Beyond national averages: a multi-method assessment of sub-national environmental sustainability and inequality in India

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Beyond national averages: a multi-method assessment of sub-national environmental sustainability and inequality in India

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Abstract: India's rapid economic growth regularly jeopardizes its environmental foundation, although important sub-national differences were typically hidden by national-level evaluations. For all 37 Indian states and union territories (UTs), this study creates the Composite index of Environmental Sustainability (CoES), a comprehensive multi-dimensional framework that integrates 36 indicators across 4 sub-indices: climate-energy, terrestrial-biodiversity, waste-pollution, and water-sanitation sectors. We employ an innovative multi-method approach, including correlation analysis, network analysis, hierarchical clustering, inequality metrics, spatial additive decomposition, and hierarchical clustering. Results reveal a distinct 'prosperity-pollution' paradox, where high agricultural yields in the northern plains were statistically tied to extreme groundwater depletion and land degradation. Industrial wastewater compliance emerged as a 'master connector', bridging terrestrial health with sanitation infrastructure. While the Northeast leads in biodiversity wealth, significant infrastructure deficits in waste processing offset these ecological gains. Although Chandigarh emerges as the national standard for sub-national sustainability, inequality indices reveal a large disparity in forest cover and renewable energy infrastructure. We conclude that without density-focused management, increasing the area of forests is not enough to mitigate climate change. We offer context-specific policy recommendations that integrate climate-energy, biodiversity, waste-pollution, and water-sanitation concerns based on our empirical findings.

Keywords: environmental sustainability; composite index; sub-national sustainability; regional inequalities; India;

1. Introduction:

Environmental sustainability has developed into a dynamic framework that strikes a balance between the long-term viability of human progress and the integrity of ecosystems. Maintaining the balance between resource extraction and the environment's potential for regeneration has become a global necessity since planetary boundaries were under unprecedented pressure. The multifaceted nature of today's sustainability issues necessitates a coordinated approach to circular resource management, terrestrial health, and atmospheric stability. Sophisticated evaluation systems that can synthesize many biophysical, social, and administrative data sources were necessary to capture these intricate relationships. Composite indices were crucial diagnostic tools that condense complex environmental factors into understandable, useful information for a variety of stakeholders. These indices offer a comprehensive picture of regional health by combining many variables, something that single-metric assessments sometimes fail to do. The inherent geographic and socioeconomic differences that exist within large, diverse nations were often overlooked by standardized national evaluations. It was possible to identify localized environmental problems and particular governance accomplishments by shifting the analytical focus toward sub-national solutions. National averages can obscure the striking differences between various regional landscapes and industrial footprints in a nation as biologically diverse as India. India has the unique task of protecting its extensive and diverse natural resource base while also pursuing rapid economic progress. Understanding how specific state-level policies and resource endowments affect the accomplishment of national sustainability goals requires sub-national study. Regional differences in topography, climate, and localized population density have a significant impact on environmental results throughout the Indian subcontinent. Many of the current frameworks for sustainability suffer from severe data lag or a narrow emphasis that leaves out important aspects such specialized waste processing. An integrated index that concurrently assesses pollution, water security, biodiversity, and climate resilience at the state level was desperately needed. Monitoring how several environmental pillars work together might help identify hidden trade-offs, such as the conflict between stable water tables and high agricultural productivity. Effective benchmarking was made possible by a thorough sub-national index, which enables underperforming regions to model their environmental strategies after their high-performing counterparts. The detail needed to help policymakers create focused, site-specific environmental initiatives was frequently lacking in current indices. To effectively localize and accomplish the Sustainable Development Goal 6 in diverse regions, thorough monitoring was necessary. The gap between broad theoretical sustainability and realistic, data-driven regional management was addressed by creating a multifaceted framework for India. The evidence base required to make the shift to a more resilient, transparent, and fair environmental future was provided by strong sub-national assessments.

2. Literature review:

There were a handful of studies that have focused on environmental sustainability (**Table 1**). Because aggregated data does not accurately reflect the distinct environmental constraints that different sub-national regions face, large-scale national assessments often conceal major internal discrepancies (Singh et al., 2019; Kumar et al., 2025). Due to the exclusion of crucial North-Eastern and Himalayan states, much research focused on India offers insufficient geographic coverage, which limits the findings' national representativeness (Mukherjee & Kathuria, 2006; Kateja & Medatwal, 2024). Current frameworks frequently rely on out-of-date datasets, like the 2011 Census, which do not account for changes in the environment today or the effects of new sustainability measures (Dash et al., 2011; Tiwari & Krishna, 2021). While ignoring more expansive ecological aspects like climate risk and biodiversity, literature often has a restricted thematic focus, such as emphasizing agricultural production or energy utility performance (Mukherjee, 2022; Pandey et al., 2022). Important sustainability pillars such specialized waste processing, wildlife protection, and water quality measurements were routinely left out of composite indices due to serious data gaps (Jain & Mohapatra, 2023; Fil Rodríguez et al., 2025). Conventional methodological techniques, such as PCA-based weighting, may ignore informative variance that was crucial for recognizing localized environmental crises and may be too sensitive to outliers (Latif, 2022; Kumar et al., 2025). Current indices noticeably lack inter-sectoral analysis, making it difficult to identify intricate relationships and trade-offs between many environmental variables (Oţoiu & Grădinaru, 2018; Garai et al., 2025).

By changing the analytical focus to a high-resolution sub-national resolution, this study closes the scale gap and makes it possible to identify localized environmental crises and governance accomplishments. By incorporating all 37 Indian states and UTs into our framework, we overcame regional exclusion and ensured a thorough national assessment that took the Northeast into account. Our study uses recent data from the NITI Aayog NDAP database to address data latency and provide a real-time reflection of sub-national sustainability development. By combining 36 different indicators across four crucial dimensions (viz. climate & energy - CE, terrestrial & biodiversity health - TB, waste pollution - WP, and water sanitation - WS, this work goes beyond single-sector assessments.

Table 1. Comparative analysis of relevant empirical studies concerning composite index for environmental sustainability.

Study	Location	Study Period	Dimensions	Drawbacks
Mukherjee & Kathuria (2006)	India states (n=14)	1990–2001	- air quality (SO_2, NO_2, SPM) - water quality (BOD, COD) - land quality (14 indicators of pressure and degradation)	- Excludes North-East and Himalayan states - Relies on SPM instead of $PM_{2.5}$ - Does not account for waste management or climate vulnerability
Dash et al. (2011)	India states (n=28)	Snapshot 2011	- air & water quality - land use & forests - waste & pollution - institutional capacity (via DPSIR framework)	- High sensitivity to missing data values for smaller states - Equal weighting of 41 indicators ignores varying regional environmental priorities - Baseline data was now over a decade old

das Neves Almeida & & García-Sánchez (2016)	Global (n=132)	2014 Snapshot	- environmental health (health impacted) - ecosystem vitality (air, water, agriculture, forest, fisheries, biodiversity, energy)	- Information asymmetry between different composite indexes (CIEP vs. EPI) - Extreme sensitivity to normalization techniques
das Neves Almeida et al. (2017)	OECD Countries	2000–2012	- air pollutants (SOx, NOx, CO_2) - water pollutants (BOD) - municipal waste	- Explicit focus on 'Environmental Damage' (pollution outputs) rather than sustainability (resource stocks) - Excludes governance and policy response indicators
Oţoiu & Grădinaru (2018)	Global (n=114)	2000–2016	- environmental state (actual conditions) - environmental sustainability (rate of change over time)	- Prohibitive data requirements for tracking 'change' across multiple years - Complexity in mathematical aggregation limits its utility for quick policy communication
Roy & Pramanick (2019)	India	1975-2010	- biophysical indicators (SDG 6) - socioeconomic indicators (SDG 6)	- National focus - Lacks sub-national granularity - Heavy focus on SDG 6 only
Shah et al. (2019)	South Asia (n=8)	2006-2017	- energy availability & efficiency - economic affordability - technology development - environmental sustainability (CO_2, Forest, NO_2)	- Regional focus lacks sub-national granularity for India - Subjective weighting via AHP method - Heavy focus on energy security over-shadows ecological health metrics
Singh et al. (2019)	22 Asian economies (incl. India)	1990–2012	- air, water, & land quality - biodiversity - energy & waste management - environmental policy response	- Use of Composite Z-score assumes equal importance of all indicators across diverse geographies - Dated study period (ends 2012)

				- National-level data masks internal state-level performance
Gómez-Limón et al. (2020)	Spain (Agricultural sector)	Snapshot 2015	- soil quality & water management - atmosphere (emissions) - biodiversity (flora/fauna)	- Farm-level focus limits direct applicability to sub-national administrative regions - Context-specific to EU CAP regulations - High sensitivity to expert-based subjective weighting
Sun et al. (2020)	South Asian countries (n=8)	2001–2015	- carbon emissions - water productivity - forest area & renewables - adjusted net savings	- DEA-like mathematical model measures 'efficiency' rather than absolute ecological state - Ignores internal regional disparities within large nations like India
Fakher et al. (2021)	Global (incl. India)	1990–2015	- CO_2 & CH_4 emissions - deforestation & agriculture - water pollution (BOD)	- Econometric orientation (EKC testing) rather than descriptive policy dashboarding - National aggregation lacks resolution for sub-national environmental management
Tiwari & Krishna (2021)	India districts (n=641)	Snapshot 2011 (Census based)	- social (health, education, amenities) - economic (infrastructure, workforce, BPL) - environmental (forest, scrub, wasteland, groundwater)	- Heavy reliance on dated Census 2011 datasets - Existing regional socio-economic gradients impede the deduction of universal local indicators - Environmental indicators remain under-integrated in micro-level policy planning
Chentouf & Allouch (2022)	MENA Region (n=17)	2008–2017	- energy diversification & dependency - energy intensity & consumption per capita	- Heavy emphasis on technical/economic energy metrics with modest focus on direct ecological health

			- electrification ratio & GDP per capita - carbon intensity & emissions per capita	- Sensitive to isolated indicator bias, which may lead to misleading regional conclusions - Significant data gaps in conflict-affected regions (e.g., Yemen, Syria) affect accuracy
Latif (2022)	Asia countries (n=48)	1996–2020	- ecological footprint - environmental quality & vulnerability - sustainability & pressure on nature - adjusted net savings	- PCA-based weighting can discard low-variance information - Simplified methodology may mask local hotspots or ecological crises - Results were highly sensitive to the specific proxy indicators selected for environmental dimensions
Mukherjee (2022)	India states (n=17)	1990–1991 to 2013–2014	sustainable land use & cropping; sustainable irrigation & livestock; agro-chemical & farm mechanization; population pressure & sustainable forest	- Agriculture-exclusive focus; excludes non-point source urban or industrial pollution - Geographically restricted to major states (excludes North-East and Hilly States) - Time-lagged data (ends 2013–14) limits real-time assessment of recent SDG initiatives
Pandey et al. (2022)	India (28 States & 8 UTs)	2019–2020	- DISCOM performance (40% weight) - access, affordability & reliability - clean energy & energy efficiency - environmental sustainability & new initiatives	- Strong operational bias toward utility performance (DISCOMs) over direct climate outcomes - Substantial data gaps at the state level for ‘New Initiatives’ (e.g., EV charging, smart meters) - One-size-fits-all indicators may not account for diverse state-specific natural resource portfolios

Alshuwaikhat et al. (2023)	Saudi Arabia	2010–2018	- air quality - CO_2 emissions - energy (consumption/intensity) - water (consumption/ treatment) - waste and land use	- Short assessment period (9 years) was susceptible to inter-annual to inter-decadal climate variability - Not all proposed index indicators (e.g., renewables, water leakages) were utilized due to local data unavailability
Jain & Mohapatra (2023)	Emerging Economies (n=20, incl. India)	1990–2020	- natural resources rent - water (productivity/ freshwater) - air pollution ($PM_{2.5}$) - CO_2 and energy (intensity/renewables)	- Omission of vital sub-indices like water quality, waste management, and biodiversity protection due to data gaps - PCA-based methodology may reduce dimensions at the cost of discarding informative variance in smaller datasets
Roy et al. (2023)	Indian cities (n=56)	2020-21	- SDG 6 - SDG 7 - SDG 13 - SDG 15	- Only focus on major cities - Focus through SDG analysis only
Kateja & Medatwal, (2024)	Indian states (n=25)	Snapshot 2019–2021	- air quality (SO_2, NO_2, PM) - water quality (groundwater, BOD) - waste (bio-medical, hazardous, MSW) - forest and soil (growing stock, fertilizers)	- Static analysis that lacks temporal trend depth required to assess the effectiveness of long-term sustainable programs - Excludes several smaller Himalayan and North-Eastern states, limiting national representativeness
Sarkar et al. (2024)	Japan, Bangladesh, & Thailand	2000–2020	- GHG/CO_2 emissions - pollution (air and water) - waste generation and management - energy (renewables share) - forest coverage and biodiversity	- Explicitly excludes the food supply chain, which was a significant driver of land degradation and water use - Reliance on aggregated secondary data may mask localized governance failures or data reporting inconsistencies

Filì et al. (2025)	Post-Soviet Republics (n=15)	Snapshot 2022	- SDG 6 - SDG 13 - SDG 15	- Restricted to only three SDGs due to a lack of harmonized data across the region - Excludes critical dimensions such as air quality, waste management, and ecological footprint
Garai et al. (2025)	Indian states & UTs (n=37)	2018–2020	- Environmental Pillar (SDGs 6, 7, 11-15) - Social Pillar (SDGs 1-5, 10, 16) - Economic Pillar (SDGs 8, 9)	- Reliance on NITI Aayog's secondary SDG data which may have reporting lagged - The 'Environment' pillar showed high spatial inequality compared to social metrics - Aggregation of 112 indicators can mask localized environmental health crises
Kumar et al. (2025)	G20 Nations (incl. India)	1990–2022	- water & air quality - natural resources - energy & waste - biodiversity	- National-level focus masks significant sub-national (state-level) environmental disparities - PCA weighting was sensitive to outliers and may discard important low-variance regional data - Performance metrics were predominantly oriented toward industrial/G20 economic structures
Mikča & Huttmanová (2025)	EU countries (n=27)	2015–2023	- environmental dimension (GHG, energy, circularity) - economic performance - social cohesion	- Heavy dependence on Eurostat's standardized reporting which was not replicable in data-poor Global South contexts - PCA-based weights vary significantly depending on the specific group of countries included in the cluster - Focuses on policy target compliance rather than

				absolute ecosystem integrity

3. Methodology:

We have used the '*missForest*' algorithm, a non-parametric Random Forest (RF) technique that captures non-linear correlations more well than simple mean imputation, to handle incomplete entries in the NITI Aayog NDAP database and guarantee a continuous dataset for multi-dimensional analysis. To avoid script failure during the forest growth phase, we worked with a numeric matrix of 37 indicators (**Table 2**), removing non-numeric labels. We monitored the Normalized Root Mean Squared Error (NRMSE) to verify the accuracy of the imputed environmental variables in comparison to the original distributions. Using this, we have collected a dataset related to 37 Indian states & UTs (**Table 3**).

Using the '*Hmisc*' package for correlation matrices and '*ggplot2*' with '*reshape2*' for high-resolution heatmap visualization, we performed Pearson's correlation to find linear relationships and inter-sectoral dependencies across the four sustainability dimensions (CE, TB, WP, and WS). We also used Ward's D2 clustering to group indicators with similar regional signatures in the correlation matrix. To avoid high-volume metrics (such CO_2 tons) skewing the correlation coefficients, we have performed Z-score scaling of the data before computation.

We have used the Fruchterman-Reingold (FR) force-directed graph to cluster highly correlated indicators in a spatial graph in order to analyze complicated environmental connections and identify important 'hub' indicators and 'bridge' connectors. The '*igraph*' and '*ggraph*' packages for sophisticated network mathematics and beautiful edge-link visualizations were used for this.

Using Ward's D2 clustering with Euclidean distance to reduce within-cluster variance and produce stable, distinct groupings, we used hierarchical clustering analysis (HCA) to classify Indian states and UTs into archetypes based on shared multi-dimensional environmental features. To avoid excessive state-level data distorting the heatmap color gradient, we have implemented Z-score scaling and capped outliers at +/-3. We generated clustered heatmaps with annotated cluster memberships using the '*pheatmap*' and '*RColorBrewer*' tools.

Our analysis uses Principal Component Analysis (PCA) with Varimax rotation to maximize the variance of the loadings, reducing data dimensionality and identifying the main latent factors driving environmental sustainability variances across India. This makes the components easier to understand for environmental policy. We used Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) to assess sampling adequacy. The Kaiser Criterion (Eigenvalues > 1) and the 'elbow' in Scree plots were used to determine which components were kept. This workflow used '*psych*' to carry out the actual rotation and extraction and '*factoextra*' for visualization.

To quantify the disparity and distribution of sustainability performance using the Theil Index, we have employed '*ineq*' and '*gglorenz*' R packages to calculate coefficients and generate standardized curves. We have applied the Theil index formula:

$$T = (1/n) \sum (x_i / x^{-}) \ln(x_i / x^{-})$$

The Evenness Index Score (EIS) measures the balance across environmental performance indicators, while the Mean Index Score (MIS) represents average performance in our dual-track research. The four quadrants of the analysis matrix were 'balanced leaders' (High MIS/High EIS), 'imbalanced leaders' (High MIS/Low EIS), 'balanced laggards' (Low MIS/High EIS), and 'distressed regions' (Low MIS/Low EIS). All scores were standardized (0-100) using Z-score scaling to ensure the 'evenness' calculation is not biased by varying indicator scales, utilizing the '*ggplot2*' package.

To decompose total sustainability variance into regional structural effects and localized performance effects, we have employed spatial additive decomposition (SAD), an additive decomposition approach ensures that the sum of regional contributions equals the total national score. We have used '*sf*' for spatial data handling and '*patchwork*' for combining regional decomposition charts. This can isolate the 'between-region' variance (structural/geographical trends), and 'within-region' variance (performance gap between neighbors).

To synthesize multi-dimensional environmental indicators into a single scalar metric, Composite index of Environmental Sustainability (CoES), for ranking the sustainability performance of Indian States and UTs. First, we categorize indicators as 'benefit' (+ve polarity, higher values indicate better sustainability) or 'cost' (-ve polarity, higher values indicate worse sustainability). Then we normalize (0–100 range based on polarity) using the following equations:

For Positive Indicators (+ve):

$$Y = \left(X - \min(X)\right) / \left(\max(X) - \min(X)\right) * 99 + 1$$

For Negative Indicators (-ve):

$$Y = (\max(X) - X) / \left(\max(X) - \min(X)\right) * 99 + 1$$

Next, we compute arithmetic means for the four sub-indices: Climate & Energy (CE), Terrestrial & Biodiversity (TB), Waste & Pollution (WP), and Water & Sanitation (WS). Each sub-index was calculated as the arithmetic mean of the normalized indicators within that specific pillar.

Climate & Energy (CE) sub-index:

$$CE_{Index} = (CE_1 + CE_2 + \ldots + CE_9) / 9$$

Terrestrial & Biodiversity (TB) sub-index:

$$TB_{Index} = (TB_1 + TB_2 + \ldots + TB_{10}) / 10$$

Waste & Pollution (WP) sub-index:

$$WP_{Index} = (WP_1 + WP_2 + \ldots + WP_{10}) / 10$$

Water & Sanitation (WS) sub-index:

$$WS_{Index} = (WS_1 + WS_2 + \ldots + WS8) / 8$$

Then we calculate the CoES index formula:

$$CoES = (CE_{SubIndex} + TB_{SubIndex} + WP_{SubIndex} + WS_{SubIndex}) / 4$$

Table 2. List of indicators included in this study.

No.	Indicator (*Abbreviation*)	Env dimensions	Justification
1	CO_2 saved from LED bulbs per 1,000 population (***CE1***)	Climate & Energy	Measures carbon mitigation and energy efficiency.
2	Disability Adjusted Life Years (DALY) - Air Pollution (***CE2***)	Climate & Energy	Impact of carbon/fuel burning on environment and health.
3	Disaster preparedness score (DRI) (***CE3***)	Climate & Energy	Adaptive capacity to climate-induced environmental risks.
4	Installed capacity of bio power (***CE4***)	Climate & Energy	Measures use of organic waste for energy.
5	Installed capacity of solar power as proportion (***CE5***)	Climate & Energy	Measures transition specifically toward solar infrastructure.
6	Number of human lives lost to extreme weather (***CE6***)	Climate & Energy	Direct outcome of environmental/ climate instability.
7	Per capita fossil fuel consumption (in kg) (***CE7***)	Climate & Energy	Primary driver of anthropogenic climate change.
8	Renewable energy out of total capacity, % (***CE8***)	Climate & Energy	Shift towards a low-carbon energy economy.
9	Renewable share of installed generating capacity, % (***CE9***)	Climate & Energy	Refined internal mix of the power grid.
10	Change in forest area from 2015 to 2017 (%) (***TB1***)	Terrestrial & Biodiversity	Measures the rate of land-use change in ecosystems.
11	Forest cover as a % of total geographical area (***TB2***)	Terrestrial & Biodiversity	Core metric for land-based ecosystem extent.
12	Number of cases under Wildlife Protection Act (1972) (***TB3***)	Terrestrial & Biodiversity	Tracks legal protection of terrestrial fauna.
13	Number of wildlife crime cases detected and reported (***TB4***)	Terrestrial & Biodiversity	Measures anthropogenic threat to biodiversity.
14	Change in carbon stock in forest cover, % (***TB5***)	Terrestrial & Biodiversity	Relates to the quality and density of forest ecosystems.
15	Change in elephant population, % (***TB6***)	Terrestrial & Biodiversity	Proxy for riparian habitat and wide-range ecosystem health.
16	Increase in area of desertification, %	Terrestrial &	Primary indicator of land

	(***TB7***)	Biodiversity	degradation and soil loss.
17	Area covered under afforestation schemes, % (***TB8***)	Terrestrial & Biodiversity	Measures restoration efforts of terrestrial land.
18	Degraded land over total land area, % (***TB9***)	Terrestrial & Biodiversity	Broad measure of terrestrial health and productivity.
19	Tree cover as a percentage of total geographical area (***TB10***)	Terrestrial & Biodiversity	Captures green cover outside recorded forest areas.
20	Hazardous waste generated per 1,000 population (***WP1***)	Waste & Pollution	Volume of toxic loading on land and water.
21	Per capita hazard waste generated (***WP2***)	Waste & Pollution	Standardizes toxic waste pressure by population size.
22	Bio Medical Waste (BMW) treated, % (***WP3***)	Waste & Pollution	Specialized focus on toxic/infectious waste streams.
23	Industries complying with env standards, % (***WP4***)	Waste & Pollution	General industrial pollution accountability.
24	Municipal Solid Waste (MSW) processed, % (***WP5***)	Waste & Pollution	Core metric for urban solid waste circularity.
25	Wards with 100% door to door collection, % (***WP6***)	Waste & Pollution	Efficiency of the waste logistics chain.
26	Wards with 100% source segregation, % (***WP7***)	Waste & Pollution	Critical precursor to sustainable waste processing.
27	Waste processed (general), % (***WP8***)	Waste & Pollution	Aggregate efficiency of the waste management system.
28	Plastic waste generated per 1,000 population (***WP9***)	Waste & Pollution	Direct pressure of non-biodegradables on the environment.
29	Quantity of hazardous waste recycled/ utilized (%) (***WP10***)	Waste & Pollution	Measures circular economy for dangerous materials.
30	Decadal change in extent of water bodies within forests (***WS1***)	Water & Sanitation	Linkage between forest health and water retention.
31	Installed sewage treatment capacity as % of generated (***WS2***)	Water & Sanitation	Measures management of liquid urban pollutants.
32	Industries complying with waste	Water &	Focuses on industrial-specific

	water treatment, % (***WS3***)	Sanitation	water pollution control.
33	Blocks/ mandals/ talukas over-exploited, % (***WS4***)	Water & Sanitation	Spatial measure of regional water crisis.
34	Ground water withdrawal against availability, % (***WS5***)	Water & Sanitation	Measures current stress on water resource availability.
35	Use of nitrogenous fertilizer, % (***WS6***)	Water & Sanitation	Measures potential run-off and chemical water health.
36	Rice and Wheat produced per unit area (kg/ha) (***WS7***)	Water & Sanitation	Water-intensive crops; proxy for agricultural water demand.
37	Stage of groundwater extraction, % (***WS8***)	Water & Sanitation	Primary measure of hydro-geological sustainability.

Table 3. List of 28 Indian states and 9 union territories (UTs) included in this study.

Area	Type	Area	Identity
Andhra Pradesh (AP)	State	Punjab (PB)	State
Arunachal Pradesh (AR)	State	Rajasthan (RJ)	State
Assam (AS)	State	Sikkim (SK)	State
Bihar (BR)	State	Tamil Nadu (TN)	State
Chhattisgarh (CG)	State	Telangana (TS)	State
Goa (GA)	State	Tripura (TR)	State
Gujarat (GJ)	State	Uttar Pradesh (UP)	State
Haryana (HR)	State	Uttarakhand (UK)	State
Himachal Pradesh (HP)	State	West Bengal (WB)	State
Jharkhand (JH)	State	Andaman and Nicobar Islands (AN)	UT
Karnataka (KA)	State	Chandigarh (CH)	UT
Kerala (KL)	State	Dadra-Nagar Haveli (DH)	UT
Madhya Pradesh (MP)	State	Daman-Diu (DD)	UT
Maharashtra (MH)	State	Delhi (DL)	UT
Manipur (MN)	State	Jammu and Kashmir (JK)	UT
Meghalaya (ML)	State	Ladakh (LA)	UT
Mizoram (MZ)	State	Lakshadweep (LD)	UT
Nagaland (NL)	State	Puducherry (PY)	UT
Odisha (OR)	State		

4. Results:

4.1. Composite index of environmental sustainability (CoES):

In the Climate & Energy (CE) sub-index (**Fig. 1a**, see **Supplementary File 1**), among the states, Karnataka led among states (0.679), followed by Tamil Nadu (0.62). Northern states (e.g., Himachal Pradesh and Uttarakhand) showed strong CE scores (0.543 & 0.58, respectively), contributing significantly to their overall top five CoES ranking. With states like Gujarat (0.524) and Punjab (0.524) exhibiting steady energy infrastructure growth, the bulk of states congregated around the 0.5 mark. West Bengal scored lower (0.419) in the CE sub-index than Karnataka and Kerala (0.591). Gujarat scored moderately (0.524) in comparison to Karnataka despite its industrial scale, indicating a difference in renewable penetration relative to total capacity. Despite its energy significance, Jharkhand has the lowest state score (0.362), indicating high per capita fossil fuel usage (CE7). Low bio-power capacity (CE4) and high DALY rates from air pollution (CE2) were the main causes of Bihar's (0.399) and Tripura's (0.405) poor performance. With a strong WP score and a high score of 0.575, Andhra Pradesh was able to keep its position at number five overall.

Chandigarh's national rank 1 was based on its dominance of the CE sub-index (0.613) among the UTs. Lakshadweep (0.571) demonstrated controllable fossil fuel usage and significant per capita savings with LED lights (CE1). Due to its significant air pollution DALY (CE2) countering its renewable gains, Delhi (0.502) performed in the median among UTs. Daman-Diu's score (0.411), which was almost 20 points lower than its WP sub-index score, indicated that industrial growth was surpassing energy sustainability. Ladakh's score of 0.476 indicates a balanced basis for a new UT, roughly matching the national average of 0.512. Only 0.003 points separated Puducherry (0.479) and Ladakh (0.476), indicating uniform energy transition policies in smaller UTs.

Despite having lower rankings in other categories, Nagaland had the highest score (0.665) among the states in the Terrestrial & Biodiversity (TB) sub-index (Fig. 1b), which had a major impact on its ecological position. The Eastern Himalayas were confirmed as the main biodiversity stronghold by Tripura (0.622) and Manipur (0.591). Due to its high degraded land (TB9) in agricultural zones and poor forest cover (TB2), Punjab had the lowest score (0.397). The TB sub-index was the main factor keeping states like Goa (0.627) in the top 15. Kerala scored just 0.413, an anomaly brought about by declining trends in carbon stock and changes in forest area, while being a hotspot for biodiversity. The biodiversity health of Madhya Pradesh (0.537) and Chhattisgarh (0.553) was very similar, indicating regional cooperation in forest management. Infrastructure deficiencies in the WP and WS categories frequently negate ecological wealth, as evidenced by Nagaland's score of 1 (0.665) but 31 overall (CoES=0.517).

Among the UTs, Delhi showed a high score (0.619), largely due to tree cover (TB10) and wildlife crime reporting (TB4), ranking it 20 overall. Lakshadweep (0.604) and Andaman-Nicobar (0.599) showed high scores, reflecting protected natural ecosystems. Most UTs clustered between 0.52 & 0.61, indicating high central oversight in protected area management. Puducherry recorded the lowest score for UTs (0.487), indicating a deficit in forest area change and carbon stock compared to other urban UTs. Chandigarh scored 0.576, proving that high urbanization (WP/WS) can coexist with high terrestrial management. Ladakh scored 0.534, significantly lower than other 'pristine' regions like Nagaland, due to the unique desertification challenges (TB7) of the cold desert.

The Waste & Pollution (WP) sub-index (**Fig.1c**) was the highest-scoring category nationally (average=0.762), indicating advanced policy maturity in waste management. Madhya Pradesh

(0.871) and Himachal Pradesh (0.868) led, driven by high MSW processing (WP5) and source segregation (WP7). Andhra Pradesh (rank 5, 0.78) was the dominant contributor to the final score. Sikkim (0.847) and Tripura (0.829) showed that topographic challenges do not prevent high waste-processing efficiency. Nagaland scored (0.547) >20 points below the national average, identifying waste management as a critical policy blind spot. Maharashtra (0.818) and Gujarat (0.627) showed a wide gap, suggesting that industrial scale in Maharashtra was better matched by recycling infrastructure (WP10). Punjab (0.746) and Odisha (0.733) were separated by only 0.013, indicating competitive MSW targets. Among the UTs, Jammu-Kashmir (0.858) and Chandigarh (0.842) led UTs in waste sustainability, likely due to high BMW treatment rates (WP3). 6 out of 9 UTs scored >0.65, highlighting the effectiveness of Swachh Bharat Mission (Urban) in these regions. Delhi scored (0.673) lower than most states and UTs, due to the sheer volume of hazardous and plastic waste generated (WP1, WP9). Daman-Diu (0.805) and Dadra-Nagar Haveli (0.676) scored a significant 13-point difference despite being adjacent and similar in industrial profile. Chandigarh's score (0.842) was the primary engine behind its national CoES rank 1.

Water & Sanitation (WS) sub-index (**Fig.1d**) was the lowest-performing category for many states, with Rajasthan scoring (0.246) the lowest across all sub-indices. Sikkim led states (0.597), while Uttarakhand (0.567) and Tripura (0.567) also showed high water sustainability. States like Punjab (0.512) and Haryana (0.479) were penalized by high stages of groundwater extraction (WS8). Tamil Nadu (0.528) and Andhra Pradesh (0.539) maintained moderate scores through industrial wastewater compliance. Rajasthan's score (0.246) was 20 points behind its next sub-index, with water being the only factor contributing to its ranking of 37. Odisha scored low (0.383) despite ranking high (0.58), suggesting a gap between water management and forest protection. In wastewater treatment (WS3), Telangana (0.577) outperformed Uttarakhand (0.567) by a narrow margin. Chandigarh became the gold standard for urban water and sewage management (WS2) among the UTs, with a national high of 0.75. Despite having a large sewage treatment capacity, Delhi's score of 0.427 indicated the pressure on groundwater (WS5). Due to significant groundwater withdrawal relative to availability, Daman-Diu received the lowest score (0.338) among UTs. With a score of 0.553, Puducherry outperformed the majority of states in terms of coastal aquifer management efficiency. Ladakh's score of 0.371 was comparable to that of the arid states, indicating the intrinsic constraints of the frigid desert environment.

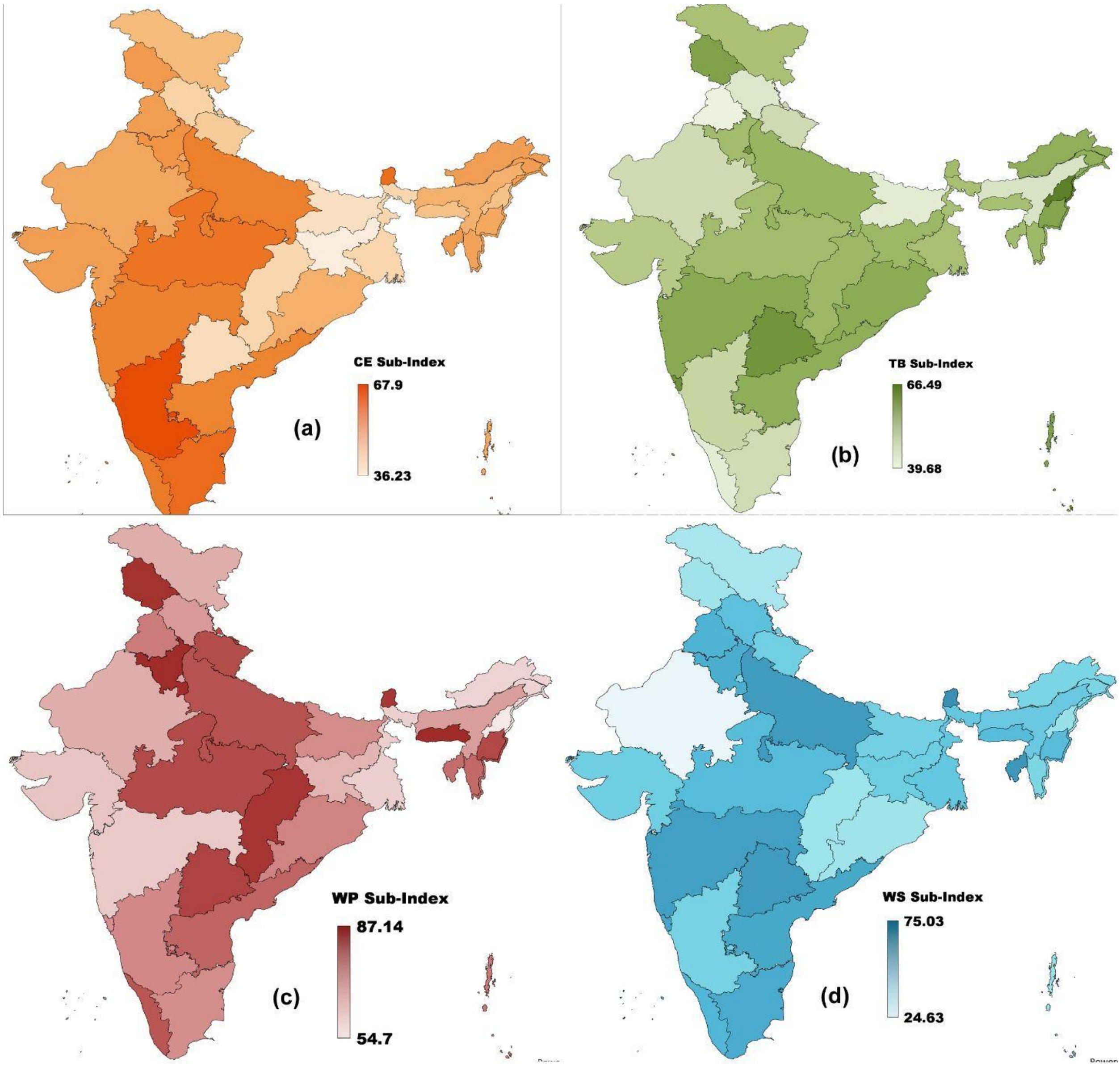


Figure. 1. Spatial distribution of environmental sustainability across four core sub-indices in India. These choropleth maps visualize the sub-national performance of 37 Indian states and UTs based on normalized scores (1–100 scale). Panels represent the 4 pillars of the CoES framework: (a) Climate & Energy (CE), reflecting renewable penetration and mitigation; (b) Terrestrial & Biodiversity (TB), indicating forest cover and land health; (c) Waste & Pollution (WP), evaluating solid and hazardous waste circularity; and (d) Water & Sanitation (WS), measuring groundwater stress and wastewater compliance. Darker hues signify higher sustainability, highlighting performance hotspots like Chandigarh and ecological strongholds in the Northeast.

4.2. Clustering the composite index of environmental sustainability (CoES):

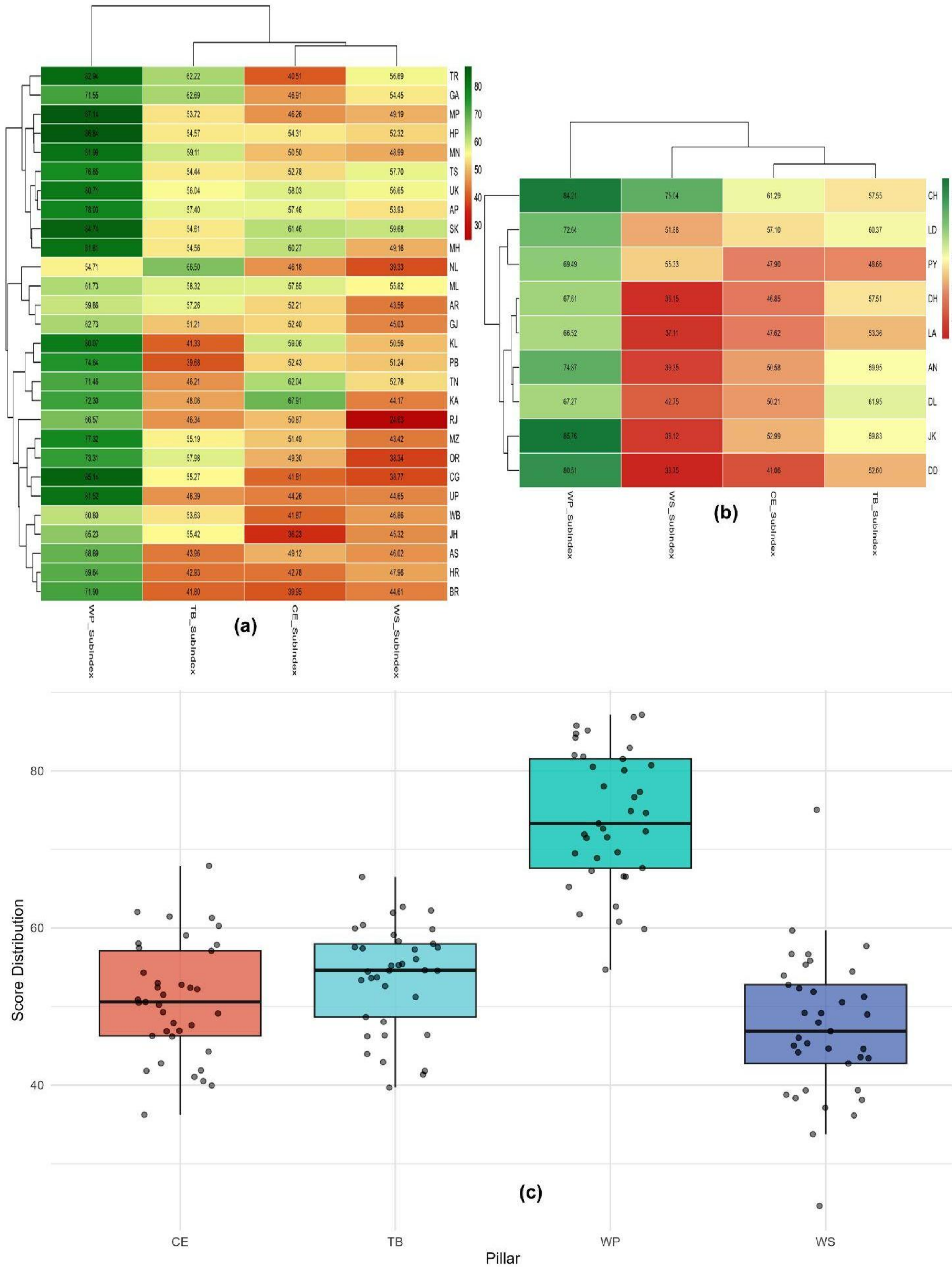
Cluster 3 (n=12, CE mean=49.19), which represents a 'diverse energy profiles' typology with very varying scores ranging from Jharkhand (36.23) to Karnataka (67.91), was the largest group in the Climate & Energy (CE) domain (**Fig. 2a, 2c**). Eighty-five percent of Indian states fell into one of two main categories: resource-intensive growth or steady transition, according to the division between Cluster 1 and Cluster 3. Within the largest cluster in the country, Jharkhand (Cluster 3) represented the lower extreme (36.23), indicating a 'pollution-compromised' sub-archetype.

Cluster 1 (n=12, mean=57.65) revealed a 'biodiversity leaders' archetype in the Terrestrial & Biodiversity (TB) domain, with Sikkim and Goa leading the way in terms of high forest cover and stable carbon stocks. The 'agricultural landscape' archetype was represented by Cluster 3 (n=12, mean=48.24), where intense land use was associated with reduced tree cover and higher degradation. As a 'green laggard' outlier that highlights the ecological cost of intensive agriculture, Punjab (Cluster 3) recorded the national low of 39.68. The largest developmental gap in terrestrial health among all state clusters was the 26.82-point difference between Punjab (Laggard) and Nagaland (Leader).

The 'waste management champions' in the Waste & Pollution (WP) sector were identified by Cluster 1 (n=12, mean=80.37), with states like Himachal Pradesh and Telangana attaining high MSW processing rates. Waste management was found to be India's best developed sustainability industry, with both major WP clusters (1 and 3) outperforming other sectors. Sikkim's exceptional performance in Cluster 1 shows that challenging topography was not a major obstacle to top-notch waste management infrastructure.

Cluster 1 (n=12, mean=54.83) created the 'sanitation specialists' archetype in the Water & Sanitation (WS) domain, with strong conformance in wastewater and sewage treatment. High agricultural output in places like Punjab and Haryana immediately jeopardizes groundwater sustainability, according to the 'aquifer stress' pattern identified by Cluster 3 (n=12, mean=44.15). The extreme strains of the 'scarcity' archetype were reflected in Rajasthan's (Cluster 3) definition of the absolute floor for water sustainability (24.63). Nagaland (Cluster 2) emerged as a 'water-rich laggard' (39.33), suggesting that natural water availability does not automatically translate into robust sanitation infrastructure.

Among the UTs (**Fig. 2b, 2c**), Chandigarh formed its own unique cluster (Cluster 1), acting as a 'gold standard' outlier and leading all entities in every category, particularly in Water & Sanitation (75.04). Cluster 2 (Lakshadweep and Puducherry) represented a distinct 'Island Resilience' archetype, focused on coastal terrestrial health and energy efficiency.



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TB_SubIndex
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WS_SubIndex
(b)
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WP_SubIndex
WS_SubIndex
CE_SubIndex
TB_SubIndex
(c)
Score Distribution
Pillar
CE
TB
WP
WS

Figure. 2. Hierarchical taxonomy of sub-national sustainability and sectoral performance variability.
Panels (a) and (b) utilize Hierarchical Clustering Analysis (HCA) with Ward's D2 method and Euclidean distance to categorize 28 States and 9 UTs into distinct environmental archetypes. The clustered heatmap highlights regional performance silos where ecological wealth was often offset by infrastructure deficits.
Panel (c) presents the score distribution (boxplot) across the 4 pillars, revealing the relative policy maturity of the Waste & Pollution sector compared to the higher variance and lower scores observed in Water & Sanitation

4.3. ***Pearson Correlation*****:**

In the Climate & Energy (CE) domain (**Fig. 3a**, see **Supplementary File 2,** see **Supplementary File 9 Fig S2, S7, S19**), solar power (CE5) correlated positively with fossil fuel consumption (CE7) (r=0.648). This suggested that regions with high energy demands and fossil fuel usage were also the ones aggressively scaling solar capacity to diversify their energy mix (i.e., solar power-fossil consumption link). Air pollution DALY (CE2) was strongly negatively correlated with forest cover (TB2) (r=-0.633), meaning high forest density was a major regional driver for reducing the air pollution DALY (i.e., climate-forest health link). CO2 saved from LEDs (CE1) was strongly negatively correlated with elephant population change (TB6) (r=-0.580). This counterintuitive link likely reflected high urbanization (where LED penetration was higher) coinciding with habitat loss for large mammals. Solar proportion (CE5) and renewable % (CE8) were strongly negatively correlated (r=-0.541). This suggested that in several regions, solar growth was occurring independently of, or even at the expense of, other renewable sources like wind or hydro.

In the Terrestrial & Biodiversity (TB) domain (see **Supplementary File 9 Fig S3, S8, S14**), forest cover (TB2) and degraded land (TB9) were strongly negatively correlated (r=-0.694), confirming that maintaining high forest % was the most prevalent factor in preventing land degradation. Degraded land (TB9) correlated very strongly with groundwater extraction (WS8) (r=0.843). Regions with high land degradation were consistently the same regions facing the most acute groundwater depletion, indicating a dual-crisis of terrestrial and water resources. Forest cover (TB2) showed a strong negative correlation with groundwater extraction (WS8) (r=-0.603). Areas with higher natural forest cover act as critical recharge zones, experiencing significantly lower levels of groundwater over-exploitation.

In the Waste & Pollution domain (see **Supplementary File 9 Fig S4, S9, S15**), MSW processed (WP5) and source segregation (WP7) correlated strongly (r=0.751). This prevalent trend confirmed that successful waste processing at the regional level was highly dependent on the efficiency of source segregation at the ward level. MSW processed (WP5) and door-to-door waste collection (WP6) showed a strong positive correlation (r=0.65). Consistent collection mechanisms were a major driver for the ultimate volume of MSW that reached processing facilities. BMW treated (WP3) correlated exceptionally strongly with groundwater extraction (WS8) (r=0.875). This suggested that regions with advanced healthcare infrastructure (high BMW treatment) were also those with the most unsustainable groundwater usage, typical of highly urbanized states/UTs (**Fig. 3b**). Industries complying with CPCB standards (WP4) and groundwater withdrawal (WS5) correlated (r=0.628). This unexpected positive link suggested that regions with high industrial density (leading to high withdrawal) also have more rigorous regulatory oversight and compliance monitoring.

In the Water & Sanitation domain (see **Supplementary File 9 Fig S5, S10, S16**), rice or wheat produced (WS7) and degraded land (TB9) were strongly positively correlated (r=0.69). This indicated that the most agriculturally productive regions in India were also those suffering from the highest levels of land degradation. Crop yield (WS7) and groundwater extraction (WS8) showed a strong positive correlation (r=0.555). This confirmed that high agricultural productivity across Indian states remains heavily reliant on unsustainable groundwater depletion. Groundwater extraction (WS8) and BMW treated (WP3) showed a nearly perfect correlation (r=0.875). This was a major trend signaling that groundwater stress was a hallmark of the same regions that have high-capacity healthcare and waste management systems. Groundwater withdrawal (WS5) and industrial CPCB compliance (WP4) correlated (r=0.628). This highlighted that industry-heavy states with the highest withdrawal rates were also the most regulated in terms of environmental standards.

4.4. *Network analysis*:

In the Climate & Energy (CE) domain (**Fig. 3c**, see **Supplementary File 3**), air pollution (CE2) was the dominant hub with the highest degree (degree=7) and betweenness centrality (0.143). This signified that air pollution-related health burdens were central to the energy-climate network, acting as a primary outcome linked to multiple energy sources. With the highest betweenness centrality (0.286) and high closeness (5.69), disaster preparedness (CE3) functioned as a crucial network bridge. The strategic connection between energy infrastructure measures and climate outcome indicators may be catastrophe readiness, according to high betweenness.

Forest cover (TB2) was the main hub of the terrestrial network with the highest degree (degree=7) in the Terrestrial & Biodiversity (TB) domain (**Fig. 3d**). It serves as the universal baseline indication and has a significant correlation with nearly all other terrestrial metrics since it was a zero-betweenness hub. In the group, tree cover (TB10) has the highest betweenness centrality (0.222) and a high degree (6). Tree cover (non-forest) was shown to be the most important ‘bridge’ indicator, most likely linking measures related to natural forests to metrics related to land use that were affected by humans. Wildlife crime instances (TB4) had strong betweenness (0.222) and high connection (degree=6). This pattern suggests that reporting of wildlife crimes was a key indicator linked to the overall condition of terrestrial health and administrative supervision rather than being isolated.

Hazardous waste created (WP1) was the most connected node (degree=7) with high closeness (3.1) in the Waste & Pollution (WP) domain (**Fig. 3e**). The most common ‘stressor’ signal in the waste and pollution network for all regions was found to be the production of hazardous waste. One major hub with a degree of seven was source segregation (WP7). Segregation was the primary operational pivot upon which municipal garbage systems were structured, as demonstrated by its high connectedness. The maximum betweenness centrality (0.333) and high degree (6) were found in plastic trash created (WP9). Because of this, plastic trash was the most significant ‘bridge’ in the network, probably connecting the effects of land degradation with urban consumption habits.

Groundwater extraction (WS8) was a primary hub (degree=7) with high closeness (8.71) in the Water & Sanitation (WS) domain (Fig. 3f). This revealed that the most common and important issue in India's water-sanitation network was groundwater extraction. Throughout the entire study, industries that adhere to waste water treatment (WS3) have the highest betweenness centrality (0.762) and closeness (10.96). The 'master connector' that connected forest water bodies, sanitation infrastructure, and agricultural water use was found to be industrial waste water compliance. Blocks that were overexploited (WS4) and those that produced wheat or rice (WS7) demonstrated high degrees (7 and 6, respectively). This validated a core network cluster in which excessive regional water resource use was inextricably linked to high agriculture output. A high-degree node (7) with a considerable betweenness (0.238) was the forest water body change (WS1). This established forest-based bodies of water as essential links between metrics related to water security and terrestrial health.

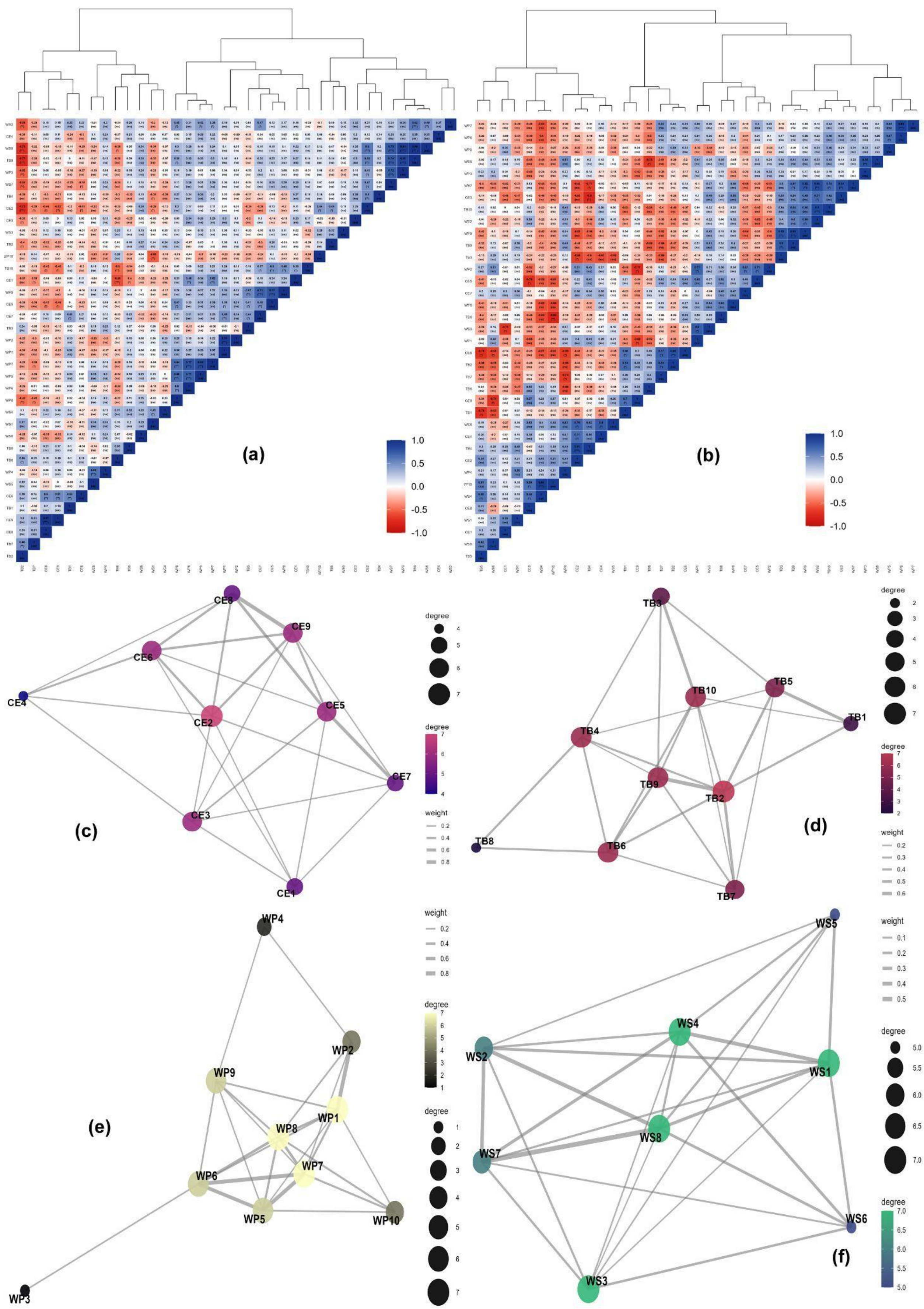

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Figure. 3. Statistical interdependencies and structural topology of the sub-national environmental sustainability network.
Panels (a) and (b) present Pearson's correlation matrices for States and UTs, identifying critical trade-offs such as the 'prosperity-pollution' link between agricultural yields and groundwater extraction.
Panels (c) through (f) utilize Fruchterman-Reingold force-directed network maps for each domain. Node size indicates degree centrality (connectivity), while node position identifies 'master connectors' (e.g., industrial wastewater compliance, WS3) and 'primary hubs' (e.g., air pollution, CE2, and groundwater extraction, WS8) that drive systemic regional sustainability

4.5. *Clustering*:

Cluster 1 (primary energy transition cluster), which includes important states like Andhra Pradesh, Gujarat, and Uttar Pradesh, was the biggest and most stable group in the Climate & Energy (CE) domain (**Fig. 4a**, see **Supplementary File 4**, see **Supplementary File 9 S18**). This implied a uniform regional approach to energy metrics, probably motivated by national programs for solar objectives and LED distribution (CE1). High-altitude, forest-rich states like Mizoram, Himachal Pradesh, and Arunachal Pradesh were grouped together in Cluster 2. These areas have comparable profiles, probably as a result of their low use of fossil fuels (CE7) and preference for conventional or hydro-based electricity over bio-power (CE4). Tamil Nadu, Maharashtra, and Karnataka made the modest yet distinctive Cluster 4 (Industrial Renewable Leaders). High renewable share (CE9) and solar capacity (CE5) were concentrated in these states, suggesting a specific 'renewable leader' profile. Despite its remote location, Tripura was remarkably placed in Cluster 1 with major mainland states. This indicated that compared to the nearby NER states in Cluster 2, its energy infrastructure and disaster readiness (CE3) measures were more in line with the national average. Delhi was distinguished from all other UTs by its exclusive assignment to Cluster 1. This revealed an energy-climate profile that was similar to big urbanized states like Maharashtra, with anticipated high LED savings (CE1) and pollution burden (CE2).

Cluster 1 was a large stable group that included Andhra Pradesh, Chhattisgarh, and Odisha in the Terrestrial & Biodiversity (TB) domain (see **Supplementary File 9 S19**). This implied that both nations have similar terrestrial baselines, probably in terms of land degradation (TB9) and forest cover (TB2). Arunachal Pradesh, Manipur, and Nagaland constituted Cluster 2 (also known as the 'NER Biodiversity Belt'), a relatively stable hierarchical group. These states were grouped according to shared patterns in wildlife crime reporting (TB3/TB4) and particularly high forest cover (TB2). Sikkim demonstrated a high merge stability and was placed in Cluster 2 with the larger NER states. This demonstrated that, in comparison to the Himalayan states in Cluster 1, Sikkim's biodiversity indicators were more robust and comparable to those of the 'biodiversity hotspot' states. Cluster 4, which was completely distinct from all other UTs and States, included Delhi and Chandigarh. An urban-tree-cover (TB10) profile specific to India's planned administrative cities was proposed by this 'singleton-pair.'

Cluster 2 (Industrial Waste Belt), which includes states like Maharashtra, Gujarat, and Tamil Nadu, was the most common group in the Waste & Pollution (WP) domain (see **Supplementary File 9 S20**). High levels of hazardous waste generation (WP1) and environmental standard compliance

(WP4) were represented in this grouping. Rajasthan, Punjab, and Haryana were included in Cluster 4 (Northern Waste Management Cluster). This revealed a common geographical pattern in source segregation (WP7) and MSW processing (WP5). Andhra Pradesh and Karnataka were part of the stable Cluster 1. These states consistently performed well in BMW treatment (WP3) and door-to-door collection (WP6). Cluster 3 ('cleaning' state outliers) contained just West Bengal and Bihar. This showed a departure from national waste processing standards, probably pointing to a source segregation (WP7) lag in comparison to Cluster 1. Cluster 1 included Chandigarh, Delhi, and Puducherry. This exemplified the 'urban model' of waste management, which was distinguished by high rates of collection (WP6) and processing (WP5). Cluster 2 included Lakshadweep and Andaman-Nicobar. This indicated a minimal generation of hazardous waste but a geographically constrained infrastructure for treatment.

Cluster 1, sometimes known as the 'groundwater stress group,' was a sizable, stable group that included Gujarat, Maharashtra, and Uttar Pradesh in the Water & Sanitation (WS) domain (see **Supplementary File 9 S21**). High levels of groundwater extraction (WS8) and substantial usage of nitrogenous fertilizers (WS6) were the driving forces behind this grouping. Rajasthan, Punjab, and Haryana were placed together in Cluster 2 (Agricultural Yield Cluster). Extreme groundwater over-exploitation (WS4) and the highest rice or wheat productivity (WS7) characterized these states. In contrast to the other Himalayan states in Cluster 3, Uttarakhand was placed in Cluster 4. This implied that Uttarakhand's water-waste profile was more urbanized than that of its neighbors. Cluster 2 (Urban Water Crisis Bridge) included both Delhi and Chandigarh. This demonstrated how their water sustainability was closely linked to the northern plains' agricultural groundwater crisis and connected them to the high-stress states of Punjab and Haryana. Puducherry was placed in Cluster 4 alongside Telangana. This revealed unique industrial wastewater compliance (WS3) patterns or an extraordinary degree of groundwater removal not observed in any other UT.

4.6. *Principal component*:

Air quality stress was described by PC1 (43.34% variance) in the Climate & Energy (CE) domain (**Fig. 4b**, see **Supplementary File 5**, **Supplementary File 9 S22-24**). The substantial negative loading of -0.92 for air pollution (CE2) indicates that air health was the main cause of regional difference. States with significant levels of pollution, such as Bihar and Haryana, were hostile to ecological clusters that perform well. The majority of UTs have good PC1 scores, with Dadra-Nagar Haveli (3.66) and Chandigarh (3.63) leading the way. UTs typically reside on the positive axis of sustainability, indicating lower air-pollution health burdens compared to large states. Delhi scored -2.39 on PC2 but 2.72 on PC1. Compared to industrial UTs like Dadra-Nagar Haveli, Delhi was an anomaly, combining strong developmental results with a sharp lag in the share of renewable energy.

Desertification (TB7) and carbon stock change (TB5) both exhibit extreme loadings (0.95) in the Terrestrial & Biodiversity (TB) domain. The main variation in India's terrestrial health was defined by the coherent 'ecological integrity' cluster of these variables. On PC2, Afforestation (TB8) loads at -0.61. Government afforestation initiatives serve as a secondary management driver and were separated from the integrity of the natural ecosystem. UTs with strong positive scores on PC1 include Andaman-Nicobar (3.13). This placement validated UTs as the main providers of steady forest biodiversity and a large carbon store.

In the Waste & Pollution (WP) domain, hazardous waste (WP2) and BMW treated (WP3) showed dominant loadings of 0.95. The ability to process specialized waste was the most significant differentiator of environmental performance between states. Door-to-door collection (WP6) loaded negatively at -0.89 (PC1). States excelling in specialized industrial waste handling often showed a statistical divergence from basic municipal collection metrics. Source segregation (WP7) loaded at 0.9 (PC1). Segregation at source was the most impactful municipal variable on the primary environmental axis. Most UTs, particularly Dadra-Nagar Haveli (3.66), scored high on PC1 indicators like BMW treated (WP3). UTs effectively served as regional leaders in specialized BMW and hazardous waste processing. Puducherry scored -2.34 (PC3). This revealed a unique variance in MSW processing efficiency compared to industrial-heavy UTs.

In the Water & Sanitation (WS) domain, waste water compliance (WS3) loads at 0.99, while over-exploited blocks (WS4) load at 0.89. There was a nearly perfect statistical alignment between industrial wastewater regulation and aquifer exploitation levels. Rice / wheat yield (WS7) showed a powerful negative loading of -0.94 (PC1). High agricultural yield was the single largest driver of water exploitation and environmental stress in the states. Groundwater extraction (WS8) loads at 0.17 (PC1) but 0.31 on PC3. Extraction stages were multifaceted and influenced by both agricultural yields and forest water body changes. Andhra Pradesh and Bihar scored -5.30 and -5.76 on PC1. These states defined the extreme for high-stress water environments driven by agricultural intensity and pollution loads. Chandigarh (3.63) and Delhi (2.72) scored high on PC1. High urban wastewater compliance (WS3) and lower agricultural yield stress (WS7) placed UTs on the positive sustainability axis. Groundwater withdrawal (WS5) loads at 0.49 on PC6. Pure withdrawal metrics were low-variance but crucial for distinguishing sustainable water management in UTs.

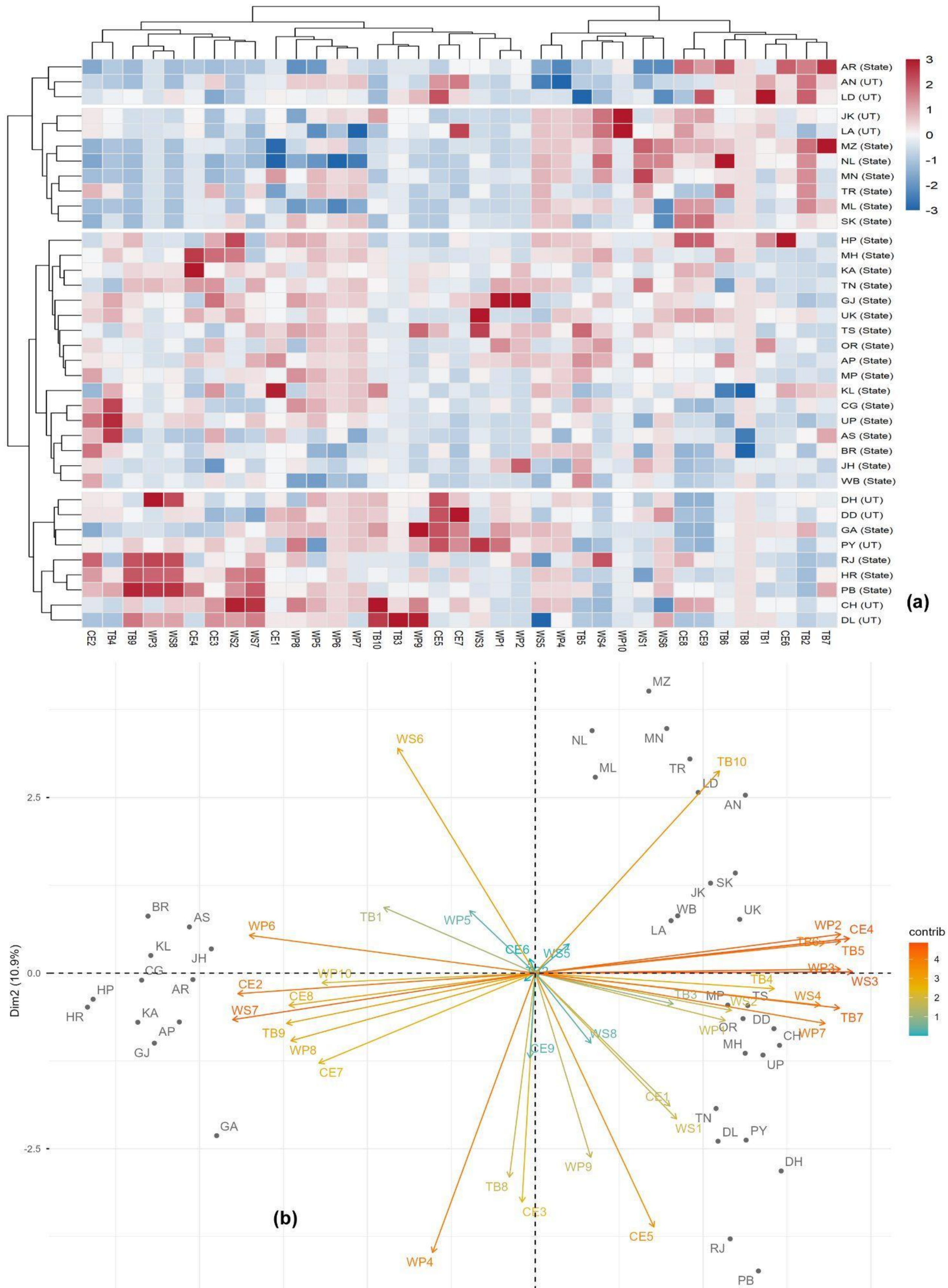
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Figure. 4. Multivariate variance drivers and hierarchical indicator clustering.
Panel (a) displays HCA applied to the 37 indicators to reveal shared regional signatures, such as the 'industrial waste belt' and 'agricultural yield cluster'.
Panel (b) presents the Principal Component Analysis (PCA) biplot with Varimax rotation. PC1 (43.3% variance) defines 'air quality stress', while PC2 (10.9%) highlights 'ecological integrity'. Vector length and direction indicate the influence of specific variables (e.g., crop yield, WS7) in polarizing regional performance between high-pollution states and high-performing ecological clusters.

4.7. ***Inequality***:

In the Climate & Energy (CE) domain (**Fig. 5a**, see **Supplementary File 6**), among the states, renewable energy (CE8) exhibited a high inequality (0.361) among states. This indicated notable regional differences in renewable energy infrastructure, perhaps as a result of differing natural resource endowments and state-level regulatory incentives. The states' total CE revealed an inequality of 0.0339. Even while certain metrics, such as CE8, were extremely unequal, the energy portfolio's more balanced indicators helped to mitigate the overall group disparity. The renewable share (CE9) among UTs revealed a very significant inequality (1.303). This revealed a clear difference between UTs that have progressed their integration of renewable energy sources and those that were still mostly reliant on conventional power sources. The inequality of solar power (CE5) was large (0.575). This demonstrated extremely localized solar adoption, with a small number of UTs controlling the majority of the solar capacity and others having very small installations.

The state with the greatest group inequality in the Terrestrial & Biodiversity (TB) domain was forest cover (TB2) (0.423). The geographical reality of India, where a few states like Mizoram and Arunachal Pradesh possessed the majority of forest resources compared to states like Haryana, was represented in this enormous imbalance. Wildlife crime instances (TB3) revealed a very high inequality (0.86) among the UTs. This suggests that there was a significant concentration of legal action against wildlife crimes in particular UTs, possibly where enforcement was more stringent or biodiversity hotspots were easier to reach. The change in forest area (TB1) showed significant inequality (0.338). This showed uneven patterns of forest increase and loss among UTs, probably due to regional developmental pressures or conservation achievements. There was a notable disparity in land degradation (TB9) (0.329). This pervasive inequity implies that land-use problems were highly confined to certain UTs, necessitating the implementation of specialized land restoration strategies.

MSW processed (WP5) showed a high inequality (0.222) among the states in the Waste & Pollution (WP) domain. This revealed a significant gap between states that still mostly rely on landfilling and those that have sophisticated waste-to-energy or composting facilities. Hazardous waste created (WP1) among UTs displayed a significant disparity (1.977). This was probably caused by the dominance of highly industrialized UTs like Daman-Diu over non-industrial ones like Lakshadweep in a single region. The generated plastic waste (WP9) showed a high degree of disparity (0.295). This showed that plastic pollution was concentrated in the most populous or tourist-heavy UTs, reflecting a variety of urban consumption and waste footprints.

Over-exploited blocks (WS4) exhibited high inequality (0.217) among the states in the Water & Sanitation (WS) domain. In contrast to states with an abundance of water, this indicated a severe geographic concentration of water crises, particularly in 'grain-bowl' states like Punjab and Haryana. The production of wheat or rice (WS7) showed substantial inequality (0.154), indicating that the success of water-intensive agriculture was highly localized and supporting the association between high water stress and high yield (WS4). Among the UTs, industrial wastewater compliance (WS3) showed very high inequality (0.801). This suggested that industrial water pollution control was highly effective in some UTs while others have significant regulatory or infrastructure gaps. There was significant inequality in groundwater exploitation (WS8) (0.482). This widespread discrepancy demonstrated that some UTs, most likely Delhi and Chandigarh, were experiencing far more severe water depletion than the island territories. The WS inequality for UTs (0.0592) was higher than the overall WaSH sustainability (0.0063). This identified WS as the most significant driver of environmental inequality among Indian UTs.

4.8. *Evenness*:

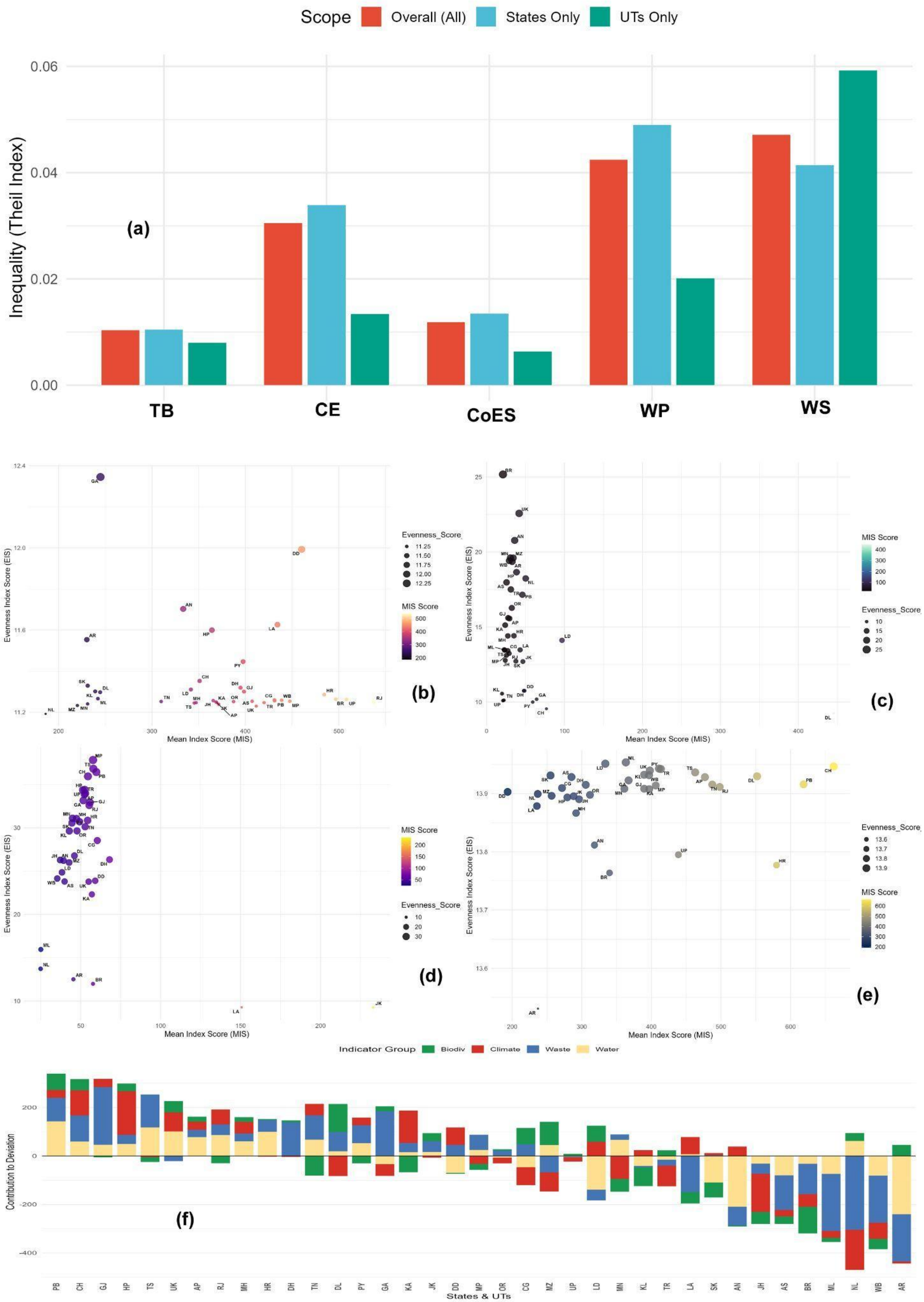
In the Climate & Energy (CE) domain (**Fig. 5b**, see **Supplementary File 7**, see **Supplementary File 9 Fig S25**), among the states, EIS values were notably uniform, ranging narrowly from 11.19 (Nagaland) to 11.6 (Himachal Pradesh). This suggested that the internal balance across CE indicators was consistent regardless of the total performance level. Nagaland (MIS=186.11, EIS=11.19) held the lowest score in both metrics. This indicated a critical need for basic infrastructure development across all 9 CE indicators. The score gap between Rajasthan (537.58) and Nagaland (186.11) was nearly 3:1. Such a massive disparity highlighted the geographical and infrastructural divide in India's climate-energy transition. Delhi (MIS=244.53, EIS=11.3) has the lowest MIS and a lower EIS than most UTs. High urban load likely disrupts the evenness of energy-climate indicators.

In the Terrestrial & Biodiversity (TB) domain (**Fig. 5c**, see **Supplementary File 9 Fig S26**), among the states, high MIS in Punjab was likely influenced by high scores in afforestation (TB8) and tree cover (TB10). Evenness scores vary drastically from 10.1 (Uttar Pradesh) to 18.24 (Nagaland). This indicated that biodiversity management was highly fragmented across different states. Uttar Pradesh (MIS=21.07, EIS=10.1) held the lowest EIS (i.e., 'imbalanced laggard'). This signified a high reliance on single indicators for biodiversity score with failures in others like forest area change (TB1). Nagaland (MIS=50.2, EIS=18.24) leads in both metrics (i.e., 'balanced leader'). This suggested a highly integrated approach to forest and wildlife management. Goa (MIS=64.27, EIS=10.19) has a very high MIS but extremely low EIS. This indicated 'imbalanced leadership' where performance was likely skewed by a single indicator (e.g., forest cover). Among the UTs, Delhi (MIS=445.15, EIS=9.24) showed a massive MIS compared to all states and UTs. However, its low EIS suggested this score was entirely dominated by extreme values in a few indicators like wildlife crime detection (TB4).

In the Waste & Pollution (WP) domain (**Fig. 5d**, see **Supplementary File 9 Fig S27**), among the states, Nagaland (MIS=24.94, EIS=13.73) and Meghalaya (MIS=25.08, EIS=15.96). Low performance was likely tied to poor source segregation and MSW processing in hilly terrains. Telangana (MIS=57.92, EIS=36.83) and Punjab (EIS=36.44) showed the highest evenness. This suggested that top performers in waste management were also the most balanced in their approach. Telangana (MIS=57.92, EIS=36.83) state showed a near-perfect correlation between high output and high evenness, serving as a model for holistic urban waste strategies. Karnataka (MIS=57.01, EIS=22.32), despite a high score, lower evenness indicated a heavy reliance on specific successes (e.g., BMW treatment) while lagging in others like door-to-door collection. Among the UTs, Delhi (MIS=46.09, EIS=26.78) scores high in collection but likely fails in recycling/utilization, creating internal disparity.

In the Water & Sanitation (WS) domain (**Fig. 5e**, see **Supplementary File 9 Fig S28**), across all states, EIS was nearly identical (approx. 13.9), except for Haryana and Maharashtra. This indicated a uniform structural relationship between water indicators nationwide. Telangana (MIS=462.92, EIS=13.94) leads in balance. High MIS-EIS suggested robust integration between groundwater management and sanitation. Haryana's (MIS=579.79, EIS=13.78) relatively lower EIS compared to top peers suggested over-performance in one area (likely agricultural output) at the expense of others (like groundwater extraction stage). Punjab (618.72) was nearly triple the MIS of Nagaland (236.73), highlighting the vast difference in water-intensive agricultural output.

Similar to states, UTs show almost perfectly uniform EIS (13.88 to 13.95), suggesting that water management balance was standardized by central policy. Chandigarh (MIS=661.92, EIS=13.95) held the highest scores in both metrics nationwide. This identified it as the benchmark for water-sanitation sustainability in India. While high in MIS, Andaman-Nicobar's (MIS=318.24, EIS=13.81) lower EIS indicated specific failures in sanitation or water withdrawal metrics.



Scope
Overall (All)
States Only
UTs Only
Inequality (Theil Index)
0.06
0.04
0.02
0.00
(a)
TB
CE
CoES
WP
WS
Evenness Index Score (EIS)
Mean Index Score (MIS)
Evenness_Score
MIS Score
(b)
(c)
(d)
(e)
Indicator Group
Biodiv
Climate
Waste
Water
Contribution to Deviation
(f)
PB CH GJ HP TS UK AP RJ MH HR DH TN DL PY GA KA JK DD MP OR CG MZ UP LD MN KL TR LA SK AN JH AS BR ML NL WB AR
States & UTs

Figure. 5. Inequality decomposition, performance-evenness balance, and spatial drivers of sustainability.
Panel (a) presents Theil index coefficients, quantifying the high disparity in renewable infrastructure (CE8/CE9) and hazardous waste processing (WP1).
Scatter plots (b) through (e) correlate Mean Index Scores (MIS) with Evenness Index Scores (EIS) to classify regions into performance quadrants, distinguishing 'balanced leaders' (e.g., Telangana) from 'imbalanced laggards' (e.g., Uttar Pradesh).
Panel (f) utilizes Spatial Additive Decomposition (SAD) to separate regional structural effects (spatial lags) from localized performance effects, isolating specific drags like high land degradation in Bihar or renewable outperformance in Himachal Pradesh.

4.9. *Spatial additive decomposition analysis (SAD)*:

In the Climate & Energy (CE) domain (**Fig. 5f**, see **Supplementary File 7**), among the states, Himachal Pradesh showed a contribution of 180.63, indicating that high renewable energy shares (94.02%) and significant CO_2 savings from LEDs (121.78) were driving a strong positive spatial structural effect. Nagaland showed a contribution of -165.14, indicating that a complete lack of bio-power (0 MW) and high human lives lost to extreme weather (56.23) were major drags on its CE performance. Among the UTs, Delhi showed a contribution of -82.61, indicating that a low renewable energy share (12.89%) and moderate fossil fuel use (206.36 kg) were significant structural drags.

In the Terrestrial & Biodiversity (TB) domain, among the states, Bihar showed a contribution of -109.03, indicating that having the lowest forest cover (7.84%) and high land degradation (45.73%) were the primary spatial inhibitors of sustainability. Mizoram showed a contribution of 95.55, indicating that the highest forest cover (84.53%) and significant afforestation (47.14%) were the state's most powerful spatial assets. Punjab showed a contribution of 66.87, indicating that intensive afforestation (16.13%) was successfully counteracting its naturally low forest cover (3.67%). Sikkim showed a contribution of -61.74, indicating that a -2.87% change in carbon stock and wildlife cases (161.5) were unique negative drivers for a 'green' state. Among the UTs, Delhi showed a contribution of 115.22, indicating that high tree cover (9.91%) and carbon stock growth (12.71%) were the dominant spatial drivers of its sustainability score.

In the Waste & Pollution (WP) domain, among the states, Meghalaya showed a contribution of -235.86, indicating that minimal waste processing (4%) and low segregation (21.62%) were the primary spatial drags. Gujarat showed a contribution of 237.95, indicating that high hazardous waste recycling (37.94%) and MSW processing (86.25%) were the state's dominant environmental strengths. West Bengal showed a contribution of -194.05, indicating that extremely low MSW processing (9.98%) and low segregation (18.86%) were dominant structural hurdles. Telangana showed a contribution of 136.02, indicating that high hazardous waste recycling (86.48%) was a unique and powerful structural asset. Among the UTs, Dadra-Nagar Haveli showed a contribution of 138.73, indicating that high recycling (141.05%) and MSW processing were the dominant sustainability drivers.

In the Water & Sanitation (WS) domain, among the states, Punjab showed a contribution of 142.91, indicating that very high sewage treatment (94.28%) and productivity (4491 kg/ha) were dominant positive drivers. Uttarakhand showed a contribution of 101.43, indicating that high sewage treatment (82.14%) and forest water body growth (14.52%) were key structural drivers. Nagaland showed a contribution of 61.6, indicating an exceptional positive trend where forest water body growth (59.27%) was the state's only major environmental strength. Among the UTs, Daman-Diu showed a contribution of -70.1, indicating that sewage treatment and high extraction (65.62%) were major structural drags.

5. Discussion:

Our study identified a 'prosperity-pollution' paradox where India's most agriculturally productive states, such as Punjab and Haryana, face the most severe groundwater depletion and land degradation. This result was consistent with Tiwari & Krishna's (2021) documentation that over-exploitation of groundwater in these 'grain-bowl' states posed a significant district-level sustainability concern, highlighting the connection between high agricultural productivity and aquifer stress. The 'prosperity-pollution' contradiction, which links high agricultural production to extreme ecological stress, was similar to past patterns in which economic expansion in Indian states regularly jeopardizes the quality of land and water (Mukherjee, 2022).

The 'master connector' in the WS network, connecting resource exploitation, forest water bodies, and sanitation infrastructure, was identified by this study as industrial wastewater treatment compliance. Although the current analysis expands this to sub-national Indian governance situations, this supports the findings of das Neves Almeida et al. (2017), who found pollution control indicators as crucial to understanding environmental damage trajectories in OECD countries.

High forest density served as the main regional buffer against the health effects of air pollution, notably lowering DALY lost, according to our analysis. This validates the cross-national validity of this ecosystem function and confirms the findings of Singh et al. (2019), who discovered a negative correlation between biodiversity and forest cover and air quality decline across 22 Asian economies.

According to this investigation, the effectiveness of ward-level source segregation, rather than just the size of processing facilities, was a crucial component of efficient MSW management. This result was in line with Sarkar et al. (2024), who found that waste segregation at the source was necessary for efficient processing in Bangladesh, Thailand, and Japan, indicating that this idea was universal.

Significant regional disparities in renewable energy infrastructure were found in this study, suggesting that the transition to green energy was sharply divided by state-level policies and natural resource endowments. This was consistent with the findings of Shah et al. (2019), who noted comparable differences in environmental sustainability and energy security among South Asian countries. However, the current study found that these differences continue even within India's administrative borders.

Our research makes a distinction between 'imbalanced laggards' like Uttar Pradesh, which depend on individual indicator successes, and 'balanced leaders' like Telangana, which uphold comprehensive waste and water programs. This typology supports the evenness approach to policy assessment, as demonstrated by Gómez-Limón et al. (2020), who discovered that agricultural sustainability in Spanish areas needed balanced performance across numerous dimensions rather than perfection in single measures.

Chandigarh received top-tier marks in waste processing and water-sanitation management, making it the national standard for urban environmental sustainability, according to our study. This validates Chandigarh's standing as a replicable example for other UTs, supporting the State Energy and Climate Index findings of Pandey et al. (2022), who placed the city among the top performers for its integrated infrastructure development.

According to this evaluation, new forest area increases frequently do not result in higher carbon sequestration, indicating that young plantations do not yet offer the density of natural ecosystems. This result was consistent with the findings of Fakher et al. (2021), who noted that land-use change and deforestation were important but complicated sources of carbon emissions, highlighting the need of forest quality as much as quantity in mitigating climate change.

According to our research, the NER states, Nagaland, Mizoram, Manipur, and Tripura, lead the TB sub-index because of their high levels of forest cover and stable carbon stocks. Although the current study includes all NER states that were previously omitted from their analysis, Mukherjee & Kathuria (2006) observed that mountainous and wooded regions generally exhibit better environmental quality indicators compared to industrial plains.

This study reveals a serious energy-environment mismatch in Delhi, where great LED savings and sophisticated developing infrastructure were significantly outweighed by a heavy load of air pollution and a slow integration of renewable energy sources. This contradiction was consistent with research by Kateja & Medatwal (2024), who found that urban centers frequently exhibit strengths in governance measures but deficiencies in atmospheric health, underscoring the necessity of integrated urban sustainability planning.

The methodological criticism of Oţoiu & Grădinaru (2018), who contended that national-level environmental indices frequently conceal important sub-national variations and suggested dynamic frameworks to capture regional disparities that aggregate data inevitably obscures, was consistent with our support for sub-national monitoring as crucial for identifying localized environmental health crises.

Sun et al. (2020) found that environmental efficiency in South Asian countries frequently showed sectoral asymmetries, where progress in one domain does not guarantee parallel advancement in others. This pattern was mirrored in states like Odisha, where high success in forest conservation does not translate into sustainable water management or high sewage treatment levels.

In line with Gómez-Limón et al. (2020), who found that agricultural sustainability in Spanish regions required balanced performance across multiple dimensions rather than excellence in single metrics, we distinguished between 'imbalanced leaders' like Goa, whose high scores were skewed by single indicators, and 'balanced laggard' profiles like Sikkim, where environmental efforts were well-distributed but limited in scale.

The work of Singh et al. (2019), who uncovered that biodiversity and forest cover were negatively correlated with air quality degradation across 22 Asian economies, was supported by the demonstration that high forest density acted as a primary regional buffer against the health burdens of air pollution, confirming the cross-national validity of this ecosystem service.

There were a few significant contributions of our work.

(a) By creating a thorough multi-dimensional index that incorporates 36 different indicators from the waste, water, biodiversity, and climate sectors, this study promotes sub-national environmental monitoring.
(b) By offering a thorough comparative analysis of environmental sustainability for each of the 37 Indian states and union territories, this study fills important gaps in earlier studies.
(c) Using network analysis, this study discovered intricate inter-sectoral linkages, identifying air pollution and industrial wastewater compliance as key ‘master connectors’ for regional sustainability.
(d) In order to identify particular regional determinants of environmental performance and differentiate between systemic structural constraints and localized distinctive strengths, our work uses spatial additive decomposition.
(e) Our analysis provides a robust policy-benchmarking framework through evenness analysis, highlighting the ‘balanced leader’ and ‘imbalanced laggard’ profiles essential for targeted regional interventions.

Like any other study, this study had a few limitations that need to be addressed in future studies.
(a) Incorporation of primary, real-time field / time series data to supplement the current reliance on secondary datasets from the NITI Aayog NDAP database, which may contain inherent reporting lagged.
(b) Expansion of the environmental pillar beyond the current 36 indicators to include missing critical dimensions, such as air quality at the micro-scale, detailed ecological footprints, and the environmental impact of food supply chains.
(c) Expansion of the current snapshot analysis into a multi-year longitudinal study to track the temporal effectiveness of long-term sustainability programs and the impact of recent national SDG initiatives.
(d) Validation of the sub-national findings through localized case studies to ensure that the aggregated state-level indices do not mask significant internal environmental health crises or governance failures at the district level.

6. Policy Recommendations

6.1. Suggestions for policymakers

This section outlines the key policy recommendations derived from our analyses, addressing the 4 sub-indices of environmental sustainability. Policymakers can create a more sustainable and equitable environmental future by focusing on these aspects.

(a) From Climate & Energy (CE) sub-index:

1. Scale up bio-power infrastructure in Nagaland as the lowest performer, via state-level capital subsidies for organic waste-to-energy plants.
2. Implement aggressive solar transition targets for West Bengal to address its lagging score (0.419), via utility-scale solar auctions and rooftop solar mandates for government & commercial buildings.
3. Launch specialized incentives for solar adoption in Bihar and Tripura to offset high air pollution DALY rates and low bio-power capacity, via low-interest ‘Green Loans’ and priority grid-access for renewable producers.

4. Expand renewable energy portfolios in Delhi beyond LED savings to mitigate the structural drag caused by its low renewable share (12.89%), through inter-state renewable energy credit trading and dedicated green energy corridors.

(b) From Terrestrial & Biodiversity (TB) sub-index:

1. Initiate intensive afforestation programs in Punjab to counteract its lowest forest cover (3.67%) and high land degradation, through mandatory canal-side and roadside plantation drives with survival/wellbeing-linked incentives.
2. Enforce strict land restoration policies in Kerala to address the structural drags of high land degradation and decline in carbon stock (3.49%), via soil health revitalization grants.
3. Implement targeted land restoration in Ladakh to mitigate spatial vulnerabilities from its degradation rate (29.23%) and low forest cover, via cold-desert plantation techniques and strict grazing management protocols.
4. Deploy localized conservation strategies for Puducherry to reverse the carbon stock loss (4.22%), through coastal mangrove restoration and urban green belt expansion.
5. Utilize the Delhi and Chandigarh 'urban model' for peripheral tree cover as a benchmark for planned administrative cities, through landscape laws requiring 33% green cover in all new urban development zones.

(c) From Waste & Pollution (WP) sub-index:

1. Establish hazardous waste recycling facilities in Nagaland and Arunachal Pradesh to address their zero-recycling status, through Public-Private Partnerships (PPP) for regional Common Hazardous Waste Treatment facilities.
2. Implement mandatory source segregation and door-to-door collection in West Bengal and Bihar to move them out of the 'cleaning' state outlier cluster, via ward-level composting units and penalties for non-segregated waste disposal.
3. Modernize waste processing in Meghalaya to overcome the minimal processing rate (4%) and segregation (21.62%), through mini-processing plants for hilly terrains and decentralized waste-to-wealth centers.
4. Replicate Telangana's holistic urban waste strategy, via integrated waste management dashboards for real-time tracking from collection to processing.
5. Strengthen industrial compliance in Punjab to close the identified gap between its waste generation scale and regulatory oversight, through automated 24/7 effluent monitoring and surprise pollution audits for manufacturing units.

(d) From Water & Sanitation (WS) sub-index:

1. Introduce water-efficient cropping patterns in Punjab and Haryana to mitigate the extreme groundwater over-exploitation, through crop-diversification subsidies for shifting from rice-wheat to millets or pulses.
2. Implement a total overhaul of Rajasthan's water policy to address its status as the national floor for water sustainability (0.246), through mandatory rainwater harvesting in all buildings and solar-powered micro-irrigation systems.
3. Deploy Chandigarh's 'gold standard' sewage and water management protocols as a national benchmark for all urban areas, via universal water metering and tiered pricing to discourage excessive urban water usage.

4. Prioritize forest water body restoration in Andaman-Nicobar to reverse the loss (15.14%), through integrated catchment area treatment and removal of invasive species near water bodies.
5. Enforce industrial wastewater compliance in Daman-Diu, via Common Effluent Treatment Plants (CETPs) for industrial estates and daily effluent reporting.
6. Target groundwater withdrawal reductions in Delhi to alleviate the extraction rate (99.13%), through incentivized reuse of treated wastewater for non-potable urban purposes (gardening, flushing).
7. Establish protective buffers for forest water bodies in Manipur and Nagaland to preserve them as vital bridges for broader water security, through declaring sensitive forest catchments as ‘eco-fragile zones’ with restricted human activity.

(e) From Cross-Connecting arenas:

1. Transition states like Kerala and Odisha from ‘balanced laggards’ to leaders by aggressively expanding solar capacity and wastewater infrastructure, through sector-specific ‘sustainability acceleration grants’ linked to index-improvement targets.
2. Address the ‘prosperity-pollution’ paradox by decoupling agricultural yield from unsustainable groundwater depletion in the northern plains, via water-use-efficiency (WUE) audits for large farms and direct-benefit transfers (DBT) for water savings.
3. Integrate biodiversity integrity into economic development plans in Nagaland to prevent infrastructure deficits from offsetting its ecological wealth, through green budgeting and biodiversity-linked development funding.
4. Target ‘imbalanced laggards’ like Uttar Pradesh with holistic multi-sectoral interventions rather than isolated indicator-based projects, via centralized ‘state sustainability missions’ coordinating between water, energy, and forest departments.
5. Use spatial additive decomposition to identify and remove systemic structural barriers like high air pollution in Bihar and Haryana, via localized ‘Clean Air Action Plans’ focusing on specific regional emission sources.

6.2. Policy integration & alignments

From the CE sub-index perspective, in the National Energy Policy, shift the ‘one-size-fits-all’ renewable target to region-specific quotas, particularly for Nagaland which currently lacks bio-power capacity, by mandating state-specific Renewable Purchase Obligations (RPOs) that prioritize locally available organic waste-to-energy. In the Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyaan (PM-KUSUM), integrate air pollution health metrics (such as DALY) into the selection criteria for solar pump distribution in high-burden states (like Bihar and Haryana), via district-level health-impact weighting during project bidding. In the Energy Conservation Building Code (ECBC), standardize the model of LED efficiency, which achieves near-zero inequality, across all state-level building codes, by requiring Energy Audit Certificates (EAC) for all commercial occupancy permits based on the Chandigarh benchmark.

From the TB sub-index perspective, in the Green India Mission (GIM), move beyond ‘tree-counting’ to ‘carbon density’ metrics to address the finding that forest area growth often fails to translate into carbon stock increase, via LiDAR-based biomass monitoring as a prerequisite for state fund releases. In the National Land Degradation Strategy, prioritize ‘balanced laggards’ (like

Rajasthan), where efforts were well-distributed but limited, for desertification-specific restoration grants, via satellite-linked soil health monitoring in over-exploited blocks.

From the WP sub-index perspective, in the Swachh Bharat Mission-Urban (SBM-U) 2.0, mandate 100% source segregation as a non-negotiable precursor to processing grants, especially for outlier states (like West Bengal and Bihar), via blocking central funds for 'Cleaning' clusters that do not meet 100% ward segregation targets. In the Hazardous Waste rules, incentivize the 'Industrial Circularity' model seen in Gujarat and Maharashtra for states with high generation-compliance gaps (like Punjab), via tax credits for industries achieving >50% recycling rates for hazardous materials.

From the WS sub-index perspective, in the Jal Jeevan Mission (JJM) / Atal Mission for Rejuvenation and Urban Transformation (AMRUT), incorporate industrial wastewater compliance as a primary performance indicator for urban water security, by making STP operational efficiency a weightage factor in the 'City Beauty' and 'Water+ Status' rankings. For the Atal Bhujal Yojana (ABY), specifically target the 'grain-bowl' states of Punjab and Haryana for immediate crop-diversification to reverse extreme groundwater stages, via 'Water-Savings Linked Direct Benefit Transfers (DBT)' for farmers switching from rice to low-water crops.

From the CoES index perspective, in the NITI Aayog SDG Index, adopt the 'spatial additive decomposition' method to identify if a state's performance was driven by its own policy or systemic regional barriers, via quarterly 'Sustainability Drag' reports for underperforming states (like Jharkhand and Uttar Pradesh). In the Inter-State Sustainability Council, create a formal body to replicate 'gold standard' outliers like Chandigarh across other urban UTs and industrial hubs, via mandatory mentorship programs where 'balanced leaders' (e.g., Telangana) provide technical training to 'imbalanced laggards'.

7. Conclusion:

The strategic 'master connector' that successfully connected resource extraction, terrestrial health, and sanitation infrastructure within the sub-national network was identified by our study as industrial wastewater treatment compliance. This study showed that the best defense against atmospheric health hazards was to maintain a high regional forest density, which greatly reduced the DALY lost to air pollution. This makes Chandigarh the gold standard for urban environmental sustainability in the country, surpassing all other organizations in integrated water-sanitation management and specialized waste processing. This revealed a 'biodiversity infrastructure' trade-off in which biologically rich nations, such as Nagaland, were frequently penalized by severe shortcomings in their ability to handle waste and water. Young plantations may not yet be able to recreate the ecological density of natural forests, as evidenced by the fact that recent forest area expansions frequently do not result in improved carbon sequestration. In order to discover localized environmental health issues that were often obscured by aggregated national-level reporting, this promoted ongoing sub-national monitoring.

List of Abbreviations:

ABY=Atal Bhujal Yojana	AMRUT=Atal Mission for Rejuvenation and Urban Transformation
BMW=Bio Medical Waste	BOD=Biochemical Oxygen Demand
BPL=Below Poverty Line	CAP=Common Agricultural Policy
CETP=Common Effluent Treatment Plant	COD=Chemical Oxygen Demand
CPCB=Central Pollution Control Board	DALY=Disability Adjusted Life Years
DBT=Direct Benefit Transfer	DPSIR=Driving force – Pressure – State – Impact – Response
DRI=Disaster Risk Index	ECBC=Energy Conservation Building Code
EIS=Evenness Index Score	EKC=Environmental Kuznets Curve
EPI=Environmental Performance Index	EU=European Union
GHG=Greenhouse Gas	GIM=Green India Mission
HCA=Hierarchical clustering analysis	JJM=Jal Jeevan Mission
LiDAr=Light Detection and Ranging	MENA=Middle East and North Africa
MIS=Mean Index Score	MSW=Municipal Solid Waste
NCr=National Capital Region	OECD=Organisation for Economic Co-operation and Development
PC=Principal component	PPP=Public-Private Partnerships
PM-KUSUM=Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyaan	PWS=Piped Water Supply
ROI=Return on investment	RPO=Renewable purchase obligation
SAD=Spatial additive decomposition	SDG=Sustainable Development Goal
SPM=Suspended Particulate Matter	STP=Sewerage Treatment Plant
UT=Union Territory	JFM=Joint Forest Management
NTFP=Non-timber forest product	DBT=Direct-benefit transfer
WUE=Water use efficiency	

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