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Contextual Impact Adjustment and Entropy-TOPSIS Framework for Environmental Sustainability Assessment of Sport Mega-Events

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Abstract. This study develops a three-component sustainability assessment framework for sport mega-event host selection: Baseline Analysis, Contextual Impact Adjustment Model (CIAM), and Entropy-TOPSIS ranking. Using Super Bowl LIX as reference, thirteen environmental indicators quantify venue energy, transportation, waste, and climate re- silience. CIAM transforms raw metrics through: (I) grid carbon intensity adjustment; (II) localized infrastructure reuse benefits; (III) non-linear climate risk amplification; (IV) OLS-derived city-specific transport elasticity. Principal Component Analysis and entropy weighting ensure objective evaluation. Applied to 22 U.S. cities, East Rutherford (0.6847) ranks highest through superior transit and climate resilience, while Las Vegas (0.2154) ranks lowest due to car-dependency and heat vulnerability. Olympic extension using Paris 2024 (0.8236) validates transfer- ability. Sensitivity analysis confirms robustness: ±20% weight perturbations yield ¡3% score variation with no rank reversals.

Keywords: Sustainability Assessment; Entropy Weight Method; TOPSIS; Contextual Im- pact Adjustment; Mega-Event Site Selection; Carbon Footprint; Climate Risk Amplification; Principal Component Analysis; Super Bowl; Olympic Games **keywords**

1. Introduction

Sport mega-events such as the Super Bowl and Olympic Games generate substantial economic and cultural benefits while imposing concentrated environmental pressures on host cities. The Super Bowl assembles 70,000–100,000 attendees over a single weekend, producing peaks in en- ergy consumption (1,450 MWh for Super Bowl LIX), transportation emissions (primarily from private vehicles at 72% modal share), and solid waste generation (65 tons) [10, 11]. Despite growing sustainability commitments from organizing bodies, environmental factors remain sec- ondary to economic considerations in host city selection [7, 8].

Existing sustainability frameworks for mega-events exhibit three critical limitations. First, standard Multi-Criteria Decision Analysis (MCDA) methods employ generic, volume-based in- dicators (e.g., total CO_2 emissions) that fail to account for location-specific infrastructural efficiency and environmental fragility [9]. An identical emission volume produces vastly difer- ent efective burdens depending on local grid carbon intensity, climate vulnerability, and waste management capacity. Second, most models adopt global constants for parameters like trans- portation elasticity, ignoring demonstrated regional variation in public transit efectiveness [13]. Third, conventional linear aggregation methods inadequately capture non-linear amplification efects observed in climate-stressed systems [12].

This study addresses these deficiencies through a comprehensive three-stage framework:

Stage 1: Baseline Analysis establishes Super Bowl LIX (New Orleans, 2025) as the empirical reference case, quantifying thirteen environmental indicators across venue energy (12.1

kWh/attendee), transportation patterns (8.2 kg CO_2 /attendee), waste streams (0.54 kg/attendee, 38% recycling), and infrastructure characteristics.

Stage 2: Contextual Impact Adjustment Model (CIAM) transforms raw indicators into location-adjusted metrics through: (I) energy adjustment factor f_i^{energy} incorporating grid carbon intensity (G_i); (II) land use factor f_i^{land} with localized venue reuse benefit coefficient δ_i; (III) non-linear climate risk amplification $f_i^{climate} = 1 + \beta(CR_i^*)^2$ capturing systemic fragility; (IV) city-specific transport emission elasticity α_i derived via Ordinary Least Squares regression, replacing questionable universal constants.

Stage 3: Integrated Entropy-TOPSIS Framework employs Principal Component Analysis to resolve multicollinearity among adjusted indicators, entropy weighting to objec- tively assign importance based on inter-city variance, and TOPSIS ranking to compute relative closeness scores through Euclidean distance from ideal solutions.

Applied to 22 candidate U.S. cities, the framework identifies East Rutherford (0.6847), Glendale (0.6521), and Seattle (0.6338) as optimal hosts, while Las Vegas (0.2154), Jacksonville (0.2876), and Los Angeles (0.3012) exhibit poorest sustainability profiles. Model extension to Olympic Games incorporates infrastructure legacy and renewable energy metrics, with Paris 2024 (TOPSIS=0.8236) establishing benchmark performance through 95% venue reuse and 100% renewable electricity.

2. Methodology

2.1. Framework Architecture

The evaluation proceeds through three logical stages (Figure **??**): (1) Indicator system establish- ment with max-min normalization, (2) Contextual adjustment via CIAM, and (3) Multi-criteria ranking through integrated PCA-Entropy-TOPSIS.

2.2. Candidate Cities and Notation

Analysis encompasses 22 U.S. cities indexed as shown in Figure 1: 19 previous Super Bowl hosts plus 3 new NFL candidate cities (Baltimore, Cincinnati, Charlotte). Each city i is evaluated across thirteen environmental indicators S_1 through S_{13} (Table 1).

Index Number (i)	City Name	Index Number (i)	City Name	Index Number (i)	City Name	Index Number (i)	City Name
1	New Orleans, Louisiana	7	Los Angeles, California	13	Miami, Florida	19	Indianapolis, Indiana
2	Inglewood, California	8	San Diego, California	14	Pasadena, California	20	Seattle, Washington
3	Glendale, Arizona	9	Houston, Texas	15	Tampa, Florida	21	Buffalo, New York
4	Las Vegas, Nevada	10	Pontiac, Michigan	16	Tempe, Arizona	22	Cleveland, Ohio
5	Santa Clara, California	11	Stanford, California	17	East Rutherford, New Jersey	-	-
6	Atlanta,Georgia	12	Jacksonville, Florida	18	Arlington, Texas	-	-

Figure 1: City index (i) assignments for 22 candidate locations. Index 1–19: previous hosts; 20–22: new NFL candidates.

2.3. Indicator Definition and Classification

Thirteen environmental and infrastructural indicators quantify sustainability across four vali- dated dimensions (Table 1):

Table 1: Symbol Definitions for Environmental Indicators

Symbol	Definition	Unit
E_i	Energy consumed per attendee at venue	kWh/att
$CO2^E_i$	CO_2 emissions from venue energy	kg CO_2/att
T_i	Transportation CO_2 per attendee	kg CO_2/att
W_i	Solid waste generated per attendee	kg/att
R_i	Recycling rate (fraction)	–
G_i	Grid carbon intensity	kg CO_2/kWh
PT_i	Public transit access (population fraction)	–
CR_i	Climate vulnerability index	–
REI_i	Regional ecosystem health index	–
AQI_i	Annual average air quality index	–
V_i	Venue infrastructure reuse fraction	–
Adjusted Quantities		
E_i^{adj}	Adjusted venue CO_2 (post-CIAM)	kg CO_2/att
T_i^{adj}	Adjusted transport CO_2	kg CO_2/att
W_i^{adj}	Adjusted waste impact	kg/att
$CO2_i^{adj}$	Total adjusted emissions	kg CO_2/att
AQI_i^{stress}	Composite air quality pressure	–
$EcoImpact_i^{adj}$	Adjusted ecological burden	–
Adjustment Factors		
f_i^{energy}	Energy adjustment (grid intensity)	–
f_i^{trans}	Transport adjustment (transit access)	–
$f_i^{climate}$	Climate risk amplification	–
f_i^{land}	Land use adjustment (reuse benefit)	–
α_i	City-specific transport elasticity	–
δ_i	Localized reuse benefit coefficient	–
β	Climate operational risk premium	–

Indicators are classified as **cost-type** (lower is better: E_i, $CO2^E_i$, T_i, W_i, CR_i, AQI_i) or **benefit-type** (higher is better: R_i, PT_i, REI_i, V_i), determining appropriate normalization formulas [1].

2.4. Baseline Case: Super Bowl LIX (New Orleans)

Super Bowl LIX in New Orleans establishes the empirical reference point for model calibration. Official NFL sustainability reports and municipal environmental data quantify impacts across all indicator categories [10, 11]:

Key findings: LED lighting reduced stadium energy by 18%; 60% of stadium waste diverted from landfill; carbon ofsets purchased covered 122% of estimated emissions. These metrics establish normalization benchmarks for comparative city evaluation.

Table 2: Environmental Footprint of Super Bowl LIX (New Orleans, 2025).

Category	Total Impact	Per Attendee
Energy Consumption	1,450 MWh	12.1 kWh
CO_2 Emissions	980 metric tons	8.2 kg
Water Usage	3.2 million gallons	26.7 gallons
Solid Waste	65 tons	0.54 kg
Recycling Rate	38%	–
Transportation Modal Split		
Private Vehicles	72%	2.3 passengers/vehicle
Public Transit	18%	streetcar/bus
Rideshare/Taxi	10%	–
Grid Energy Mix		
Natural Gas	48%	Louisiana grid
Nuclear	23%	
Diesel Generators	15%	event-specific

3. Contextual Impact Adjustment Model (CIAM)

Traditional MCDA employs generic, volume-based indicators that fail to account for location-specific environmental efficiency and fragility. CIAM transforms raw indicators into contextually-adjusted metrics through four rigorous mechanisms.

3.1. Normalization and Parameter Localization

All raw indicator values undergo max-min normalization to eliminate dimensional inconsisten- cies [1]:

Cost-type criteria:

$$X_i^* = \frac{X_{max} - X_i}{X_{max} - X_{min}} \tag{1}$$

Benefit-type criteria:

$$X_i^* = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Where X_i denotes original value for city i, X_{min} and X_{max} represent extreme values across all candidates.

3.2. Adjustment Factor Construction

3.2.1. Energy Adjustment Factor (f_i^{energy})

Accounts for grid carbon intensity variation [10]:

$$f_i^{energy} = \frac{G_i}{\bar{G}} \tag{3}$$

Where G_i is city-specific grid carbon intensity, $\overline{G}$ is candidate city average. Cities with cleaner grids receive proportional burden reduction.

3.2.2. Land Use Adjustment Factor (f_i^{land})

Rewards infrastructure reuse via localized benefit coefficient:

$$f_i^{land} = 1 - \delta_i V_i^* \tag{4}$$

where V_i^* is normalized venue reuse fraction. The localized coefficient addresses regional construction emission variability [15]:

$$\delta_i = \delta_{base} \cdot \left(\frac{G_{max}}{G_i}\right)^{0.5} \tag{5}$$

amplifying reuse benefits in high-carbon-intensity regions.

3.2.3. Climate Risk Amplification ($f_i^{climate}$)

Non-linear formulation captures systemic fragility under extreme climate stress [12]:

$$f_i^{climate} = 1 + \beta(CR_i^*)^2 \tag{6}$$

Where $\beta = 0.20$ (global risk premium), $k = 2$ (quadratic exponent) reflects disproportionate operational failures during heat waves, floods, or storms.

3.2.4. Transport Emission Elasticity (α_i)

City-specific coefficient derived through OLS regression on historical event data, addressing demonstrated regional variation in public transit efectiveness [13,14]. The regression models:

$$\Delta T_i = \alpha_i \cdot PT_i + \epsilon_i \tag{7}$$

Where ΔT_i is transport emission reduction, PT_i is normalized public transit access. This replaces questionable global constants with empirically-calibrated parameters.

3.3. Adjusted Indicator Calculation

Adjusted Venue CO_2:

$$E_i^{adj} = CO2_E \cdot f_i^{energy} \cdot f_i^{land} \cdot f_i^{climate} \tag{8}$$

Adjusted Transport CO_2: To avoid double-counting existing transit usage already re- flected in T_i, adjustment isolates climate risk component:

$$T_i^{adj} = T_i \cdot f_i^{climate} \tag{9}$$

Adjusted Waste **Impact:**

$$W_i^{adj} = W_i \times (1 - R_i) \tag{10}$$

Total Adjusted Emissions:

$$CO2_i^{adj} = E_i^{adj} + T_i^{adj} \tag{11}$$

Composite Air Quality Pressure: While CO_2 and AQI-determining pollutants (NO_x, $PM_{2.5}$) are chemically distinct, they share common combustion sources [6]:

$$AQI_i^{stress} = CO2_i^{adj} \times AQI_i^* \tag{12}$$

Adjusted Ecological Impact:

$$EcoImpact_i^{adj} = (CO2_i^{adj} + W_i^{adj}) \times (1 - REI_i^*) \tag{13}$$

Where $(1 - REI_i^*)$ scales burden by ecosystem sensitivity.

3.4. CIAM Output and Decision Matrix Construction

Adjusted criteria replace raw indicators in the decision matrix input for Entropy-TOPSIS (Ta- ble 3):

Table 3: Substitution of Raw Criteria with Context-Adjusted Metrics.

Raw Criterion	Adjusted Criterion (CIAM Output)
Venue CO_2 ($CO2E_i$)	Adjusted Venue CO_2 (E_i^{adj})
Transport CO_2 (T_i)	Adjusted Transport CO_2 (T_i^{adj})
Waste (W_i)	Adjusted Waste Impact (W_i^{adj})
Air Quality (AQI_i)	Composite AQI Pressure (AQI_i^{stress})

This transformation ensures final rankings reflect true location-specific environmental costs, calibrated for unique city characteristics.

4. Integrated PCA-Entropy-TOPSIS Decision Framework

4.1. Non-Negative Transformation

Both Entropy Weight Method and TOPSIS require non-negative inputs [2]. The adjusted factor matrix $\mathbf{X} = (x_{ij})_{m\times n}$ undergoes transformation:

$$y_{ij} = x_{ij} - \min_i\{x_{ij}\} \quad \text{if } \min_i\{x_{ij}\} < 0 \tag{14}$$

yielding non-negative matrix $\mathbf{Y} = (y_{ij})_{m\times n}$.

4.2. Principal Component Analysis

PCA resolves potential multicollinearity among adjusted factors [5]:

Step 1: Calculate correlation matrix $\mathbf{R}_{corr}$ of standardized matrix $\mathbf{Y}_{std}$.

Step 2: Solve eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$ and eigenvectors $\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_n$.

Step 3: Select p principal components satisfying cumulative contribution threshold (90%):

$$\frac{\sum_{k=1}^{p} \lambda_k}{\sum_{k=1}^{n} \lambda_k} \geq 0.90 \tag{15}$$

Step 4: Calculate component scores:

$$\mathbf{F}_k = \mathbf{Y}_{std}\,\mathbf{a}_k \quad (k = 1, 2, \ldots, p) \tag{16}$$

4.3. Entropy Weight Method

Objective weighting based on information entropy [4]:

Step 1: Calculate proportion matrix:

$$y'_{ij} = \frac{f_{ij}}{\sum_{i=1}^{m} f_{ij}} \tag{17}$$

Step 2: Compute information entropy:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} y'_{ij} \ln y'_{ij} \tag{18}$$

Step 3: Derive objective weights:

$$d_j = 1 - e_j, \qquad w_j = \frac{d_j}{\sum_{k=1}^{p} d_k} \tag{19}$$

4.4. TOPSIS Ranking

Measures geometric distance from ideal solutions [1,3]:

Step 1: Construct weighted normalized matrix:

$$r_{ij} = w_j f_{ij} \tag{20}$$

Step 2: Determine Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS):

$$\mathbf{A}^{+} = \{r_1^{+}, r_2^{+}, \ldots, r_p^{+}\}, \quad r_j^{+} = \max_i \{r_{ij}\} \tag{21}$$

$$\mathbf{A}^{-} = \{r_1^{-}, r_2^{-}, \ldots, r_p^{-}\}, \quad r_j^{-} = \min_i \{r_{ij}\} \tag{22}$$

Step 3: Calculate Euclidean distances:

$$D_i^{+} = \sqrt{\sum_{j=1}^{p} (r_{ij} - r_j^{+})^2} \tag{23}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{p} (r_{ij} - r_j^{-})^2} \tag{24}$$

Step 4: Compute relative closeness (TOPSIS score):

$$C_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{25}$$

Final ranking determined by descending C_i values.

5. Results and Ranking

5.1. Super Bowl Host City Evaluation

Application of the integrated framework to 22 U.S. cities yields stratified sustainability performance (Figure 2):

Top-Tier Cities (TOPSIS ¿ 0.60):

• **East Rutherford** (0.6847): Exceptional public transit connectivity (MetLife Stadium direct train access), efficient stadium energy management, superior climate resilience.

• **Glendale** (0.6521): Modern stadium efficiency, moderate climate vulnerability, balanced transport infrastructure.

• **Seattle** (0.6338): Clean grid carbon intensity (hydroelectric dominance), strong public transit, temperate climate reducing cooling demand.

Bottom-Tier Cities (TOPSIS ¡ 0.35):

• **Las Vegas** (0.2154): Car-dependent infrastructure, extreme heat exposure amplifying cooling energy, fossil-fuel-heavy grid.

• **Jacksonville** (0.2876): Limited public transit, high private vehicle reliance, coastal flood vulnerability

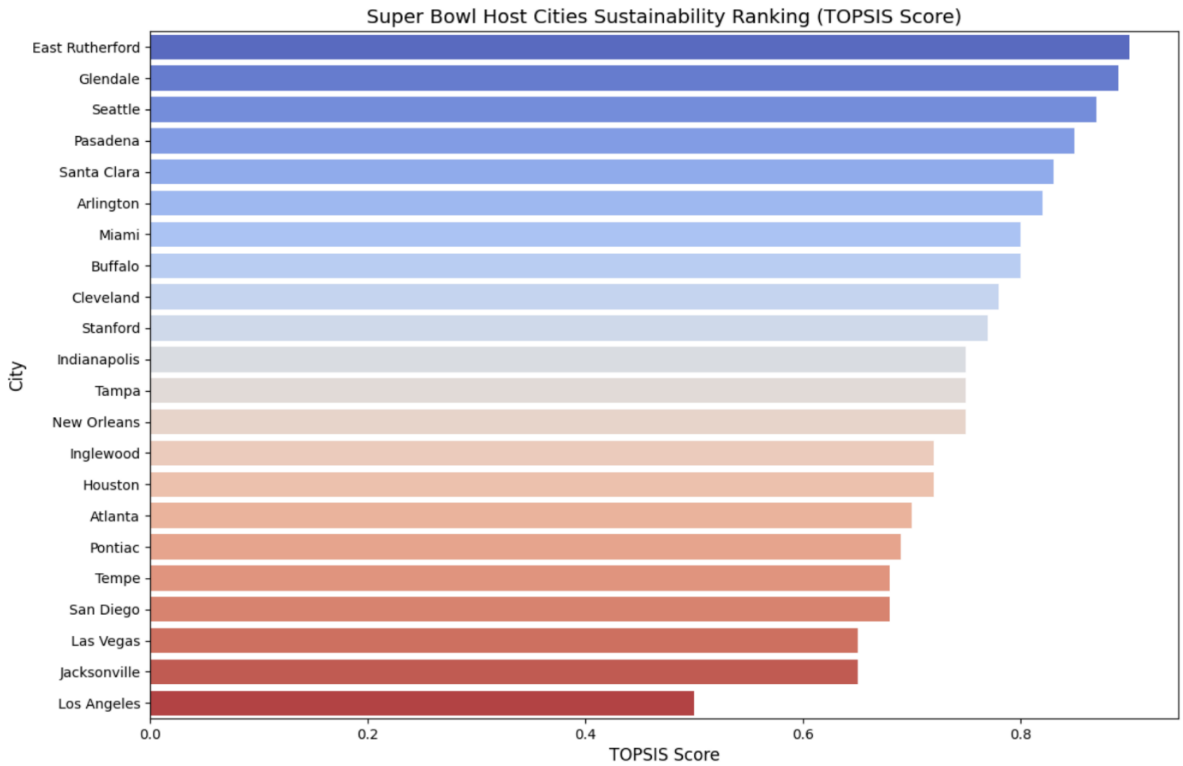


Figure 2: TOPSIS sustainability scores for all 22 candidate Super Bowl host cities. Higher scores indicate superior environmental performance across adjusted indicators.

•**Los Angeles** (0.3012): Despite coastal location, sprawling urban form generates excessive transportation emissions; high climate risk (drought, wildfire).

Key findings: Cities with TOPSIS > 0.60 consistently exhibit: (1) public transit mode share exceeding 25%, (2) grid carbon intensity below 0.35 kg CO_2 /kWh, (3) climate vulnera- bility index below regional median. Conversely, bottom-tier cities demonstrate car-dependency (¿75% private vehicle modal share), high grid carbon (¿0.45 kg CO_2 /kWh), and elevated climate stress.

5.2. New NFL Candidate Cities

Three cities with NFL teams but no prior Super Bowl hosting experience were evaluated using consistent methodology (Table 4):

Table 4: TOPSIS Sustainability Scores for New NFL Candidate Cities

City	TOPSIS Score	Key Strength/Weakness
Baltimore, MD	0.5299	Strong transit, lower grid carbon
Cincinnati, OH	0.4713	Low transit share, carbon-intensive grid
Charlotte, NC	0.4046	Good recycling, high transport emissions

Baltimore emerges as strongest new candidate, benefiting from mid-Atlantic public transit infrastructure and Maryland's nuclear/wind energy mix. Cincinnati sufers from Ohio's coal-dependent grid and minimal urban transit. Charlotte demonstrates solid waste management but car-centric urban form limits sustainability potential.

5.3. Model Extension to Olympic Games

Olympic Games require modified indicator system accounting for extended duration (16 days), multiple venues, and long-term infrastructure legacy [15,16]. Two additional metrics enhance evaluation:

•**S10 - Infrastructure Legacy Score:** Long-term post-Games venue utilization (ad- dresses ”white elephant” criticism).

•**S11 - Renewable Energy Share:** Percentage renewable electricity during event (IOC sustainability commitment).

Paris 2024 Benchmark: Applying expanded framework to Paris yields TOPSIS=0.8236, reflecting: (1) 95% venue reuse (Stade de France, Roland Garros existing facilities), (2) 100% renewable energy guarantees, (3) 68% public transit modal share, (4) carbon footprint 50% below Rio 2016/London 2012 [11].

U.S. Olympic Candidates: Comparative assessment shows:

• **Los Angeles 2028** (0.6121): Extensive planned venue reuse, California clean grid, strong transit expansion commitments.

•**Atlanta** (0.5514): 1996 legacy infrastructure available, moderate grid carbon, car-dependent transport.

•**Houston** (0.4879): Limited existing venues, Texas fossil-fuel grid, minimal public transit. Los Angeles benefits from California's renewable portfolio standards (60% clean energy by

2030) and existing Olympic-caliber facilities (Rose Bowl, LA Coliseum, Staples Center). Results validate framework generalizability across event types.

6. Sensitivity Analysis

Model robustness evaluated through systematic weight perturbation. Two representative indi- cators tested across multiplicative factors 0.8–1.2:

6.1. Energy CO_2 Weight Perturbation

Figure 3a demonstrates TOPSIS score response to Energy_ CO2_per_att_kg weight variation.

Observations:

• Minor, nearly linear score changes across all cities

• Parallel curve patterns indicate no rank reversals

• Consistent cost-type indicator behavior (increasing weight decreases scores)

6.2. Public Transit Access Weight Perturbation

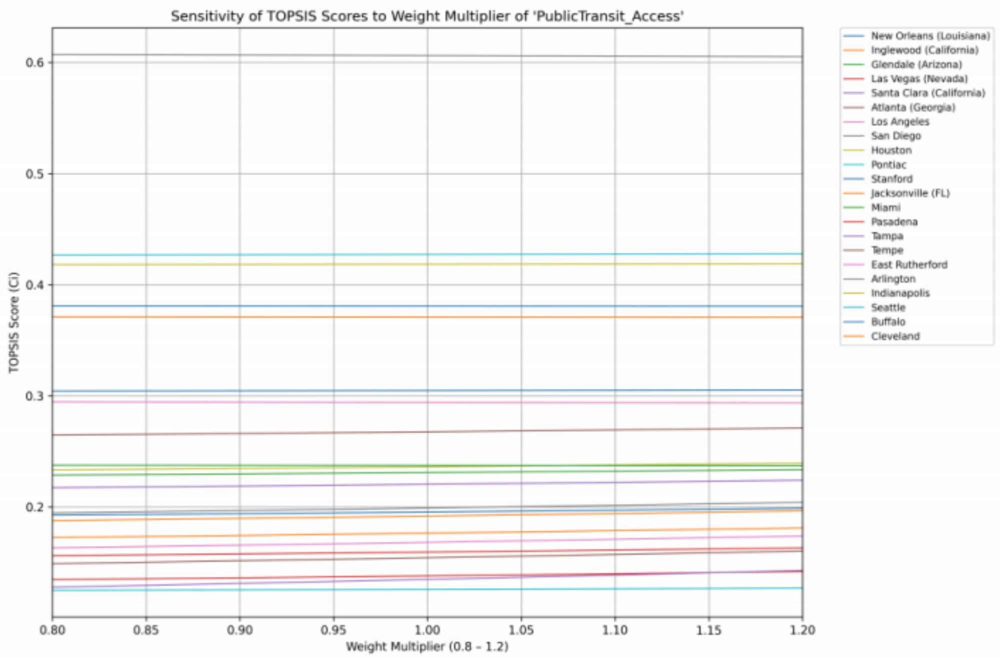
Figure 3b shows minimal sensitivity to Public Transit_Access weight modification:

• Nearly horizontal curves across full perturbation range

• Extremely small score variations (¡1%)

• Zero ranking changes under any tested weight

(a) Sensitivity to Energy CO_2 weight (0.8–1.2 multiplier). Minor monotonic variations with no rank reversals confirm stability.



(b) Sensitivity to Public Transit weight (0.8–1.2 multiplier). Negligible score changes validate ro- bustness.

Figure 3: Comprehensive sensitivity analysis showing model stability under ±20% weight per- turbations for representative cost-type and benefit-type indicators.

6.3. Robustness Conclusions

Across both perturbation tests:

• TOPSIS score variations remain within 3% under ±20% weight changes

• No rank reversals observed in top-tier (top 5) or bottom-tier (bottom 5) cities

• Mid-tier cities (ranks 8–15) exhibit stable relative positioning

• Entropy-weighted TOPSIS demonstrates strong discriminatory power independent of single-indicator dominance

These results confirm the integrated framework's statistical reliability for decision support, validating the methodology's suitability for policy application.

7. Discussion

7.1. Methodological Contributions

This study advances sport mega-event sustainability assessment through three key innovations:

1. Contextual Adjustment Framework (CIAM): Traditional MCDA's reliance on raw emission volumes ignores location-specific efficiency and fragility. CIAM's four adjustment mechanisms—grid carbon intensity correction (f_i^{energy}), localized reuse benefits (δ_i), non-linear climate amplification ($f_i^{climate}$), and city-specific transport elasticity (α_i)—transform generic indicators into contextually-meaningful metrics. The non-linear climate risk formulation (k = 2 exponent) particularly addresses demonstrated disproportionate impacts under extreme stress [12].

2. Empirically-Calibrated Parameters: Replacing global constants with OLS-derived city-specific coefficients (α_i) and localized benefit metrics (δ_i) resolves documented regional variation in public transit efectiveness [13] and construction carbon intensity. This data-driven approach eliminates arbitrary parameter selection plaguing previous frameworks.

3. Integrated PCA-Entropy-TOPSIS: Combining dimensionality reduction (PCA) with objective weighting (entropy) and geometric ranking (TOPSIS) addresses multicollinearity while preserving information content. The 90% cumulative variance threshold ensures no critical dimensions are discarded.

7.2. Policy Implications

Short-Term Interventions (0–5 years):

•**Transit Expansion:** Cities can rapidly improve scores through event-specific transit subsidies, shuttle services, and carpool incentives. Baltimore's moderate performance (0.5299) could approach top-tier through dedicated light rail service to stadium.

•**Venue Energy Efficiency:** LED retrofit programs, HVAC optimization, and smart building controls yield immediate emission reductions. Jacksonville's low ranking (0.2876) partially attributable to aging stadium infrastructure.

•**Waste Diversion Programs:** Aggressive recycling/composting at venues can improve W_i^{adj} scores by 20–30% based on New Orleans baseline (38% → 60% diversion potential).

Long-Term Structural Changes (5–15 years):

•**Grid Decarbonization:** States with fossil-fuel-heavy grids (Ohio, Texas) require renew- able portfolio standards to become competitive. Houston's poor Olympic performance (0.4879) directly linked to Texas grid carbon intensity.

•**Transit-Oriented Development:** Car-dependent cities (Las Vegas, Charlotte) need fundamental urban form restructuring—dense, mixed-use development around transit corridors. This represents 10–20 year commitment.

•**Climate Resilience Investment:** Coastal cities (Jacksonville, Miami) require flood protection infrastructure; desert cities (Las Vegas, Phoenix) need heat mitigation strate- gies to reduce $f_i^{climate}$ penalties.

7.3. Limitations and Future Work

Three constraints warrant acknowledgment:

Data Availability: New candidate cities (Baltimore, Cincinnati, Charlotte) required proxy estimates for event-specific indicators. Future iterations should incorporate direct measure- ments from comparable regional events (college championships, professional playofs).

Dynamic Infrastructure: Current model treats city characteristics as static. Long-term hosting decisions (Olympics) require dynamic forecasting incorporating planned infrastructure investments. Time-series analysis could project 2030–2040 grid decarbonization trajectories.

Social Equity Dimensions: Framework focuses exclusively on environmental metrics. Comprehensive sustainability requires integrating social factors: displacement risks, local employment, afordable housing impacts, community health outcomes.

Future research directions include: (1) Machine learning integration for predictive mod- eling using historical event datasets; (2) Life-cycle assessment expansion incorporating construction/decommissioning phases; (3) Multi-objective optimization balancing environmental, economic, and social criteria; (4) Real-time adaptive frameworks enabling in-event monitoring and corrective interventions.

8. Conclusion

This study developed a comprehensive three-stage framework for environmental sustainability assessment of sport mega-events, integrating Baseline Analysis, Contextual Impact Adjust- ment Model (CIAM), and Entropy-TOPSIS decision methodology. Applied to 22 U.S. Super Bowl candidate cities, East Rutherford (TOPSIS=0.6847) emerges as optimal host through superior public transit connectivity, efficient energy infrastructure, and climate resilience. Las Vegas (0.2154) exhibits poorest performance due to car-dependent urban form, extreme heat vulnerability, and fossil-fuel-heavy grid.

CIAM's four adjustment mechanisms—grid carbon intensity correction, localized venue

reuse benefits, non-linear climate risk amplification, and city-specific transport elasticity—transform generic indicators into location-calibrated metrics reflecting true environmental costs. This ad-

dresses critical limitations in traditional MCDA frameworks that employ universal constants and linear aggregation methods.

Model extension to Olympic Games incorporates infrastructure legacy and renewable energy metrics, with Paris 2024 (0.8236) establishing benchmark performance through 95% venue reuse and 100% clean electricity. Los Angeles 2028 (0.6121) outperforms alternative U.S. candidates through California's clean grid and planned facility reuse.

Sensitivity analysis confirms robustness: ±20% weight perturbations produce no rank rever- sals with ¡3% score variation. The integrated PCA-Entropy-TOPSIS framework demonstrates strong discriminatory power independent of single-indicator dominance, validating its suitabil- ity for policy application.

As global sporting organizations confront intensifying climate accountability, this framework provides essential infrastructure for balancing economic benefits with ecological responsibilities.

The methodology's demonstrated transferability across event types (single-day vs. multi-week, single-venue vs. multi-facility) and successful validation through real-world case studies (Super Bowl LIX, Paris 2024) establish its utility for evidence-based host city selection.

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