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

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Abstract

This study provides the first sensitivity audit and rank volatility analysis of India’s State Energy and Climate Index (SECI Round 1, 2022). We identify a significant methodological distortion: the 40% weight assigned to power distribution companies (DISCOMs), which prioritises legacy fiscal health over decarbonisation outcomes. Using stepwise grid simulations for 28 states, we find high rank fragility (τ< 0.80) when DISCOM weights drop below 20%, revealing that current rankings mask true transition leaders like Maharashtra, while rewarding coal-heavy grids like Punjab. Cross-sectional OLS estimation identifies literacy as the dominant enabler of performance (β= 0.612, p< 0.01). Conversely, forest cover emerges as a structural barrier; mediation analysis reveals that 95% of its negative impact is indirect, operating through suppressed literacy in remote terrains. These findings expose a ‘green paradox’ where ecologically rich states are penalised for maintaining carbon sinks. We conclude that the SECI is fundamentally non-aligned with India's Net-Zero 2070 goals. An urgent recalibration to a 20% DISCOM threshold is recommended to incentivise genuine climate action in the ensuing SECI-Round 2.

Keywords: Index bias, SECI, India, energy transition, sustainability metrics, human capital, non-fossil renewable energy, Net Zero policy.

JEL Codes: I32, O13, Q43, Q54.

1. Introduction

The efforts towards decarbonisation and economic development in India will define its pathways towards Net-Zero emissions by 2070 (COP26, Glasgow, 2021). This is a difficult balance for India, being the third-largest energy consumer in the world and given its federal context. In India, the policy maker (centre) lays down achievable national targets, monitors and guides pathways, providing incentives for effective implementation. The implementation, however, rests with the states. The construction and announcement of the State Energy and Climate Index (SECI, Round 1, April, 2022) is one such measurement tool used by the centre. It tracks the sustainability activities of the sub-nationals and encourages them, providing a basis for cooperative federalism in the energy and climate space, aiming for Net-Zero.

The first round of the SECI (and the only one so far) was welcomed in the country for being innovative. However, it is criticised for 40 per cent of the total weight in the composite score is placed on one factor, the financial stability of its distribution companies (DISCOMs). The weight of DISCOM is very high than that of the second largest parameter at 15 per cent, demonstrating an imbalance, lacking theoretical and empirical justification.

To diagnose the human costs of this DISCOM-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 ₹15,000 crore during 2019-2021 to clear its DISCOM debt, helping it fund its coal-heavy grid to the extent of 60 per cent. When we simulate the DISCOM weight in our study from 40% to 10%, the rank of Punjab slips drastically from 4th to 12th, and Gujarat falls from 2nd to 7th, showing how sensitive the present state ranking is. This means the current SECI recognised a financial debt wash and not a green transition. In contrast, clean energy leaders Maharashtra ranks 7th and climbs up the ranks when the DISCOM-heaviness 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. SECI ignores this.

We show that the SECI Round 1 is not a neutral scoreboard. It gives wrong recognition to states (like Punjab, Gujarat), ignores social barriers (e.g. Bihar) and discourages leaders (Maharashtra, Tamil Nadu), listing them lower in state ranks. This leads us to ask: Is the SECI an actual advance by the sub-nationals towards Net Zero? Our results show that high fragility (τ = 0.741) once the SECI is made DISCOM-light, suggesting the current index measures legacy fiscal health rather than the 'actual' transition readiness required for Net Zero.

This paper answers this query in four steps. First, we construct a stress test of the current SECI weighing scheme with a focus on DISCOM weights. It measures how fragile the current SECI state rankings are to the shift in weights, to identify states whose positions are fairly stable/volatile in the rank list. Second, we reweight the index and relate the original and the re-weighted scores to re-rank the states. This finds rank instability of the states. Thirdly, the socio-economic variables like state income, forest cover, industrial structure and literacy rates are associated with the original and re-weighted index to determine the socio-economic barriers/drivers of state performance. Finally, we subject the results to robust tests. This draws policy lessons in revising the weighting scheme in the future SECI rounds and state rankings.

Our analysis is broadly situated within the political economy of measurement. We show that the current index design is not neutral. Ranking decides the kind of incentives and investment priorities of the states, and allows for political credit, leading to the possibility of governance distortion. The weight-bias led to recognition of ‘wrong’ leaders and rewarded them for having legacy institutions, and penalised those who do not have them. Energy transitions in India are heavily influenced by socio-economic path-dependencies. Having wider forest cover, higher poverty, and a more disadvantaged population may be a stress factor masking genuine performance on the SECI indicators.

Against the above backdrop, this study answers two questions: 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). Our fundamental contribution is to provide a basis for needed revision in the current SECI design that well aligns the energy, climate and development goals. The study treats the SECI as a governance instrument whose choices can influence the determination of rewards, funds and recognition; rather than as a technical tool of performance measurement.

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. However, when we discuss the SECI construction in light of the methodological literature and other global indices involving its parameter choices, critical shortcomings emerge. Most are with respect to the weighing schemes, normalisation and aggregation.

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. 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. The aim is to check if the 'leaders' remain as 'leaders' under reasonable alternative assumptions.

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

The interactions of growth and sustainability have been well researched. Among other factors, economic growth is considered the prime factor in energy transition and is often studied using the Environmental Kuznets Curve (EKC) framework. The EKC literature examines whether pollution first rises and then falls with income. The evidence is mixed depending on the pollutant, country group and period. While the original Kuznets hypothesis (1955) focused on income inequality, later scholars adapted this framework to suggest environmental degradation. The EKC follows an inverted 'U' trajectory, rising during the early stages of industrialisation and falling once a certain wealth threshold facilitates greener technologies (Stern, 2004; Dinda, 2004). 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.

Economic theories assume that there is a direct correlation between income, energy and climate activities. Income acts as the driver of energy consumption and facilitates the adoption of technology and efficient energy practices, enabling a positive force of transition. This is not merely a function of wealth but is complicated by deep-seated structural inequalities. 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 traditionally seen as a barrier, it is the lack of human capital (literacy) often associated with poverty that serves as the true bottleneck for SECI performance. The capacity of a sub-national entity to transition, therefore, depends more on socio-economic enablers than on national income alone.

Qualitative factors like literacy and governance quality are as important as income. 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. The drivers of India’s energy transition are not uniform. Our empirical modelling across states shows that the energy ladder is often complicated by structural inequalities, where literacy and industry share act as primary drivers, while forest cover and poverty act as significant friction factors. While early-stage industrialisation may necessitate a spike in emissions, a ‘necessary evil’ for development (Chakravarty & Tavoni, 2013), the eventual decoupling of growth from carbon depends on underlying 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 Comparison with Global Climate Indices: Outlier Status of SECI

When compared alongside the energy and climate indices of major global economies, India's SECI emerges as a methodological outlier (see Table A1, Appendix). The divergence is most visible in India's index weighting architecture. In the SECI framework, a single parameter bias is well illustrated and stands in sharp contrast to the evaluation models used by peers like China. China's Green Development Indicator system prioritises physical climate outcomes, heavily weighting carbon intensity and environmental carrying capacity, rather than the balance sheets of structural institutions.

The 'DISCOM-heaviness' in the Indian context is not merely a methodological limitation; it represents a departure from global best practices. Frameworks like the World Energy Trilemma typically balance security, equity, and sustainability, ensuring no single operational metric distorts the broader picture. By alternating the weights of NDC alignments to the financial solvency of the utility (DISCOM), the SECI recognises legacy rather than sustainability actions.

Furthermore, this design flaw has profound implications for cooperative federalism. In a policy landscape where measurement drives resource allocation, a skewed index creates skewed incentives. It signals that cleaning up utility accounts makes more sense to rank high on the SECI than actually following clean energy initiatives (weighted at only 15%). This validates our hypothesis of 'political economy of measurement' posited by scholars like Greco et al. (2019) and Turnbull (2019): 'the index is not a neutral mirror of reality, but a political tool that narrows the scope of performance to quantitative financial variables'. This conveniently sidelines the qualitative drivers of genuine transition.

This study relates to affordable and clean energy (SDG 7) to limit climate change (SDG 13) and hints at the need to decrease barriers to inequality (SDG 10). We underline the necessity of an integrated energy policy covering socio-economic aspects of poverty (SDG 1), education (SDG 4), and economic growth (SDG 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 alternative weight simulation uses stepwise, iterative reduction to measure the extent of distortion that is created by the present SECI. 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 work is extended by evaluating the effect of the qualitative factors, like LiFE, on the quantitative energy performance, which is not considered by the existing SECI. We check how socio-economic inequalities are impacted through shifting the established role of technology and capital to the variables like poverty, literacy, and forest cover.

3.1 Variables

The dependent variable is the composite score in SECI Round 1 (2022) of 28 Indian states as published in the NITI report. Eight union territories are excluded from the analysis as they have a different DISCOM structure (Delhi and Puducherry skew heavily). Unlike the original SECI Round 1 publication, which reports separate rankings for larger states, smaller states and UTs, this study constructs a unified 'all-states' universe. All 28 states in our sample are ranked in a single pooled list using the underlying SECI parameter scores, without any large/small classification. This 'unified universe' is retained for all simulated weighting scenarios, while the regression analysis is restricted to n= 27 due to missing data for Jammu & Kashmir. The dependent variable is the SECI score (calculated as a composite score of SECI). The raw data extracted from the ground-truth parameter scores and archived as 'seci_rankings.csv' for reproducibility.

All independent variables of the study represent theoretically important drivers and are defined and justified in Appendix Table A2, 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), which yield consistent or stronger coefficients (Section 4.4, Table 7), 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

The existing SECI incorporates a fixed subjective weight to DISCOM, which is relatively higher when compared to the other five parameters (see Table A1). To measure this bias, we step-wise grid-simulate DISCOM 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 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 $(W_1^{(orig)}, \dots, W_6^{(orig)}) = (0.40, 0.15, 0.15, 0.06, 0.12, 0.12)$

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 only given to clean energy parameters, and used for robustness. The new scores for five parameters under each regime are: original scores + extra adds from DISCOMs at each stage.

The robustness check with focused redistribution (Section 4.4.1) to clean energy parameters (confirms similar rank sensitivity (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:

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

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). 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 is small (*n*=27, excludes Jammu and Kashmir), 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 Analysis

This is used to explain the mediation path from Forests to literacy to SECI. The use of the Sobel Test and Monte Carlo simulations (10,000 iterations) to validate 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, eliminates bias in measurement (4.1) and charts the socio-economic forces behind just transitions (4.2), providing a viable interface on policy making and reform.

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 two parts corresponding to our two key research questions.

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 weight of 40 per cent of DISCOM. The baseline (40%) 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% scheme is chosen to facilitate comparison for its relatively higher net-zero alignment, prioritising 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%, prioritising decarbonisation outcomes.

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. The 10 per cent situation is used as a standard of comparison. The sorting of the composite score in descending order generates scenario-wise ranks. The new ranks reflect the extent of change dramatically as the DISCOM is dis-weighted under an iterative scenario, indicating volatility. This generates the drastic changes in ranks, which will cast doubts on the unbiasedness of the current index (Appendix Table A3).

Recalculation of the ranks under the alternative condition shifts the performers onto the real-world action on climatic matters instead of imposing a premium on the structural heritage of the states. 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).

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

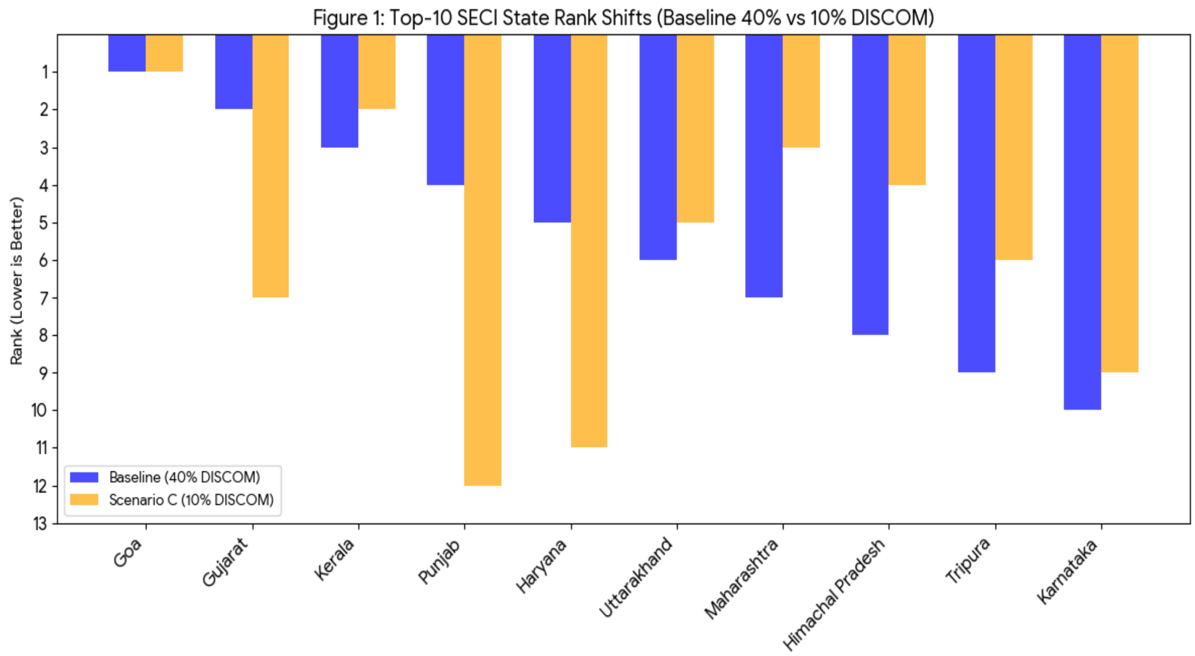

Figure 1. Bar Chart of Top-10 SECI State Rank Shifts (Baseline 40% vs 10% DISCOM)

Source: Authors' calculations (sourced from Table A3, appendix). **Notes:** For all States, see Table A3 (appendix).

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. Maharashtra (increases from 7 to 3), Uttarakhand (increases from 6 to 5), Himachal Pradesh (increases from 8 to 4), and Tripura (increases from 9 to 6) receive a boost, and indicate a repressed renewable potential that the DISCOM prejudice concealed.

4.2 Volatility Clustering and Sensitivity

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 states are classified in 3 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*)	Avg. 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	0.9	Small to medium rank changes (range 2–3). "Stuck" in the bottom tier.	Tripura, Tamil Nadu, Assam, Telangana, Andhra Pradesh, Uttar Pradesh, 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.

On the criteria of rank volatility, three main clusters emerge among the 28 states/UTs, identified through K-means clustering (K=3) on two standardised features: Rank Range (max − min rank across the four DISCOM-weight scenarios) and Average |ΔRank| (mean absolute rank change between consecutive scenarios).

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

This group exhibits minimal rank shifts (average range 0.80 positions; average |ΔRank| 0.27). States here perform consistently regardless of DISCOM weighting, reflecting balanced strengths across fiscal health and decarbonisation metrics. Members on this cluster are Goa, Kerala, Uttarakhand, Karnataka, and West Bengal. 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. 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 (average range 2.60 positions; average |ΔRank| 0.91). Most remain stuck in mid- to bottom tiers 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 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.

States in this cluster are: Tripura, Tamil Nadu, Assam, Telangana, Andhra Pradesh, Uttar Pradesh, Bihar, Odisha, Manipur, Mizoram, Jharkhand, Madhya Pradesh, Chhattisgarh, Meghalaya, and Nagaland. 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 (average range 5.13 positions; average |ΔRank| 1.71), highlighting methodological sensitivity. Volatility arises from disproportionate reliance on high DISCOM scores (causing drops when de-weighted) or strengths in decarbonisation parameters (causing rises).

Members: Gujarat, Punjab, Haryana, Maharashtra, Himachal Pradesh, Rajasthan, Sikkim, Arunachal Pradesh. Former baseline leaders like Gujarat (from 2 to 7), Punjab (4 to 12), and Haryana (5 to 11) fall sharply as DISCOM weight drops from 40% to 10%. Conversely, sustainability-strong states like Himachal Pradesh (8 to 4), Sikkim (23 to 18), and Arunachal Pradesh (28 to 23) climb. Maharashtra rises notably (7 to 3), confirming its leadership in climate metrics despite volatility.

Overall, only 18% of states (n=5) exhibit true rank stability, while 54% (n=15) remain relatively stuck in mid- to lower tiers. The high-volatility group (29%, n=8) reveals clear methodological artefacts: baseline top performers like Gujarat and Punjab owe much of their position to the heavy 40% DISCOM 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, undermining focus on actual energy transition and net-zero alignment. In order to quantify the similarity of the manner of two different sets of rankings, sensitivity analysis with the aid of the *Tau* (*τ*) statistic is applied to measure the similarity, to demonstrate the level of agreement between the two differing ranking lists.

Table 3 provides the Sensitivity results. This table measures the similarity between the original NITI Aayog ranking (40 per cent DISCOM) and the three alternate scenarios. A lower Tau (τ) value indicates higher "fragility" or sensitivity to the weightage methodology.

Table 3. Sensitivity Analysis through the Kendal'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. While the Kendall's is (0.926), significant volatility already exists for specific 'fiscal-legacy' states like Punjab.
B	0.815	Moderate similarity & Noticeable fragility. Increased divergence as DISCOM influence drops, with moderate reordering (e.g., volatility in DISCOM-heavy states becomes evident).
C	0.741	Low similarity & High fragility. Substantial reordering occurs when DISCOM 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.

The sensitivity analysis (Table 3) shows that the SECI ranking retains strong similarity to the original only at modest adjustments (τ = 0.926 at 30% DISCOM). Similarity deteriorates to moderate levels at 20% (τ = 0.815) and becomes notably low at 10% (τ = 0.741) in the even-distribution scenario and 0.56 in the focused Net-Zero regime. Since Kendall's *τ* falls below the conventional threshold of ~0.8 when DISCOM weight drops to 20% 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. The robust test of the above fragility audit is presented in Section 4.4.1 using alternate 'Net Zero-Focussed' scenarios.

4.3 Qualitative Factors Influencing Energy Transitions

With the quantitative bias of the SECI (Round 1) unearthed in the earlier section, 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 (r) with SECI	OLS Coefficient (β)	Std. Error	p-value
(Intercept)	-	-8.918	24.779	0.719
Literacy Rate (%)	0.40	**0.611**	0.258	**0.018***
Forest Cover (%)	-0.42	**-0.179**	0.058	**0.002****
Industrial Share (%)	0.48	0.195	0.382	0.611
Per Capita Income (Rs. 000)	0.44	0.008	0.042	0.841
Poverty Rate (%)	-0.50	-0.060	0.327	0.853
R^2 = 0.679, Adj. R^2 = 0.603, *N* = 27				

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 (Jammu & Kashmir excluded due to missing SECI score in the dataset).

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 performance. SECI with Per Capita Income (r = 0.44) and literacy (r = 0.40) 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 (sustainability) with operational/legacy factors.

Next, we consider the hypothesis that persistent socio-economic disparities limit SECI advances through a regression model (Table 5). Regressions are estimated on the original SECI, and on the SECI (simulated) with a 10 per cent weight on the DISCOM, based on the specifications and data presented in section 3.

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

(27 observations; using clean 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. Income scaled to thousands INR for interpretability. The recalculated model uses the 10% DISCOM weighting scheme (Scenario C: Table 1).

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 DISCOM weighting), forest cover has a stronger negative effect; literacy drives more. In the recalculated 10% (de-emphasising DISCOM), effects are slightly attenuated but directionally consistent. Income and poverty are insignificant in the multivariate model, and attribute this to multicollinearity/shared variance with literacy (Literacy correlates 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 results support index fragility.

Multicollinearity noted (high condition number), but estimates remain stable. Poverty and industrial share are non-significant in both. The model validation using diagnostic tests (heteroskedasticity-consistent standard errors, VIF evidence of multicollinearity, Jarque-Bera to test normality, Ramsey RESET, test specification).

4.4 Robustness Checks

4.4.1 robustness through the Alternate 10% DISCOM Net-Zero Focussed Scenario

In order to stress-test our rank fragility audit, we propose a very stringent alteration by using the 'DISCOM Net-Zero Focused' scenarios. This regime is very similar to our main simulation, where the 40 per cent DISCOM acts as the baseline and under three scenarios, the DISCOM weights are step-wise negatively iterated as: Scenario Alpha (30% DISCOM), Beta (20% DISCOM) and Theta (20% DISCOM). 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. The 'focused' weight allocations are presented in Appendix Table A4. Applying Table A4 to our raw data table yields Appendix Table A5.

The focused reweighting exposes even greater methodological sensitivity, with true decarbonisation leaders (e.g., Maharashtra, Tamil Nadu, Karnataka) rising consistently and legacy DISCOM performers falling dramatically. This robustly supports the 'structural legacy' bias critique. Kendall's Tau 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% DISCOM). This sharper decline (from the baseline $\tau = 1.00$) signals extreme sensitivity and fragility when legacy utility fiscal health is de-emphasised in favour of direct net-zero-aligned outcomes.

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). This is substantially higher than the even-distribution 10% scenario, where fewer states exhibited such large swings.

Shifting excess weight exclusively to decarbonisation exposes legacy DISCOM bias even more starkly, rewarding true transition leaders (e.g., Maharashtra, Himachal Pradesh) and penalising fiscal-health-dependent states. These results demonstrate that the current SECI ranking is highly unstable and misaligned with India's Net Zero/NDC and validate the need for rebalancing the index to better incentivise genuine transition actions.

4.4.2 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)

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. SECI scores: NITI Aayog (2022), State Energy & Climate Index – Round I. All regressions include the full set of controls used in OLS Result, Table 5 (per capita income, poverty rate, industrial share of GSDP, forest cover). Coefficients (β) standardised for comparability; significance: *** $p < 0.01$, ** $p < 0.05$. Human-capital proxies 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 (mean years of schooling and % women with ≥10 years schooling) 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.

4.4.4 Mediation Paths and Null Result Analysis

The income and poverty variables in the current and recalculated SECI (OLS Results, Table 5) are insignificant, though poverty has retained its expected negative sign (in Table 7).

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

(Indirect Effect on SECI via Literacy; 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 (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. *** $p < 0.01$, ** $p < 0.05$.

We test whether the forest acts as an indirect barrier to literacy and find that the path is clear and statistically significant. 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, $r \approx 0.65$ with income, $r \approx -0.72$ with poverty). When literacy is included, income/poverty adds no unique explanatory power (partial correlations near zero).

Forest cover acts as a clear and statistically significant indirect barrier; higher forest states face structural challenges (remote/hilly terrain, dispersed population) that hinder literacy development, which in turn drags down SECI performance. Around 95% of the forest's negative effect on SECI is mediated through literacy. 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.

Collapsing clusters into binary groups (Volatile n=8 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 3 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 (remote access hindering reliability/fiscal health), while 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.

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).

4.4.5 Cluster-specific Diagnostics

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 8. Cluster-wise OLS Regression Results: Socio-Economic Factors on Baseline SECI Score

(Volatile n=8 vs. Stable n=20; 27 observations total)

Variables	Volatile cluster (n=8)	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:** *N*=28, all States. *p* < 0.01***. Standard errors are heteroskedasticity-robust. Income scaled to thousands INR for interpretability. The recalculated model uses the 10% DISCOM weighting scheme (detailed in Section 4.5). 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). Coefficients (β) rounded to three decimals; *** p < 0.01.

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 ($\beta = -0.179$, $p < 0.01$). 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=8), no variable reaches significance. Coefficients are weaker, and p-values are high, indicating 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).

Test of EKC for SECI ~ Forest + Forest^2 (quadratic) yielded 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. Reweighting exposes this inequity, confirming fragility and poor alignment with balanced net-zero incentives.

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

5. Discussion

As of December 27th, 2025, NITI Aayog continues to develop SECI Round 2. While specific details on the revised DISCOM weight remain undisclosed, this ongoing recalibration partially addresses the concerns raised here regarding bias in Round 1. 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.

The recommendations in this paper, particularly for further reducing DISCOM emphasis and emphasising equity-driven metrics, remain relevant to inform the finalisation and implementation of Round 2, ensuring stronger alignment with India's Net-Zero 2070 goals. Realigning the weights of SECI parameters in the process of lowering the DISCOM-heaviness 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 *Tau* sensitivity. The SECI performance changes are only stable in the top-4 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 (*Tau* < 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 illustrating 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 Rate (%): 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 non-significant in multivariate regression, suggest they support performance indirectly (e.g., wealthier/industrialised states afford better DISCOM infrastructure). Poverty reduction aligns with higher SECI but overlaps with literacy/income.

Forest Cover (%) 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% 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. Economic variables (income, industry) show positive links but lack independence in models (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. Policy must focus fon on digital and educational connectivity, as the 'forest barrier' is primarily an indirect result of suppressed literacy in remote areas. The results support the need for an equitable pattern and to incorporate LiFE indicators in the subnational NDCs.

5.1 Policy Implications

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. It rewards historical financial bailouts rather than current 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% 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 DISCOM 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 laggards demand structural reforms, beyond mere index tweaks.

2. Implications from the Socio-economic Model

Table 9 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 9. 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 ($\beta \sim -0.18$, $p < 0.01$). 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.

5.2 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=28 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 revisions, some findings may be partially preempted 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, it is rank-responsive and unstable (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 its 30 per cent DISCOM recalibration, our Scenario A is recapitulated as the forthcoming Round 2 is an inevitable move in the right direction. However, our sensitivity analysis shows that more radical changes need to be made (*Tau* < 0.80 when DISCOM is below 20%). To achieve Net-Zero, it is necessary to weigh indices based on the climate outcomes.

Two lessons are obvious: First, redefining the SECI 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.

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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 (40%)**, 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: DISCOMs).	**PCA/Expert Weighting** (Balanced weighting of sub-indices).	**Fixed/Subjective** (Heavy on GHG; adjusted for equity/PC).	**Top-Down Mandates** (Targets tied to 5-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. Government of India. (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 (Jiang et al., 2019)

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 All 28 States Across Four (40%, 30%, 20% and 10%) DISCOM Weighted Scenarios

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 ∑(Raw Parameter Score × Scenario Weight) are derived directly by applying Table 1 to the baseline parameter scores in the NITI Aayog 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

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.

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 weights specified in Table A4.

Updated Volatility Clusters (K-means, k =3): K-means (K=3, random_state=42) 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.

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