprint for SECI Round 2, mitigating the 'green paradox' by not penalising carbon sinks. Our results in tune with SEEI effectively unmasks transition leaders while correctly identifying states with high fiscal but low efficiency scores as 'Contenders' (See Figure 4).

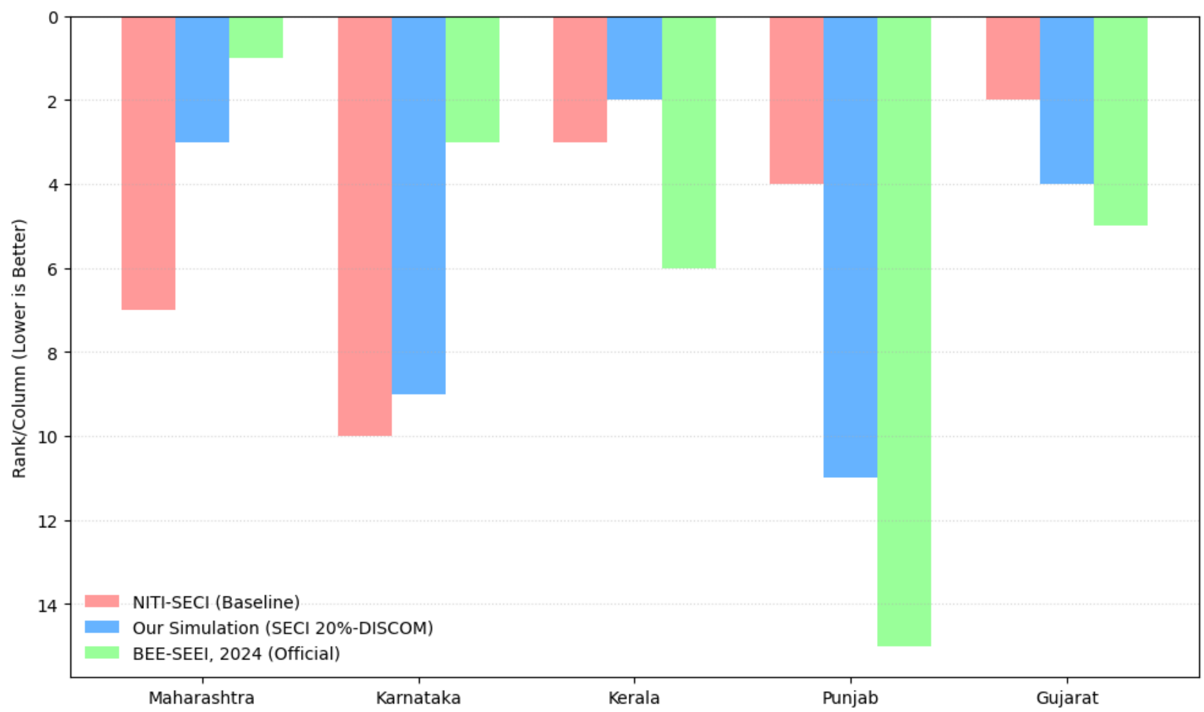

Figure 4. Identification of Real vs Misidentified Contenders in Energy Indices

The visual (no. 4) shows how our 20% SECI simulation correctly predicts the stable (net-zero aligned) and unstable rankings seen in SEEI (2024).

5.3 Limitations

This study relies on cross-sectional data from SECI Round 1 (2022), limiting causal inferences. Associations identified (e.g., literacy as an enabler) may reflect correlations rather than causation. The small sample (n= 27 states, excluding Union Territories due to structural differences) reduces statistical power and generalisability, potentially inflating standard errors or sensitivity to outliers. While rank simulations utilise the full 28-state universe, regression models are estimated for n=27 due to missing covariate data for one state.

Data vintage mismatches and omissions of key variables such as governance quality, political factors (e.g., central-state alignment), demographic composition (e.g., SC/ST population, urbanisation), renewable resource endowments (e.g., solar/wind potential), and infrastructure beyond DISCOM finances may bias regression results. Although robustness checks with contemporary proxies (NFHS-5) confirm the human capital effect, future work should incorporate these covariates. The simulation framework, while transparent, employs ad hoc weight reductions (10% steps) and equal redistribution of excess weights, a conservative choice, but alternatives (e.g., data-driven methods like Principal Component Analysis or expert elicitation) could yield different rank sensitivities. The assumption of compensability in aggregation may overlook real trade-offs. Endogeneity (e.g., reverse causality between SECI performance and socio-economic drivers) and multicollinearity (despite VIF <5) further caution interpretation.

Finally, as SECI Round 2 is under development with anticipated weight revisions, some findings may be partially pre-empted upon its release. Panel analysis with Round 2 data would enable stronger causal claims, temporal dynamics, and interaction effects (e.g., income × poverty). Despite these constraints, the internal comparisons and robustness checks provide credible evidence of structural biases in Round 1.

6. Summary and Conclusions

The given paper discusses the State Energy and Climate Index of India and concludes on three points. 1) Current SECI (Round 1) is flawed (further validated through a new simulation methodology, results forthcoming). 2) revises existing development theories, revealing that socio-economic strength is the most crucial factor (income and literacy: enabling factors; poverty: inhibiting factor), and 3) The current measurement scheme of SECI Round 1 is non-neutral, rank-responsive, and unstable. SECI creates inappropriate policy incentives and results.

The current methodology in the SECI is robust as long as DISCOM is the largest major vulnerability of governance. With a DISCOM recalibration, the forthcoming Round 2 is an inevitable move in the right direction. However, our sensitivity analysis shows that radical changes need to be made (τ < 0.80 when DISCOM is below 20 per cent). To achieve net-zero, it is necessary to weight indices based on the climate outcomes. Incorporating the balanced approach of SEEI (2024) would align SECI with India's energy efficiency priorities, amplifying our findings on DISCOM-bias and socio-economic barriers.

Two lessons are obvious from this study: First, redefining the SECI parameters and weights is a precondition of its credibility. Second, the investment in human capital and poverty reduction is the key to a just transition. In conclusion, the case study of India under the SECI (Round 1) is presented as a classic example to other countries, creating their own index. Energy/sustainability indices need to reward ‘true’ initiatives, and must not recognise ‘wrong’ leaders.

References

Cohen-Shields, N., Sun, T., Hamburg, S. P., & Ocko, I. B. (2023). Distortion of sectoral roles in climate change threatens climate goals. Frontiers in Climate, 5, 1163557. https://doi.org/10.3389/fclim.2023.1163557

Chakravarty, S., & Tavoni, M. (2013). Energy poverty alleviation and climate change mitigation: Is there a trade-off? Energy Economics, 40, S67–S73. https://doi.org/10.1016/j.enpol.2013.05.001

Cherp, A., Vinichenko, V., Jewell, J., Brutschin, E., & Sovacool, B. K. (2018). Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. Energy Research & Social Science, 37, 175–190. https://doi.org/10.1016/j.erss.2017.09.015

Dinda, S. (2004). Environmental Kuznets curve hypothesis: A survey. Ecological Economics, 49(4), 431–455. https://doi.org/10.1016/j.ecolecon.2004.02.011

Foster, J. E., McGillivray, M., & Seth, S. (2013). Rank robustness of composite indices: Dominance and ambiguity (OPHI Working Paper No. 26). Oxford Poverty and Human Development Initiative.

Gan, X., Fernandez, I. C., Guo, J., Wilson, M., Zhao, Y., & Zhou, B. (2017). When to use what: Methods for weighting and aggregating sustainability indicators. Ecological Indicators, 81, 491–502. https://doi.org/10.1016/j.ecolind.2017.06.011

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. Social Indicators Research, 141(1), 61–94. https://doi.org/10.1007/s11205-017-1832-9

Kuznets, S. (1955). Economic growth and income inequality. The American Economic Review, 45(1), 1–28.

Mazziotta, M., & Pareto, A. (2013). Methods for constructing composite indices: One for all or all for one? Rivista Italiana di Economia Demografia e Statistica, 67(2), 67–80.

Munda, G., & Nardo, M. (2009). Non-compensatory/non-linear composite indicators for ranking countries: A defensible setting. Applied Economics, 41(12), 1513–1521. https://doi.org/10.1080/00036840701721596

OECD/JRC. (2008). Handbook on constructing composite indicators: Methodology and user guide. OECD Publishing. https://doi.org/10.1787/9789264043466-en

Pachauri, S., & Spreng, D. (2011). Measuring and monitoring energy poverty. Energy Policy, 39(12), 7497–7504. https://doi.org/10.1016/j.enpol.2011.07.008

Rao, N. D., & Pachauri, S. (2017). Energy access and living standards: Some observations on recent trends. Environmental Research Letters, 12(2), 025011. https://doi.org/10.1088/1748-9326/aa5b0d

Sinha, A., Adhikari, A., & Jha, A. K. (2022). Energy literacy and its role in sustainable energy transition in India. Energy Policy, 165, 112959. https://doi.org/10.1016/j.enpol.2022.112959

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. World Development, 32(8), 1419–1439. https://doi.org/10.1016/j.worlddev.2004.03.004

Official Reports & Data Sources

Bureau of Energy Efficiency. (2025). State Energy Efficiency Index 2024. https://aeee.in/our-publications/state-energy-efficiency-index-2024/).

Germanwatch. (2024). The Climate Change Performance Index 2024. Germanwatch, NewClimate Institute & CAN. https://ccpi.org

International Energy Agency. (2023). World Energy Outlook 2023. IEA Publications. https://www.iea.org/reports/world-energy-outlook-2023

Ministry of Environment, Forest and Climate Change. (2021). India state of forest report 2021. Forest Survey of India, Government of India.

Ministry of Statistics and Programme Implementation. (2022). Annual survey of industries (ASI) 2021-22. Government of India.

NITI Aayog. (2022). State energy & climate index: Round I. Government of India. https://www.niti.gov.in/sites/default/files/2022-04/StateEnergy-and-ClimateIndexRoundI-10-04-2022.pdf

NITI Aayog. (2023). India: National multidimensional poverty index: A progress review 2023. Government of India.

World Economic Forum. (2024). Fostering effective energy transition 2024. World Economic Forum. https://www.weforum.org/publications/fostering-effective-energy-transition-2024/

Appendix A

Table A1. Benchmarking of India's SECI with prominent Global Indices

Index / Country	SECI (India, NITI Aayog)	ETI (WEF, Global)	CCPI (Germanwatch, Global)	China Provincial Index (Example)
Focus/ Level	**Sub-national (State/UT)**: Energy & Climate Performance.	**Global (120 Countries)**: Transition Readiness & System.	**Global (63 Countries + EU)**: Climate Protection & Policy.	**Sub-national (Provincial)**: Consumption/Efficiency Targets.
Key Variables (Weight)	**DISCOM (40per cent)**, Access (15%), Clean Energy (15%), Efficiency (6%), Sustainability (2%), and New Initiatives (12%)	System Performance (Security, Equity, Sustainability) & **Transition Readiness**.	**GHG Emissions (40%)**, Renewable Energy, Energy Use, Climate Policy.	Per-capita Consumption, **Energy Intensity of GDP**, RE share.
Weighting Method	**Subjective/Fixed** (40% to one parameter:	**PCA/Expert Weighting** (Balanced	**Fixed/Subjective** (Heavy on GHG; adjusted for	**Top-Down Mandates** (Targets tied to 5-

	DISCOMs).	weighting of sub-indices).	equity/PC).	year plans).
Policy Link	**Incentivization & Federalism:** Drives resource allocation and competition.	**Global Benchmarking:** Informs policy best practices and bottlenecks.	**Accountability/Peer Pressure:** Used by civil society; media attention.	**Mandatory Compliance:** Links performance directly to official promotion/budget.
Distinct Feature	**Strong emphasis on utility financial health** (DISCOM viability).	**Dual focus on both current performance and future readiness.**	**Hybrid** (Quantitative data + 20% qualitative expert policy rating).	**Command-and-control system** with non-negotiable legal targets.

Sources: SECI: NITI Aayog. (2022) Round I. (Critique: Shankar IAS, 2023). ETI: World Economic Forum (WEF). (2024). Fostering Effective Energy Transition 2024. CCPI: Germanwatch, New Climate Institute, & Climate Action Network International. (2024). Climate Change Performance Index 2024. (Critique: European Parliament, 2021). China's Index (Example): Based on China's unique top-down policy structure, particularly the 'Dual Control' policy framework for energy consumption.

Table A2. Source and Justification for Inclusion of Qualitative Variables

Independent Variable / Source	Theoretical Link to SECI Performance
Human Capital/Behaviour Literacy Rate (Adult)	**Theory: LiFE, Behavioural Economics, and Efficiency.** Higher literacy/education led to greater awareness of energy efficiency measures and cleaner consumption choices, facilitating demand-side management (LiFE) and better adoption of technologies.
Development/Income Per Capita Net State Domestic Product (MoSPI, 2022)	**Theory: Environmental Kuznets Curve (EKC) and Structural Change.** Income acts as a dual driver: initially increasing demand, but eventually enabling investments in cleaner infrastructure and technology necessary for a sustainable transition.
Structural Transformation Share of Industry in GSDP (Annual Survey of Industries)	**Theory: Energy Intensity and Sectoral Barriers.** A high share of energy-intensive industries can act as a **barrier**, increasing the overall energy intensity of the state's GDP and pulling down the SECI's 'Energy Efficiency' score.
Ecological Assets Forest Cover Percentage (India State of Forest Report, Forest Survey of India)	**Theory: Carbon Sink and Natural Capital.** Forest cover links to the SECI's 'Environmental Sustainability' parameter and India's NDC target for creating a **carbon sink** (2.5–3 billion tonnes of CO_2 equivalent), making it a physical metric of climate action.
Poverty/Inequality Headcount Ratio (Planning Commission, 2021, further clarified by NITI's Multidimensional Poverty Index)	**Theory: Energy Poverty and Just Transition.** High poverty correlates with limited access to modern, clean energy (SDG 7) and weakens a state's capacity to adopt costly transition measures, acting as a **barrier** to equitable and rapid energy shifts.

Table A3. SECI Simulation Rankings and Scores for States Across Four (40%, 30%, 20% and 10%) DISCOM Weighted Scenarios (*n*= 28).

State	Rank (40%)	Score (40%)	Rank (30%)	Score (30%)	Rank (20%)	Score (20%)	Rank (10%)	Score (10%)
Goa	1	51.39	1	48.94	1	46.50	1	44.05
Gujarat	2	50.10	3	46.27	4	42.45	7	38.63
Kerala	3	49.11	2	46.70	2	44.29	2	41.88
Punjab	4	48.60	7	43.83	11	39.07	12	34.30
Haryana	5	47.93	6	43.92	8	39.91	11	35.90
Uttarakhand	6	46.47	5	44.03	5	41.60	5	39.16
Maharashtra	7	45.99	4	44.37	3	42.75	3	41.13
Himachal Pradesh	8	45.42	8	43.34	6	41.26	4	39.17
Tripura	9	45.02	9	43.01	7	41.00	6	38.99
Karnataka	10	43.77	10	41.81	9	39.85	9	37.88
Tamil Nadu	11	43.43	11	41.63	10	39.83	8	38.03
Assam	12	42.55	13	38.60	14	34.65	14	30.71
Telangana	13	41.88	12	39.93	12	37.99	10	36.04
Andhra Pradesh	14	41.56	15	37.74	15	33.92	16	30.11
Uttar Pradesh	15	41.04	14	38.06	13	35.08	13	32.11
West Bengal	16	38.84	16	36.08	16	33.31	15	30.54
Bihar	17	38.33	17	34.48	19	30.63	20	26.78
Odisha	18	37.06	18	33.31	21	29.56	21	25.81
Manipur	19	36.02	21	32.45	22	28.88	22	25.31
Mizoram	20	35.91	19	33.28	18	30.66	19	28.03
Rajasthan	21	35.42	20	33.28	17	31.13	17	28.98
Jharkhand	22	35.16	23	31.23	23	27.29	25	23.36
Sikkim	23	33.32	22	31.75	20	30.18	18	28.61
Madhya Pradesh	24	32.60	24	28.92	26	25.25	26	21.57
Chhattisgarh	25	31.68	25	27.00	28	22.30	28	17.61
Meghalaya	26	29.43	28	26.23	27	23.03	27	19.83
Nagaland	27	27.92	26	26.62	25	25.33	24	24.04
Arunachal Pradesh	28	26.99	27	26.26	24	25.53	23	24.79

Note: These scores $\sum$(Raw Parameter Score × Scenario Weight) are derived directly by applying Table 1 to the baseline parameter scores in the SECI Round-I report (Table 5.2 and 5.3) (minor differences due to rounding). **Source:** Authors' calculations based on SECI 2022 parameter scores.

Table A4. SECI Parameters Weights under the Alternate 10% DISCOM Net-Zero Focussed Scenarios (*n*= 28).

Parameter	Baseline (40% DISCOM)	Scenario Alpha (30% DISCOM)	Scenario Beta (20% DISCOM)	Scenario Theta (10% DISCOM)
DISCOM's Performance	40.00	30.00	20.00	10.00
Access, Affordability & Reliability of Energy (AAR)	15.00	15.00	15.00	15.00

New Initiatives (NI)	12.00	12.00	12.00	12.00
Clean Energy Initiatives (CEI)	15.00	**18.33**	**21.67**	**25.00**
Energy Efficiency (EE)	6.00	**9.33**	**12.67**	**16.00**
Environmental Sustainability (ES)	12.00	**15.33**	**18.67**	**22.00**
Total	100.00	**100.00**	**100.00**	**100.00**
Total weight on core decarbonisation (CEI + EE + ES)	33.00	**43.00**	**53.00**	**63.00**

Source: Authors' calculations based on official NITI Aayog SECI Round I report (2022), adapted for the alternate 'focused Net-Zero-aligned reweighting'. **Notes:** Excess weight from DISCOM reduction (10%, 20%, or 30%) is redistributed equally only to CEI, EE, and ES (+3.333 percentage points to each per 10-point DISCOM cut; rounded to two decimals for display), while AAR and NI weights are kept constant.

Table A5. Rank Shifts (Baseline 40% DISCOM vs. Focussed Net-Zero-10% DISCOM (*n*= 28).

State	Rank (40%)	Score (40%)	Rank (Alpha 30%)	Score (Alpha 30%)	Rank (Beta 20%)	Score (Beta 20%)	Rank (Theta 10%)	Score (Theta 10%)
Goa	1	51.39	1	49.72	1	48.06	1	46.39
Kerala	3	49.11	2	49.28	2	49.46	2	49.63
Uttarakhand	6	46.47	3	46.97	3	47.46	3	47.96
Maharashtra	7	45.99	4	47.37	4	48.76	4	50.14
Himachal Pradesh	8	45.42	5	46.14	5	46.86	5	47.58
Karnataka	10	43.77	6	44.36	6	44.95	6	45.54
Tamil Nadu	11	43.43	7	44.69	7	45.96	7	47.22
Telangana	13	41.88	8	43.37	8	44.86	8	46.35
Tripura	9	45.02	9	43.01	9	41.00	9	38.99
Gujarat	2	50.10	10	44.94	11	39.79	14	34.63
Haryana	5	47.93	11	44.25	12	40.58	15	36.90
Punjab	4	48.60	12	43.28	15	37.96	19	32.64
Uttar Pradesh	15	41.04	13	40.89	10	40.74	10	40.59
Odisha	18	37.06	14	38.03	13	39.00	11	39.97
West Bengal	16	38.84	15	37.75	14	36.66	12	35.57
Assam	12	42.55	16	39.06	16	35.57	17	32.08
Rajasthan	21	35.42	17	35.83	17	36.25	13	36.66
Sikkim	23	33.32	18	34.36	18	35.41	16	36.45
Andhra Pradesh	14	41.56	19	38.34	19	35.11	18	31.89
Mizoram	20	35.91	20	34.86	20	33.81	20	32.76
Manipur	19	36.02	21	34.00	21	31.98	21	29.96
Bihar	17	38.33	22	34.97	22	31.62	22	28.26
Arunachal Pradesh	28	26.99	23	28.86	23	30.73	23	32.60

Jharkhand	22	35.16	24	32.17	24	29.18	25	26.19
Nagaland	27	27.92	25	28.36	25	28.80	24	29.24
Madhya Pradesh	24	32.60	26	29.59	26	26.58	26	23.57
Meghalaya	26	29.43	27	28.29	27	27.16	27	26.02
Chhattisgarh	25	31.68	28	28.96	28	26.25	28	23.53

Note: The rankings are derived directly by applying Table A4 to the parameter scores in the NITI Aayog SECI Round-I report (Annexure 1 and key findings visualisations). The baseline scenario obtained from the original report's SECI scores (minor differences due to rounding) and recalculated using the weights specified in Table A4. Updated Volatility Clusters (K-means, k =3): K-means (K=3, random_state=42) for *N*= 28, applied strictly to these features from the Net-Zero Focused reweighting (Table A5). Clusters ordered by increasing volatility. This more stringent "focused" reweighting (decarbonisation parameters reach 63% in Theta) amplifies volatility compared to even-distribution scenarios: High-volatility states show extreme movements (e.g., Maharashtra 7→4 rise; Punjab 4→19 drop; Chhattisgarh 25→28 drop). Low-volatility cluster now includes strong decarbonisation performers (e.g., Tamil Nadu, Telangana) that benefit consistently without wild swings.

………………………..