Two-Phase Dynamic Assessment of Host City Environmental Sustainability for Sport Mega-Events

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Abstract—**Sport mega-events (SMEs) generate substantial socio-economic benefits but impose severe environmental burdens, including high carbon emissions, intensive energy consumption, and large-scale spectator travel. Traditional host city selection prioritizes economic and logistical factors, lacking a systematic environmental evaluation framework that integrates both current performance and long-term sustainability potential. This study proposes a two-phase dynamic assessment model combining the entropy weight method, TOPSIS, and Monte Carlo simulation to evaluate candidate cities comprehensively. The framework covers six core environmental dimensions with eighteen measurable indicators, balancing static baseline performance and dynamic future trajectories. Empirical results show that Seattle achieves the highest Composite Sustainability Index (0.596) due to its 85% renewable energy share, while Indianapolis leads in carbon minimization with a GHG score of 88.9, attributed to its central geographic location. For the 2029 Super Bowl, Santa Clara is recommended among experienced hosts, and Seattle is the optimal new candidate. Sensitivity analysis reveals that spectator attendance and travel distance dominate environmental impacts, explaining over 75% of total variation. The proposed model provides a robust, data-driven tool for balancing operational feasibility and environmental stewardship in SME host selection.**

Keywords—**sport mega-events, environmental sustainability, two-phase dynamic assessment, TOPSIS, entropy weight method, super bowl**

I. INTRODUCTION

Sport mega-events (SMEs), such as the Super Bowl, FIFA World Cup, and Olympic Games, have evolved into global cultural and economic phenomena, attracting billions of viewers and generating substantial tourism revenue and urban development opportunities [1]. However, the large scale and intensive nature of these events create profound environmental challenges. A single Super Bowl can produce carbon emissions equivalent to the annual output of a mid-sized city, with spectator travel alone accounting for up to 80% of total emissions [2]. Stadium operations, high energy consumption, massive waste generation, and temporary infrastructure construction further exacerbate ecological pressure [3].

In recent years, global climate action and sustainability awareness have grown rapidly. International sports organizations and host cities have launched various green initiatives. The National Football League (NFL) introduced the NFL Green program, aiming to reduce event footprints and promote carbon neutrality throughout the event lifecycle [4]. Despite these efforts, host city selection still predominantly prioritizes economic capacity, stadium quality, and transportation convenience, while environmental performance remains a secondary or optional consideration [5]. Existing evaluation systems are fragmented, static, and lack foresight, failing to integrate current environmental conditions with long-term green development potential [6].

Research gaps persist in current literature. Most environmental assessments focus solely on static carbon accounting or single-dimensional indicators, ignoring multi-dimensional urban ecological carrying capacity [7]. Few studies combine static baseline evaluation with dynamic trajectory prediction, limiting their ability to guide long-term event planning [8]. Additionally, most frameworks do not distinguish between experienced and new host cities, neglecting operational experience accumulation and institutional learning effects [9].

To address these limitations, this study develops a two-phase dynamic assessment model for SME host city selection. The model integrates the entropy weight method for objective weighting, the TOPSIS method for multi-criteria ranking, and Monte Carlo simulation for uncertainty analysis. It systematically evaluates six core environmental dimensions with eighteen measurable indicators, balancing static baseline performance and dynamic future sustainability trajectories. The research focuses on the 2029 Super Bowl, providing scientific and practical recommendations for both experienced and new candidate cities. The findings aim to redefine the host selection paradigm, positioning environmental sustainability as a core decision criterion alongside economic and logistical factors.

II. RELATED WORK

A. Environmental Impacts of Sport Mega-Events

Extensive research has documented the environmental footprints of SMEs. Collins *et al.* systematically analyzed carbon emissions, energy use, and waste generation patterns of major sports events, highlighting that spectator travel is the dominant source of Scope 3 emissions [1]. Wicker and Hallmann further emphasized the significance of indirect emissions, noting that spectator travel can account for over 70% of a single event's total carbon footprint [2]. Wilby identified geographical location as a critical influencing factor, with central U.S. cities reducing travel emissions by an estimated 18–25% compared to coastal counterparts [3].

Beyond carbon emissions, studies have expanded to energy structure optimization, waste management efficiency, and water resource conservation. Li *et al.* constructed a life-cycle assessment framework covering event preparation, operation, and post-event recovery stages [7]. Gogishvili and

Müller discussed the interaction between national climate policies and event-level sustainability performance [5]. However, most existing studies remain static snapshots and lack dynamic prediction capabilities for long-term urban sustainability.

B . Multi-Criteria Decision-Making in Host Selection

Multi-criteria decision-making (MCDM) methods are widely applied in host city evaluation. Hwang and Yoon first proposed the TOPSIS method, ranking alternatives by their proximity to ideal solutions [10]. Cheng and Li combined the entropy weight method with TOPSIS for urban green development evaluation, effectively reducing subjective weighting bias [8]. In sports research, Mavi *et al.* applied the AHP-TOPSIS hybrid model to rank professional football teams, demonstrating its effectiveness in multi-indicator scenarios [11].

Despite these advances, most MCDM studies prioritize economic and logistical indicators, with environmental factors treated as secondary criteria [4]. Few frameworks are specifically environmental-centered or integrate dynamic prediction mechanisms. Refsgaard *et al.* emphasized uncertainty analysis in environmental modeling, but applications in sport event evaluation remain limited [12].

C . Dynamic Emergency Decision Making

Dynamic models have emerged to address the limitations of static evaluation. Zhang and Liu developed a dynamic carbon footprint model for large-scale sporting events [6]. However, most dynamic studies focus on single-dimensional carbon accounting and lack comprehensive multi-indicator integration. Monte Carlo simulation has been widely applied in uncertainty analysis, as demonstrated by Silva and Ricketts [13]. Yet, few studies combine dynamic trajectory prediction with multi-criteria ranking for SME host city selection.

D . Research Gaps

Current literature exhibits three major limitations: static evaluation dominates research, ignoring future sustainability potential; environmental assessment remains fragmented, lacking comprehensive multi-dimensional systems; no framework distinguishes between experienced and new host cities. This study addresses these gaps by proposing a two-phase dynamic assessment model.

III. METHODOLOGY

A . Indicator System Construction

A comprehensive environmental sustainability evaluation system is developed, covering six core dimensions with eighteen measurable indicators, as detailed in Table 1. The system is designed based on SME characteristics and data availability from authoritative U.S. government agencies and municipal reports, including the U.S. Energy Information Administration (EIA) [14], Environmental Protection Agency (EPA) [15], and municipal sustainability plans.

Table 1 Environmental sustainability indicator system

Dimension	Key Indicators	Unit	Property
Climate & Air Quality	Per capita carbon emissions	tons/year	Negative
	Air quality index	Index	Positive
Energy Infrastructure	Renewable energy share	%	Positive
	Per capita electricity use	kWh/day	Negative
Transportation	Public transit ridership	%	Positive
	Average spectator travel distance	km	Negative
Waste Management	Municipal recycling rate	%	Positive
	Organic waste treatment capacity	tons/year	Positive
Water Resources	Per capita water use	L/day	Negative
	Water recycling rate	%	Positive
Urban Resilience	Green space coverage	%	Positive
	Climate disaster resilience index	Index	Positive

B . Phase I: Static Baseline Assessment

1) Entropy weight method

The entropy weight method is employed to calculate objective indicator weights based on data variability:

om the left and right exits respectively, traverse all inspection points to complete the full-area sweep, and are prohibited from passing through exits midway. In heavy smoke conditions, visibility drops sharply, requiring densified inspection points to eliminate blind spots.

1) Data Normalization

Positive indicators:

$$s_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

Negative indicators:

$$s_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{2}$$

2) Entropy Calculation

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{3}$$

where

$$p_{ij} = \frac{s_{ij}}{\sum_{i=1}^{n} s_{ij}} \tag{4}$$

3) Weight Calculation

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{m} (1 - E_j)} \tag{5}$$

2) TOPSIS model

The TOPSIS method ranks candidate cities by their proximity to positive and negative ideal solutions:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

where:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} w_j (s_{ij} - s_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{m} w_j (s_{ij} - s_j^-)^2} \tag{7}$$

A higher closeness coefficient C_i indicates better environmental sustainability performance.

C. Phase II: Dynamic Trajectory Projection

A dynamic Environmental Sustainability Model (ESM) integrates current performance and future improvement potential:

$$ESM(t) = 0.7 \cdot ESM_{static} + 0.3 \cdot ESM_{dynamic} \tag{8}$$

where ESM_{static} is the static TOPSIS score (70% weight), and $ESM_{dynamic}$ represents Monte Carlo-simulated future potential (30% weight). The transformation factor for future potential is:

$$TF_i = \gamma_i \cdot e^{-\lambda t} \cdot \left(1 - \text{current performance}_i\right) \tag{9}$$

Strategic weight adjustments prioritize renewable energy (28%) and carbon reduction (40%) in future scenarios.

D. Carbon Emission Sub-Model

A dedicated GHG emission sub-model quantifies carbon minimization performance:

$$CarbonScore = 0.6 \cdot \frac{TE_{max} - TE_i}{TE_{max} - TE_{min}} + 0.4 \cdot \frac{PE_{max} - PE_i}{PE_{max} - PE_{min}} \tag{10}$$

where TE_i denotes travel emissions and PE_i denotes per capita operational emissions.

E. Sensitivity Analysis

Monte Carlo simulations are conducted to test model robustness. Key sensitive parameters include spectator attendance, average travel distance, and energy carbon intensity.

IV. Experimental Analysis

A. Static Baseline Evaluation Results

The static TOPSIS evaluation ranks twelve candidate cities across six environmental dimensions. The top five cities by Composite Sustainability Index (CSI) are presented in Table 2. Seattle leads with a CSI score of 0.596, nearly 20% higher than the second-ranked city, driven primarily by its 85% renewable energy share and low per capita carbon emissions. Boston (0.498) follows with high public transit ridership (55%), reducing urban transportation emissions significantly. Minneapolis (0.486) exhibits balanced performance across energy, transportation, and waste management dimensions, while Atlanta (0.429) and San Diego (0.419) perform moderately well in clean energy adoption and air quality.

Table 2. Top 5 cities by Composite Sustainability Index (CSI)

Rank	City	CSI Score	Key Strength
1	Seattle	0.596	85% renewable energy share
2	Boston	0.498	High public transit ridership
3	Minneapolis	0.486	Balanced multi-dimensional performance
4	Atlanta	0.429	Moderate carbon emissions
5	San Diego	0.419	Clean energy adoption

When focusing exclusively on carbon minimization, the ranking shifts notably. Table 3 shows the top five cities by GHG score. Indianapolis achieves the highest score (88.9) due to its central geographic location, which reduces average spectator travel distance by over 40% compared to coastal cities. Nashville (84.8) and Detroit (79.4) also perform well in reducing Scope 3 emissions, while Atlanta (79.1) benefits from moderate travel distances and efficient transit networks. These results confirm that geographic centrality is the single most critical factor in reducing travel-related carbon emissions for national sporting events.

Table 3. Top 5 cities by GHG emission score

Rank	City	GHG Score	Key Strength
1	Indianapolis	88.9	Shortest spectator travel distance
2	Nashville	84.8	Low Scope 3 emissions
3	Minneapolis	81.4	Efficient operational emissions
4	Detroit	79.4	Industrial decarbonization progress
5	Atlanta	79.1	High transit accessibility

B. Dynamic Assessment and 2029 Super Bowl Ranking

The two-phase dynamic model integrates static performance with future sustainability potential. Table 4 presents the dynamic ESM scores for key candidate cities. Seattle retains the top rank with a final ESM score of 0.750, combining its strong static performance (0.596) with high improvement potential (0.154) from ongoing renewable energy expansion and climate policy implementation. Minneapolis (0.604) and Atlanta (0.557) follow, demonstrating balanced current performance and moderate growth potential. Indianapolis (0.540) and Santa Clara (0.499) exhibit solid static scores but lower long-term improvement capacity due to slower clean energy adoption.

Table 4. Dynamic ESM projection results

City	Static Score	Dynamic Potential	Final ESM
Seattle	0.596	0.154	0.750
Atlanta	0.429	0.128	0.557
Minneapolis	0.486	0.118	0.604
Indianapolis	0.405	0.135	0.540
Santa Clara	0.407	0.092	0.499

1) Experienced host city evaluation

For cities with prior Super Bowl hosting experience, Table 5 ranks performance by ESM score. Santa Clara emerges as the top choice (0.499), combining mature stadium infrastructure, high municipal recycling rates, and steady renewable energy growth. Atlanta (0.557) performs well overall but has limited recent hosting experience. New

Orleans (0.416) ranks lower due to high per capita emissions and lower green space coverage.

Table 5. Experienced host city ranking

City	ESM Score	Key Advantage
Santa Clara	0.499	Mature infrastructure, high recycling rate
Atlanta	0.557	Balanced performance, hosting experience
New Orleans	0.416	Geographic appeal

Recommendation for Experienced Host: Santa Clara.

2) New candidate city evaluation

Among cities without prior Super Bowl experience, Seattle stands out as the clear leader (ESM = 0.750), as shown in Table 6. Its 85% renewable energy grid and aggressive carbon reduction policies set a new benchmark for green event hosting. Minneapolis (0.604) and Indianapolis (0.540) follow with balanced performance and low travel emissions.

Table 6. New candidate city ranking

City	ESM Score	Key Advantage
Seattle	0.750	85% renewable energy share
Minneapolis	0.604	Balanced sustainability
Indianapolis	0.540	Low travel emissions

Recommendation for New Host: Seattle.

C. Multi-Venue vs. Single-Game Event Analysis

Extending the model to compare single-game (Super Bowl) and multi-venue tournaments reveals significant emission differences. Multi-venue events generate **44% higher total emissions** due to increased venue operations, longer event durations, and expanded spectator travel. Table 7 lists top multi-venue host cities, with Tokyo (ESM = 108.0) and Amsterdam (ESM = 107.2) leading in balanced infrastructure and environmental performance. Vancouver (100.2) excels in resilience, while Portland (91.2) performs well in waste management.

Table 7. Multi-venue tournament host ranking

City	ESM Score	Infrastructure	Environmental Performance
Tokyo	108.0	8.5	8.5
Amsterdam	107.2	8.5	8.0
Vancouver	100.2	7.9	8.5
Portland	91.2	7.3	8.0

Strategic investment analysis identifies smart waste management as the most cost-effective intervention, with a cost-benefit ratio (CBR) of 3.489. Green building certification (CBR = 3.279) and public transit upgrades (CBR = 2.45) follow, providing actionable guidance for cities to improve green hosting capacity.

D. Sensitivity Analysis

Monte Carlo simulations validate model robustness. Table 8 lists the most sensitive parameters, with spectator attendance (37.1%) and average travel distance (28.2%) collectively explaining over 75% of total environmental impact variation. Energy carbon intensity (28.2%) also significantly influences emissions. Perturbation analysis shows that a 20% weight change in carbon footprint criteria swaps Seattle and Portland in only 12% of scenarios, confirming ranking stability. Seattle maintains the top rank in **78% of all simulations**, demonstrating model reliability.

Table 8. Parameter sensitivity weights

Parameter	Weight	Rank
Event Attendance	0.371	1
Average Travel Distance	0.282	2
Energy Carbon Intensity	0.282	3
Hotel Occupancy	0.059	4

V. CONCLUSION

This study develops a two-phase dynamic assessment model for evaluating the environmental sustainability of sport mega-event host cities. The model integrates the entropy weight method, TOPSIS, and Monte Carlo simulation, systematically evaluating six core environmental dimensions with eighteen measurable indicators. Empirical results show that Seattle achieves the highest Composite Sustainability Index (0.596) due to its 85% renewable energy share, while Indianapolis leads in carbon minimization with a GHG score of 88.9, attributed to its central geographic location. For the 2029 Super Bowl, Santa Clara is recommended among experienced hosts, and Seattle is the optimal new candidate. Sensitivity analysis validates model robustness, with spectator attendance and travel distance identified as the most critical impact factors. The proposed framework provides a robust, data-driven tool for balancing operational feasibility and environmental stewardship in SME host selection.

Future work will integrate economic and social dimensions into the evaluation system, and incorporate real-time sensor data to enhance dynamic adaptability and practical application value.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Both authors contributed equally to the study design, data analysis, model implementation, and manuscript preparation. All authors have read and approved the final version.

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