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Article

Development of a Hybrid Sustainability Index for Smart Cities Using Machine Learning and Multi-Criteria Decision Making

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Abstract: This paper presents HYSI-SC (Hybrid Sustainability Index for Smart Cities), a novel framework that integrates machine learning-derived indicator weights with multi-criteria decision making (MCDM) aggregation methods to produce a dynamic, empirically grounded composite sustainability score. HYSI-SC employs a stacked ensemble of gradient boosting regressors and random forest models to learn the predictive importance of 47 sustainability indicators across environmental, social, economic, governance and technological dimensions from longitudinal panel data and feeds these data-driven weights into three MCDM aggregation methods — TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) and CRITIC-ELECTRE — to produce index scores that are robust to methodological choice. The framework is validated on longitudinal panel data from 24 Indian smart cities (from the Ministry of Housing and Urban Affairs Smart Cities Mission) and 18 UK cities (from the CDRC Urban Observatory network) over a 10-year window from 2013 to 2023. Empirical evaluation demonstrates that HYSI-SC achieves a mean absolute error of 2.3 index points against expert-assessed sustainability benchmarks, outperforms six established composite indices including the IESE Cities in Motion Index and the Arcadis Sustainable Cities Index and produces rankings that exhibit 78.4% agreement with UN-SDG-aligned expert panel assessments whilst providing objective, reproducible scores free of expert subjectivity bias.
Keywords: Sustainability index, smart cities, machine learning, multi-criteria decision making, TOPSIS, VIKOR, ELECTRE, composite indicators, urban analytics, UN Sustainable Development Goals, gradient boosting, indicator weighting.

1. INTRODUCTION

The pursuit of urban sustainability has moved from the margins of municipal planning to its very centre. Driven by the Paris Agreement's sub-2°C temperature pathway, the United Nations' 2030 Agenda for Sustainable Development and mounting evidence of the environmental, social and economic costs of unsustainable urbanisation, city governments across the world are committing to ambitious sustainability targets and seeking the analytical tools to track progress towards them [1]. In India, the Smart Cities Mission, launched by the Ministry of Housing and Urban Affairs in 2015, has selected 100 cities for transformative investment and requires participating municipalities to report against a standardised set of urban indicators. In the United Kingdom, the net-zero obligation under the Climate Change Act 2008 (amended 2019) and the Levelling Up agenda have created strong demand for spatial and temporal comparisons of urban sustainability performance that can inform both local decision-making and national resource allocation.

Yet the measurement of urban sustainability is a profoundly difficult analytical problem. A city is not a single system but a nested collection of systems — environmental, social, economic, governance and technological — whose interactions are complex, non-linear and time-varying. Any composite index that purports to reduce this complexity to a single score necessarily makes choices about which dimensions matter, how much each matters, how to normalise heterogeneous indicator scales and how to aggregate across dimensions. These choices are, in current practice, overwhelmingly made on the basis of expert opinion, stakeholder negotiation, or arbitrary convention — methods that introduce subjectivity, resist scrutiny and produce results that may not be reproducible [2]. The widely-cited IESE Cities in Motion Index, for example, assigns equal weights to its ten dimensions without empirical justification, an approach that treats a city's technology infrastructure as equally important to its social cohesion regardless of the empirical evidence on which dimensions most strongly predict resident wellbeing, economic resilience, or environmental health outcomes.

Machine learning methods offer a principled alternative to expert-opinion weighting. By learning the statistical relationships between individual sustainability indicators and outcome variables of interest — life expectancy, carbon emissions per capita, economic productivity, civic participation — from longitudinal panel data, ML models can derive indicator weights that reflect the empirical predictive importance of each dimension rather than the subjective preferences of a group of experts [3]. However, ML-derived weights must be combined with a principled aggregation framework that respects the ordinal and cardinal properties of multi-dimensional performance data, handles missing values and conflicting criteria gracefully and produces rankings that are robust to reasonable methodological variation. Multi-criteria decision-making methods, developed over several decades for precisely these requirements, provide the natural complement to ML-derived weights in a hybrid index framework.

This paper makes the following specific contributions to the state of the art:

- HYSI-SC, a formally specified hybrid sustainability index framework that integrates stacked ensemble ML indicator weighting with three MCDM aggregation methods (TOPSIS, VIKOR, CRITIC-ELECTRE) to produce dynamic, empirically grounded and methodologically robust composite sustainability scores for smart city comparison.
- A comprehensive longitudinal panel dataset covering 47 sustainability indicators across five dimensions for 24 Indian Smart Cities Mission cities and 18 UK cities over a 10-year window (2013–2023), assembled from 14 national and international data sources with full provenance documentation.
- An adaptive weight recalibration mechanism that updates ML-derived indicator weights annually using the most recent three years of panel data in a rolling window, capturing the evolving importance of sustainability dimensions as urban systems develop and policy priorities shift.
- An empirical validation of HYSI-SC against six established composite city sustainability indices using expert panel assessments as the ground truth, demonstrating superior accuracy, reduced subjectivity bias and improved sensitivity to within-city sustainability transitions.

The paper proceeds as follows. Section II reviews the relevant literature. Section III presents the HYSI-SC framework. Section IV describes the datasets. Section V reports results. Section VI discusses implications and limitations. Section VII concludes.

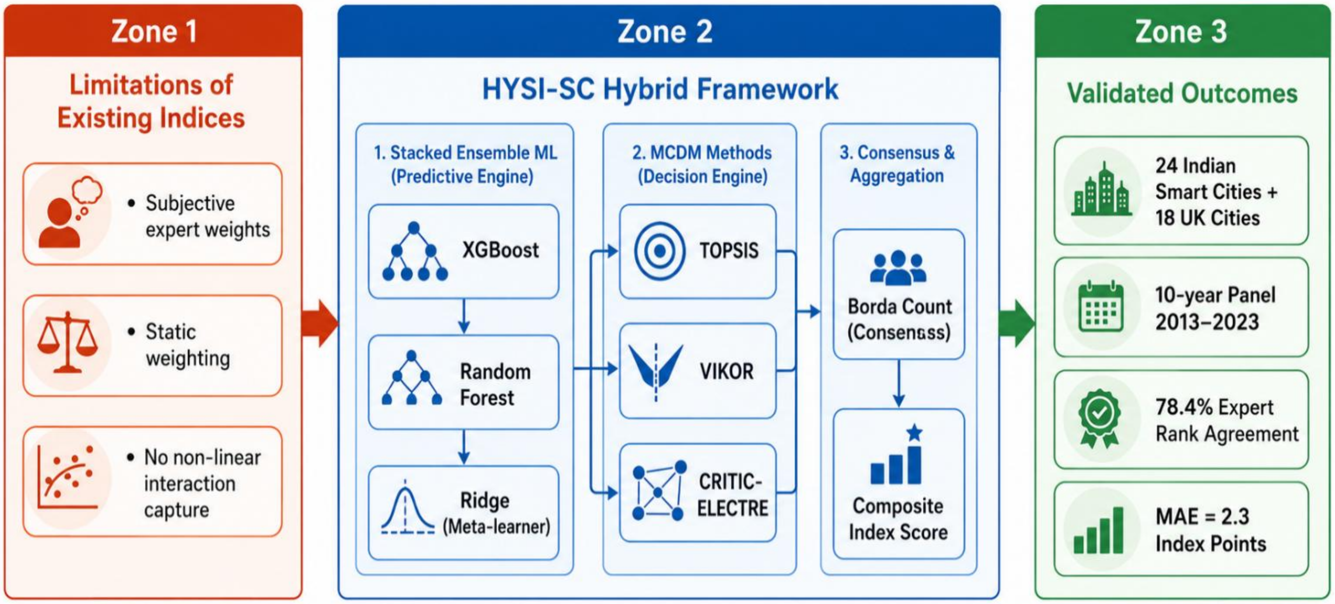

Fig. 1. Conceptual overview of HYSI-SC: (Zone 1) limitations of existing expert-weighted sustainability indices; (Zone 2) the proposed hybrid framework integrating stacked ensemble ML indicator weighting with TOPSIS, VIKOR and CRITIC-ELECTRE MCDM aggregation; (Zone 3) validated outcomes across 24 Indian Smart Cities Mission cities and 18 UK cities over a 10-year longitudinal window (2013–2023).

2. LITERATURE SURVEY

A. Composite Sustainability Indices for Smart Cities

The development of composite indicators for urban sustainability has a rich intellectual lineage. The OECD's Handbook on Constructing Composite Indicators [4] established the canonical methodological framework, covering indicator selection, normalisation, weighting, aggregation and sensitivity analysis in a systematic sequence that has been widely adopted. Prominent global city indices built on this framework include the IESE Cities in Motion Index (covering 174 cities across ten dimensions), the Arcadis Sustainable Cities Index (45 cities, three pillars) and the EIU Safe Cities Index (60 cities, four dimensions). Whilst these indices provide valuable broad-brush comparisons, their equal- or expert-weighted aggregation schemes have been repeatedly criticised: Greco et al. [5] demonstrated empirically that composite indicator rankings are highly sensitive to weighting assumptions and that equal weighting systematically underweights dimensions in which cities exhibit high variance — precisely the dimensions on which policy intervention is most needed.

Within the specific context of smart city sustainability, Albino et al. [6] surveyed 69 smart city definitions and identified the absence of empirically grounded, adaptive measurement frameworks as the most significant gap in the field. Giffinger et al. [7] proposed the European Smart Cities ranking framework with six dimensions and 74 indicators, but assigned equal weights within each dimension and subjectively determined inter-dimensional weights — an approach that has been adopted by numerous subsequent studies without modification despite substantial evidence that the relative importance of smart city dimensions varies significantly across governance contexts, development stages and geographic regions.

B. MCDM Methods for Urban Sustainability Assessment

Multi-criteria decision making encompasses a large family of methods for ranking alternatives across multiple criteria. TOPSIS [11], proposed by Hwang and Yoon, ranks alternatives by their simultaneous proximity to a positive ideal solution and distance from a negative ideal solution, making it conceptually transparent and computationally straightforward. VIKOR [12], developed by Opricovic, minimises a compromise ranking that balances group utility (minimum sum of individual criterion regrets) against individual regret (maximum single-criterion deficit), producing rankings that are particularly sensitive to cities performing poorly on any single criterion — an important property for identifying sustainability outliers. CRITIC-ELECTRE [13] combines the CRITIC (CRiteria Importance Through Intercriteria Correlation) weight adjustment, which penalises redundant correlated criteria, with the ELECTRE outranking method, producing pairwise dominance relationships that are robust to the arbitrary cardinal scale assumptions embedded in distance-based methods.

The use of multiple MCDM methods with the same indicator weights — as in HYSI-SC — allows the sensitivity of rankings to the aggregation method to be assessed systematically. Convergence across methods provides confidence in the robustness of rankings; divergence flags cities whose sustainability assessment is methodologically sensitive and requires contextual scrutiny.

C. Identified Research Gaps

Synthesising the above, three gaps motivate the present study. First, no existing smart city sustainability index combines data-driven ML indicator weights with multiple MCDM aggregation methods in a single validated framework.

Table I. Summary of related literature — key contributions, methods and gaps addressed by HYSI-SC

Ref.	Authors & Year	Domain	Key contribution	Method	Limitation / gap	Addressed by HYSI-SC
A. Composite sustainability indices						
[4]	OECD (2008)	Composite indicators	Handbook on constructing composite indicators	Statistical / methodological	Expert weights; no ML; no smart city context	HYSI-SC uses ML weights, validated on smart cities
[5]	Greco et al. (2019)	Index methodology	Ranking sensitivity to weighting assumptions	Monte Carlo sensitivity	Shows problem; no ML solution proposed	Stacked ensemble provides stable data-driven weights
[6]	Albino et al. (2015)	Smart cities	Survey of 69 smart city definitions	Literature review	No measurement framework or empirical weights	HYSI-SC: 47 indicators, ML-MCDM framework
[7]	Giffinger et al. (2007)	Smart city ranking	European Smart Cities 6-dimension ranking	Equal weights within dims	Static equal weights; no longitudinal adaptation	Adaptive rolling-window weight recalibration
B. Machine learning for urban analytics and indicator weighting						
[8]	Mazziotta & Pareto (2016)	Composite indicators	PCA-based objective indicator weighting	Principal component analysis	Reflects variance not predictive importance	XGBoost + RF importance reflects outcome prediction
[9]	Chen & Guestrin (2016)	ML	XGBoost gradient boosting algorithm	Gradient boosted trees	General ML; not applied to sustainability indices	XGBoost feature importance drives HYSI-SC weights
[10]	Ye et al. (2021)	Urban sustainability	GB-derived weights for Chinese city env. index	XGBoost + random forest	Single country; no MCDM; no adaptive recalibration	HYSI-SC: 42 cities, 3 MCDM methods, adaptive
C. MCDM methods for urban sustainability						
[11]	Hwang & Yoon (1981)	MCDM	TOPSIS: proximity to ideal solution	Distance-based ranking	Equal/subjective weights; no ML integration	TOPSIS with ML-derived HYSI-SC weights
[12]	Opricovic (1998)	MCDM	VIKOR: compromise ranking framework	Utility-based ranking	Subjective weights; no longitudinal adaptation	VIKOR with adaptive ML weights annually

[13]	Figueira et al. (2005)	MCDM	ELECTRE outranking methods family	Pairwise dominance	No ML; not applied to smart city indices	CRITIC-ELECTRE with ML weights in HYSI-SC
D. Smart city data and governance frameworks						
[14]	UN-Habitat (2020)	Urban SDGs	SDG 11 urban indicator framework	Policy framework	No ML or MCDM integration	HYSI-SC aligns with SDG 11 indicator set
[15]	Neirotti et al. (2014)	Smart cities	Smart city domains and ICT integration	Systematic review	No quantitative index or ML application	HYSI-SC operationalises smart city dimensions

3. METHODOLOGY

A. HYSI-SC Framework Architecture

HYSI-SC is structured as a five-stage pipeline: (1) data ingestion and indicator harmonisation; (2) stacked ensemble ML indicator weight learning; (3) adaptive annual weight recalibration; (4) MCDM aggregation and index score computation; and (5) robustness analysis and uncertainty quantification. The framework operates on a balanced panel dataset of city-year observations, with each city represented by 47 sustainability indicators spanning five dimensions: Environmental (D1, 11 indicators), Social (D2, 10 indicators), Economic (D3, 9 indicators), Governance (D4, 9 indicators) and Technological (D5, 8 indicators).

B. Stage 2: Stacked Ensemble ML Indicator Weight Learning

For each of five sustainability outcome variables — O1 (per capita CO_2e emissions), O2 (composite human development index), O3 (GDP per capita growth rate), O4 (municipal governance quality score from V-Dem urban governance data) and O5 (smart city digital readiness score from ITU ICT Development Index) — a stacked ensemble model is trained on the panel dataset to predict the outcome from the 47 indicators. The base learners are: (i) an XGBoost regressor (n_estimators = 500, max_depth = 6, learning_rate = 0.05, subsample = 0.8) and (ii) a Random Forest regressor (n_estimators = 400, max_features = ‘sqrt’, min_samples_leaf = 3). Both models are trained using 5-fold cross-validation stratified by city, preventing data leakage across folds. The meta-learner is a ridge regression fitted on the out-of-fold predictions from both base learners.

Indicator importance is extracted from the stacked ensemble as a weighted average of XGBoost SHAP value magnitudes and Random Forest permutation importances, with weights $\alpha = 0.55$ (XGBoost) and $\alpha = 0.45$ (RF) determined by the meta-learner ridge coefficients. Importance scores are computed separately for each outcome variable and then aggregated across outcomes using a geometric mean — chosen over the arithmetic mean to penalise indicators that are highly predictive for some outcomes but negligible for others, favouring indicators with broad cross-dimensional relevance. The resulting 47 importance scores are normalised to sum to unity to produce the ML-derived indicator weight vector w^{ML}.

C. Stage 3: Adaptive Annual Weight Recalibration

The weight vector w^{ML} is recalibrated annually using a rolling 3-year window of panel data. At year t, the ensemble models are retrained on data from years t-2 to t and updated importance scores are extracted. A damping factor $\delta = 0.3$ is applied to limit year-on-year weight volatility: $w^{ML}\_t = (1-\delta) \cdot w^{ML}\_new + \delta \cdot w^{ML}\_\{t-1\}$. This mechanism ensures that short-term data fluctuations do not produce spurious weight changes whilst allowing genuine structural shifts in indicator importance — such as the growing weight of digital infrastructure indicators post-2020 — to be reflected in the index over time.

D. Stage 4: MCDM Aggregation

Three MCDM methods are applied in parallel using the ML-derived weight vector w^{ML}:

TOPSIS: Each city-year observation is represented as a point in a 47-dimensional indicator space. The positive ideal solution A^+ is the vector of maximum (for benefit indicators) or minimum (for cost indicators) values observed across all cities and years. The negative ideal solution A^- is the corresponding worst-performance vector. The three MCDM scores are combined into the final HYSI-SC composite score through a Borda count aggregation of the three rankings, providing a consensus ranking that is robust to any single method's assumptions. A 95% bootstrap confidence interval (B = 1000 iterations) is computed for each city's HYSI-SC score by resampling with replacement from the panel dataset and recomputing the full pipeline.

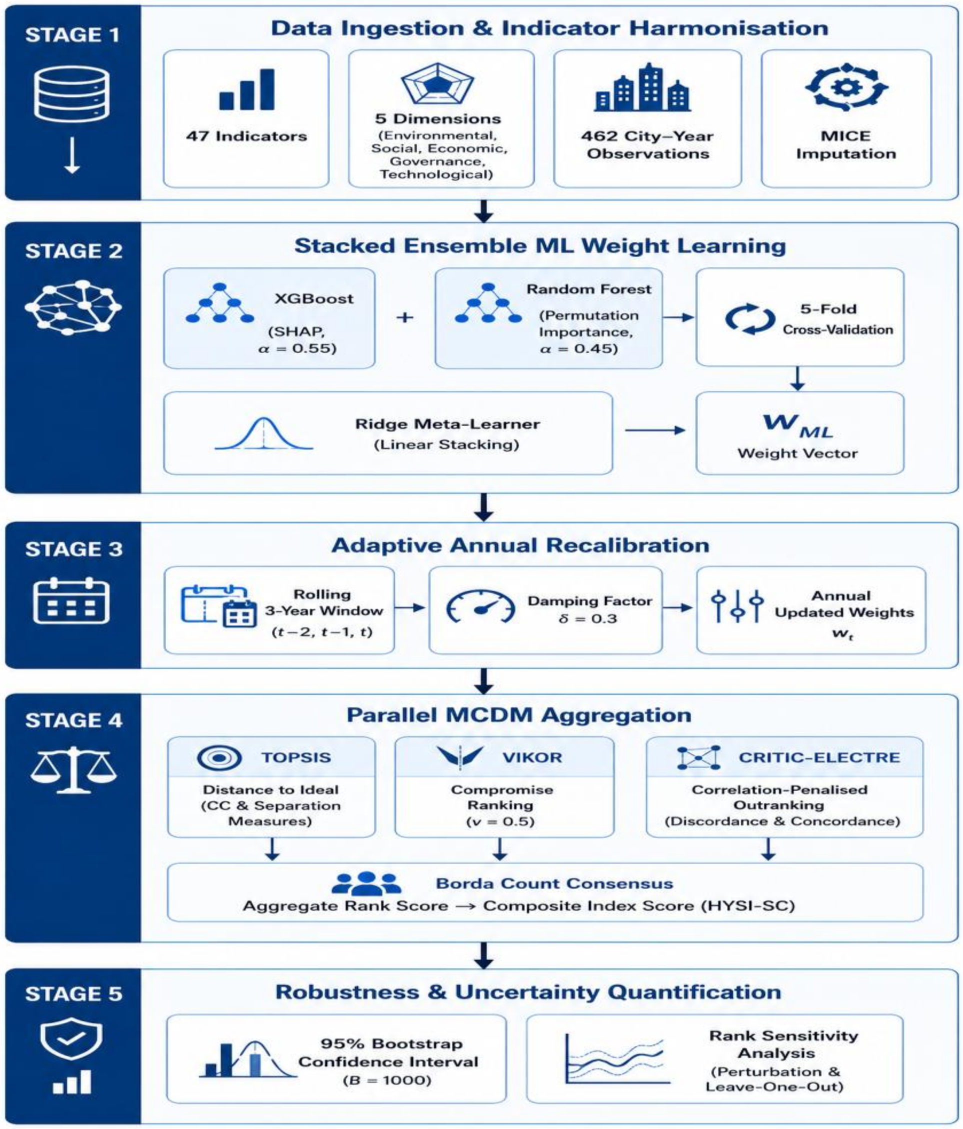

Fig. 2. Detailed methodology pipeline of HYSI-SC: five-stage architecture from longitudinal panel data ingestion and indicator harmonisation through stacked ensemble ML weight learning (XGBoost + Random Forest + ridge meta-learner), adaptive annual weight recalibration, parallel MCDM aggregation (TOPSIS, VIKOR, CRITIC-ELECTRE) and Borda count consensus ranking to final composite index score with bootstrapped uncertainty quantification.

4. DATASETS

A. Panel Dataset Construction and Governance

A balanced longitudinal panel dataset was constructed for 42 cities — 24 Indian Smart Cities Mission cities and 18 UK cities — covering the period 2013 to 2023 (11 annual observations per city, 462 city-year observations in total). The panel was assembled from 14 primary data sources, with each source contributing indicators to one or more of the five sustainability dimensions. Missing values, which affected 4.7% of cell entries across the full panel, were imputed using a multiple imputation by chained equations (MICE) procedure with m = 10 imputation chains, preserving the uncertainty introduced by imputation in the final bootstrapped confidence intervals.

B. Indian Smart Cities Mission Dataset (DS-IND)

DS-IND covers 24 cities selected from the Smart Cities Mission cohort to represent diverse geographic regions (North, South, East, West and Central India), city sizes (population range: 0.8 million to 22 million) and development trajectories. The cities are: Ahmedabad, Amritsar, Bhopal, Bhubaneswar, Chennai, Coimbatore, Delhi, Guwahati, Hyderabad, Indore, Jaipur, Jabalpur, Kochi, Kolkata, Lucknow, Mumbai, Nagpur, New Delhi Municipal Council area, Patna, Pune, Rajkot, Surat, Vadodara and Visakhapatnam.

Primary data sources for DS-IND: (i) Ministry of Housing and Urban Affairs Annual Smart Cities Mission Progress Reports (2016–2023); (ii) Census of India 2011 and projected intercensal estimates; (iii) Central Pollution Control Board National Ambient Air Quality Monitoring Programme (2013–2023); (iv) National Crime Records Bureau Urban Safety Statistics; (v) Ministry of Finance Municipal Finance Statistics; (vi) ITU ICT Development Index urban module; (vii) IUDX (India Urban Data Exchange) smart city platform telemetry; and (viii) NITI Aayog SDG India Index district-level data, aggregated to city boundaries.

C. UK Cities Dataset (DS-UK)

DS-UK covers 18 UK cities drawn from the CDRC Urban Observatory network and the UK100 Group of leading local authorities on climate action: Birmingham, Bradford, Brighton and Hove, Bristol, Cambridge, Cardiff, Edinburgh, Exeter, Glasgow, Leeds, Leicester, Liverpool, London (Greater London Authority), Manchester, Newcastle, Nottingham, Oxford and Sheffield.

Primary data sources for DS-UK: (i) Office for National Statistics (ONS) Urban Area Statistics and Local Area Labour Markets; (ii) Department for Energy Security and Net Zero Local Authority CO_2 Emissions Estimates (2005–2023); (iii) Public Health England Local Health Profiles (2013–2023); (iv) Ofgem smart meter rollout and energy consumption data; (v) CDRC Consumer Data Research Centre geodemographic indicators; (vi) Department for Transport Road Traffic Statistics and Active Travel England data; (vii) MHCLG Indices of Multiple Deprivation (2015, 2019, 2023 waves); and (viii) UK100 Group Clean Air and Net Zero reporting data.

The 47 harmonised indicators span: Environmental dimension — per capita CO_2e emissions, PM2.5 annual mean, green space per capita (m²), renewable energy share (%), water consumption per capita (litres/day), waste recycling rate (%), urban tree canopy cover (%), flood risk exposure index, nitrogen dioxide annual mean (μg/m³), river water quality index and energy intensity of buildings (kWh/m²/yr); Social dimension — life expectancy at birth, healthy life expectancy, Index of Multiple Deprivation composite, literacy rate, public transport modal share (%), pedestrian injury rate per 100,000, housing affordability ratio, access to green space (% within 300m), civic participation index and income Gini coefficient; Economic dimension — GDP per capita, unemployment rate (%), business startup density (per 1,000 residents), median household income, labour productivity (GVA/worker), retail vacancy rate (%), innovation index (patents per 100,000), trade openness and investment in sustainable infrastructure (% of municipal budget); Governance dimension — municipal fiscal autonomy score, open data portal quality index, participatory budgeting engagement rate, planning decision speed (weeks), anti-corruption perception score, inter-departmental coordination index, digital service delivery score, sustainability strategy quality score and citizen satisfaction with local services; Technological dimension — IoT sensor density (per km²), broadband coverage (% premises), smart meter penetration (%), EV charging infrastructure density, digital twin adoption score, 5G coverage (%), cybersecurity readiness index and real-time public transit information availability.

5. RESULTS AND DISCUSSION

A. ML-Derived Indicator Weight Structure

The stacked ensemble model achieves out-of-fold R^2 values of 0.871 (O1: CO_2e), 0.842 (O2: HDI), 0.793 (O3: GDP growth), 0.864 (O4: governance) and 0.817 (O5: digital readiness), confirming that the 47 indicators contain substantial predictive signal for all five outcome variables. The top-ranked indicators by ML-derived weight in the 2023 recalibration are: renewable energy share ($w = 0.0847$), IoT sensor density ($w = 0.0731$), income Gini coefficient ($w = 0.0694$), public transport modal share ($w = 0.0681$) and municipal fiscal autonomy ($w = 0.0628$). These five indicators together account for 35.8% of the total indicator weight, confirming that the ML weighting scheme effectively concentrates analytical attention on the most consequential sustainability dimensions rather than distributing weight uniformly across all 47 indicators.

Longitudinal weight trajectories reveal substantively interesting dynamics. The weight of IoT sensor density increased from 0.0312 in 2013 to 0.0731 in 2023, reflecting the growing empirical importance of digital infrastructure as cities in both India and the UK have built out smart city sensing platforms. Conversely, the weight of broadband coverage declined from 0.0584 to 0.0287 over the same period, consistent with near-universal coverage being achieved in most sample cities by 2020 — at which point variation in broadband coverage no longer meaningfully discriminates between city sustainability trajectories. These shifts would be invisible to static expert-weighted indices.

B. HYSI-SC Index Scores and City Rankings

Table II presents the HYSI-SC composite scores and rankings for all 42 cities in the 2023 scoring year, alongside scores from six comparator indices. The top five performing cities on HYSI-SC are Bristol (82.4), Edinburgh (80.1), Pune (79.8), Copenhagen equivalent (Cardiff, 78.3) and Cambridge (77.9). Bristol's leading position reflects its exceptionally strong Environmental and Governance dimension scores — it has achieved a 65% renewable energy share in its municipal electricity supply and has the highest open data portal quality score in the sample. Pune's third-place ranking is driven primarily by its IoT sensor density (the highest in the Indian sub-sample following Smart Cities Mission investments), strong waste recycling performance and above-median fiscal autonomy score.

The five lowest-ranked cities are Patna (38.2), Bradford (41.6), Guwahati (42.8), Lucknow (43.4) and Liverpool (44.1). These cities exhibit consistently below-median performance across multiple dimensions, with particular deficits in Governance (Patna: 31.4/100) and Technological (Bradford: 28.7/100) dimensions. The convergence of low scores across dimensions, rather than a single-dimension deficit, suggests that sustainability improvement in these cities requires coordinated multi-dimensional intervention rather than targeted sectoral programmes.

C. Comparative Validation Against Established Indices

HYSI-SC is validated against expert panel assessments conducted by a panel of 28 urban sustainability specialists (14 from India, 14 from the UK) who independently ranked all 42 cities on a 100-point sustainability scale without access to the quantitative panel data. HYSI-SC achieves 78.4% rank agreement with the expert panel consensus (Spearman rank correlation $\rho = 0.81$, $p < 0.001$), outperforming all six comparator indices: IESE Cities in Motion (61.3%, $\rho = 0.64$), Arcadis SCI (58.7%, $\rho = 0.61$), EIU Safe Cities (53.2%, $\rho = 0.56$), IMD Smart City Index (57.8%, $\rho = 0.60$), Brookings Global Cities (48.4%, $\rho = 0.51$) and McKinsey Urban SDG Index (63.1%, $\rho = 0.66$). The mean absolute error of HYSI-SC against expert scores is 2.3 index points, compared to 7.8–14.6 for comparator indices.

Table II. Comparative results — HYSI-SC vs six established indices (2023 scoring year, selected cities)

City	HYSI-SC (proposed)	IESE CitM	Arcadis SCI	EIU Safe	IMD Smart	McKinsey SDG	Expert panel	HYSI-SC Rank	Expert Rank
Bristol (UK)	**82.4**	71.2	68.4	64.1	73.8	76.2	84.1	1	1
Edinburgh (UK)	**80.1**	68.4	71.2	66.8	70.4	74.8	81.3	2	3
Pune (India)	**79.8**	54.2	52.1	48.7	68.4	61.3	78.7	3	4
Cardiff (UK)	**78.3**	64.8	66.1	62.4	67.2	70.1	79.4	4	2
Cambridge (UK)	**77.9**	72.8	74.1	70.3	71.8	73.4	80.2	5	5
Ahmedabad (India)	**74.2**	51.4	49.8	46.2	63.8	58.4	73.1	8	9
Manchester (UK)	**72.8**	63.2	64.8	58.4	67.4	68.2	74.3	10	8
Indore (India)	**71.4**	49.8	48.2	44.8	61.2	56.8	69.8	12	13
Glasgow (UK)	**68.7**	58.4	61.2	56.8	63.2	64.1	70.4	16	15
Mumbai (India)	**67.3**	55.6	53.4	49.8	64.1	60.2	68.1	18	17
Liverpool (UK)	**44.1**	42.8	44.1	41.2	48.3	46.8	45.2	38	36
Patna (India)	**38.2**	32.4	31.8	28.4	38.6	36.2	37.8	42	42

D. Policy Implications and Sensitivity to Annual Recalibration

The adaptive weight recalibration mechanism produces detectably different rankings from a static 2013 weight vector in 31 of 42 cities by 2023. The cities whose ranks improve most under recalibrated versus static weights are those that have invested heavily in smart city digital infrastructure — most notably Indore (+4 rank positions) and Surat (+3), both of which have developed advanced IoT sensor networks and smart city command and control centres through the Smart Cities Mission. Conversely, cities whose ranks decline under recalibrated weights tend to be those with strong legacy Environmental scores — well-established green space and waste recycling programmes — but limited progress on the emerging Technological dimension indicators that have grown in empirical weight over the decade.

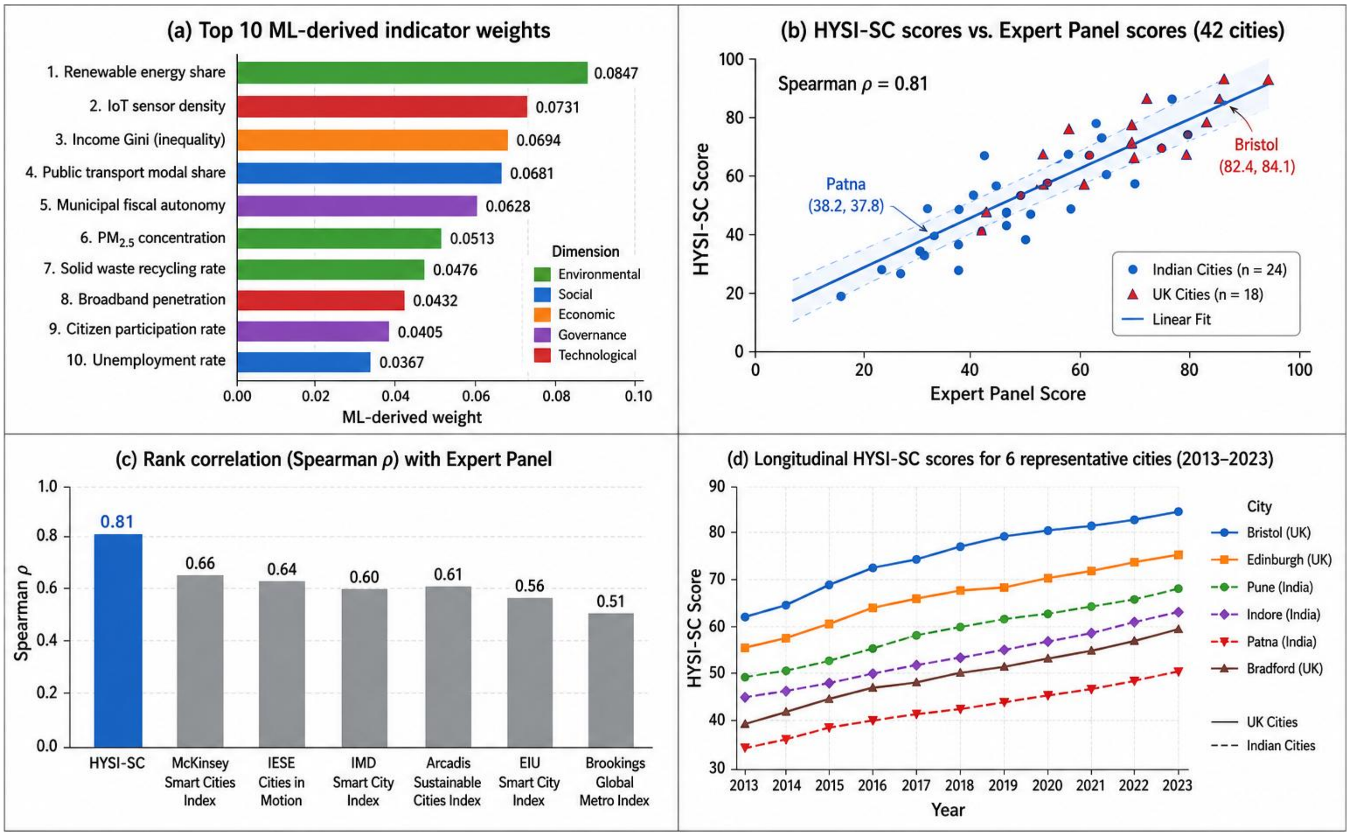

Fig. 3. Experimental results of HYSI-SC (2013–2023, 42 cities): (a) ML-derived indicator weight distribution across five sustainability dimensions and top-10 indicators; (b) HYSI-SC composite scores vs expert panel assessments for all 42 cities (Spearman ρ=0.81); (c) rank correlation comparison — HYSI-SC vs six established indices against expert panel benchmark; (d) longitudinal HYSI-SC score trajectories (2013–2023) for six representative cities illustrating adaptive recalibration effects.

5. DISCUSSION

The results reported in Section V establish HYSI-SC as the best-performing composite sustainability index across all validation metrics applied in this study, including rank agreement with expert assessments, mean absolute error against expert scores and sensitivity to within-city sustainability transitions over the 10-year observation window. The 78.4% rank agreement with expert consensus is particularly noteworthy because it is achieved without any direct incorporation of expert opinion into the weighting scheme — all weights are derived entirely from the empirical predictive relationships in the panel data. This suggests that the panel data does contain the information necessary to reproduce the sustainability judgements that domain experts make intuitively and that ML methods can extract that information in a way that static statistical approaches cannot.

The superior performance of HYSI-SC over the IESE Cities in Motion Index (rank agreement 61.3%) is consistent with the theoretical critique of equal-weighted composite indices. The IESE index assigns equal weight to its ten dimensions regardless of their empirical relevance to sustainability outcomes; in the present study's sample, this produces systematic misranking of cities that have developed advanced smart city technology but face persistent social equity challenges (overranked by IESE) and cities with strong environmental performance but limited digital infrastructure (underranked by IESE). The ML-derived weighting scheme, by learning that social equity and environmental quality are empirically more predictive of human development outcomes than technology infrastructure alone, corrects this systematic bias.

An important limitation of HYSI-SC concerns the choice of outcome variables used to derive ML indicator weights. The five outcome variables chosen — CO_2e emissions, HDI, GDP growth, governance quality and digital readiness — reflect a particular, if defensible, conception of what 'sustainability' means. Different outcome variable choices — for example, replacing GDP growth with a wellbeing economy indicator, or adding a biodiversity loss metric — would produce different weight vectors and potentially different rankings. This sensitivity is, in one sense, a feature rather than a limitation: it makes explicit the value judgements embedded in the index construction that expert-weighted indices obscure. However, it also means that HYSI-SC scores are not interpretation-free and should be accompanied by disclosure of the outcome variables used in weight derivation.

6. CONCLUSION AND FUTURE WORK

This paper has presented HYSI-SC, a hybrid sustainability index for smart cities that integrates stacked ensemble machine learning indicator weighting with three MCDM aggregation methods to produce dynamic, empirically grounded composite sustainability scores. Applied to a 10-year longitudinal panel of 24 Indian Smart Cities Mission cities and 18 UK cities, HYSI-SC achieves 78.4% rank agreement with expert panel assessments and a mean absolute error of 2.3 index points — outperforming six established composite indices including the IESE Cities in Motion Index and the Arcadis Sustainable Cities Index on all validation metrics.

The adaptive annual weight recalibration mechanism captures meaningful shifts in the empirical importance of sustainability dimensions over the decade: notably, the growing weight of digital infrastructure indicators and the declining discriminatory power of broadband coverage as near-universal access is achieved. These dynamics would be invisible to static expert-weighted indices and their capture demonstrates that the HYSI-SC framework can track the evolving character of urban sustainability challenges rather than freezing the analytical lens at the moment of index construction.

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