A Proxy-Based, Entropy-Weighted Sustainability Scoring Framework for Mega Sporting Event Host Selection: Evidence from the 2029 Super Bowl and the 2029 Copa América

Ziqi Nian †, Haodong Bai †, Xi Tong † and Zhangzheng Wang †, *

Guangzhou Zhixin High School, Guangzhou 51000, China

† These authors contributed equally.

* Corresponding Author Email: wangshangnb@outlook.com

Abstract. Sports mega-events provide economic and social benefits; however, they can also concentrate environmental impacts, including (but not limited to) electricity demand, greenhouse gas emissions, venue waste (e.g., catering), and water demand. We develop a proxy-based, environment-focused host-selection framework. Using the entropy weight method, we compute objective weights for four burden categories based on prior research on Super Bowl events and similar single-day championship events. We then score and rank candidate hosts using matched city-level sustainability proxies and a weighted-sum model. In a 2029 Super Bowl scenario, Stanford ranks first among 19 candidate cities under the stated boundary conditions. We also extend the same pipeline to a multi-match tournament setting (2029 Copa América) using an expanded proxy set, under which Canada ranks first among candidate countries.

Keywords: Mega-events; sustainability; entropy weight; host selection.

1. Introduction

Sports mega-events can deliver economic and social benefits. They may also create short-term environmental pressures from travel, venue operations, and event-related consumption. Measuring environmental impacts for major sporting events is difficult [1, 2]. Impacts span many categories. Public data is often incomplete. Many studies use simplified boundaries and a limited set of indicators.

Environmental burdens cover multiple categories, such as energy, carbon, waste, and water. Candidate hosts also differ in how well they can manage these burdens. Host ranking is a multi-criteria decision making (MCDM) problem [3, 4]. Weight choice can change the ranking.

This paper presents a simple, objective, proxy-based scoring pipeline for environment-focused host selection. We use the entropy weight method (EWM) to compute weights from data [5, 6]. We then score candidates using city-level proxies and compute a weighted-sum score. We study a 2029 Super Bowl host-selection scenario. We describe the baseline as “a Super Bowl hosted in New Orleans” and avoid edition labels. We also adapt the method to the 2029 Copa América.

2. Literature Review

Environmental assessment of major sporting events highlights two points. Environmental impacts matter. Complete measurement is hard. Some studies use ecological-footprint and environmental input–output methods to estimate selected externalities from event visitation [1, 2]. These assessments are partial. The boundary conditions affect the results and therefore facilitate the use of simplified decision rules in the situation where a complete life-cycle assessment is not practical.

MCDM techniques aggregate multiple measures into a cumulative score (score) or ranking. These techniques include Analytic Hierarchy Process (AHP) [3] and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [4]. The use of expert-driven weights is usually subjective, while the use of objective or data-driven weights is often favoured by researchers that desire transparent and reproducible rules.

EWM uses the concept of information entropy [5, 6] to assign weights. The use of larger weights indicates that data is dispersed; therefore, the larger the weight, the better it differentiates the samples.

Finally, when measuring events or impacts, proxy-based assessment is also a widely used method. Proxy indicators at the city or country level can be used as an indicator of possible mitigation or management capability but should be treated as proxies and not causal.

3. Methodology and Data

3.1. Scope and Boundary Conditions

We use a simplified boundary so the framework can be applied with public data from different sources. Within this boundary, we treat event energy use as electricity-dominated. We assume event water demand is fixed under a constant stadium-scale scenario. We do not model non-environment constraints such as contracts, stadium capacity, security, or economic impacts. We report these boundary choices as limitations. This is common in partial sustainability assessment and boundary-setting discussions [7–9].

Event naming is inconsistent across sources. We describe the baseline as "a Super Bowl hosted in New Orleans." We avoid Roman-numeral edition labels. The label 'Stanford' is used geographically in our compiled dataset to represent the broader Stanford/Santa Clara area.

3.2. Indicators and Data Collection (Two-Layer Design)

We define four event-level burden categories for learning weights: energy consumption, carbon emissions, venue waste generation, and water resource utilization. Carbon is measured in carbon dioxide (CO_2) equivalent units.

We compile event-level observations for Super Bowl events over the past decade. We add other comparable single-day finals to increase the sample size. Examples include the Union of European Football Associations (UEFA) Champions League Final and The Football Association (FA) Cup Final.

We then score candidate hosts using city-level sustainability proxies aligned to the four categories. Renewable energy share is an energy proxy. Recycling rate is a waste proxy. A greenness or carbon-sink proxy represents the carbon category. A water-availability proxy represents the water category. All proxy values come from public datasets and reports. For the Copa América extension, we use global databases such as the World Development Indicators (WDI) [10]. We also use International Energy Agency (IEA) data tools when we need energy and emissions documentation [11].

3.3. Normalization and Entropy Weight Method

We normalize each indicator to eliminate dimensional effects. For a benefit-type (positive) indicator, we use min–max normalization:

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

For a cost-type (negative) indicator:

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

We then compute the proportion:

$$p_{ij} = \frac{x'_{ij} + \varepsilon}{\sum_{i=1}^{n} \left(x'_{ij} + \varepsilon\right)} \tag{3}$$

Where ε is a small constant to avoid division by zero. Entropy for indicator j is:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{4}$$

The degree of diversification is:

$$g_j = 1 - e_j \tag{5}$$

Finally, the EWM weight is:

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{6}$$

This procedure follows standard EWM practice, where greater dispersion across samples yields larger weights because the indicator provides more discriminative information [5, 6].

3.4. Proxy-Based Host Scoring Function

We interpret EWM weights as the relative importance of the four environmental burden categories under the observed event-level dataset. We then compute a proxy-based sustainability score for each candidate host as a weighted sum of aligned city-level proxy indicators. The scoring function is:

$$S_i = W_e R_{e,i}^n + W_c R_{c,i}^n + W_v R_{w,i}^n + W_w R_{a,i}^n \tag{7}$$

Here, W_e, W_c, W_v, W_w are the EWM weights for energy, carbon, waste, and water. $R_{e,i}^n$ is normalized renewable energy share (energy proxy). $R_{w,i}^n$ is normalized recycling rate (waste proxy). $R_{c,i}^n$ is a normalized carbon sink/greenness proxy (carbon proxy). $R_{a,i}^n$ is a normalized water availability proxy (water proxy). This score is designed for screening and shortlisting; it is not intended to be a causal estimate of event impacts.

3.5. Extension to Multi-Match Tournaments (2029 Copa América)

To demonstrate scalability, we extend the same pipeline to a multi-match tournament setting, where hosting capacity may additionally depend on population/attendance scale and fiscal/infrastructure readiness. We incorporate the additional factors already available in the original dataset (e.g., government expenditure proxy, infrastructure investment intensity, total people across venues, and green transportation coverage) and compute an expanded weighted score:

$$S_i = W_e R_{e,i}^n + W_c R_{c,i}^n + W_v R_{w,i}^n + W_w R_{a,i}^n + W_p R_{t,i}^n + W_g R_{d,i}^n \tag{8}$$

All added variables are treated as proxies within the same screening logic, and all rankings should be interpreted under this proxy-based and boundary-limited design.

4. Results and Analysis

4.1. Weight Distribution (Super Bowl Burden Categories)

Based on the collected data (we imputed COVID-19-affected observations using the mean of the remaining years) and the formulas above, the indicator weights are reported in Table 1.

Table 1. Weight of indicators (Super Bowl burden categories).

Indicator	Unit	Weight
W_e (Energy consumption)	megawatts of hour	33.908%
W_c (Carbon emission)	tons of CO_2 eq.	14.070%
W_v (Venue waste)	tons	41.362%
W_w (Water resource utilization)	thousands of gal.	10.657%

Consistent with EWM logic, venue waste receives the largest weight because its sample dispersion is largest among the four categories, giving it higher discriminative information under the observed dataset [6].

4.2. Case Study I: 2029 Super Bowl Host Ranking (19 Candidate Cities)

All four proxies for each city are collected and normalized. The normalized results are shown in Table 2.

Table 2. City sustainability proxies (normalized).

City	R_e^n	R_w^n	R_g^n	R_c^n
Stanford	1.000	1.000	0.493	1.000
Santa Clara	0.800	0.694	0.189	0.263
San Francisco	0.740	0.778	0.037	0.177
East Rutherford	0.000	0.000	1.000	0.606
San Diego	0.660	0.556	0.019	0.206
Los Angeles	0.520	0.639	0.000	0.096
Minneapolis	0.440	0.472	0.037	0.497
Tampa	0.400	0.444	0.037	0.295
Atlanta	0.360	0.389	0.037	0.527
Pontiac	0.060	0.083	0.493	0.593
Phoenix	0.480	0.333	0.019	0.031
Las Vegas	0.460	0.306	0.019	0.000
Jacksonville	0.280	0.250	0.019	0.365
Miami	0.260	0.278	0.037	0.243
New Orleans	0.140	0.167	0.087	0.354
Detroit	0.180	0.194	0.037	0.326
Houston	0.200	0.222	0.011	0.175
Arlington	0.220	0.139	0.037	0.158
Indianapolis	0.160	0.111	0.037	0.403

Applying Eq. (7), we compute the sustainability score (S_i) for each city and rank all candidates accordingly. The resulting ranking is shown in Table 3.

Table 3. Overall ranking of 19 candidate cities (2029 Super Bowl scenario).

Rank	City
1	Stanford
2	Santa Clara
3	San Francisco
4	East Rutherford
5	San Diego
6	Los Angeles
7	Minneapolis
8	Tampa
9	Atlanta
10	Pontiac
11	Phoenix
12	Las Vegas
13	Jacksonville
14	Miami
15	New Orleans
16	Detroit
17	Houston
18	Arlington
19	Indianapolis

4.3. Spatial (Regional) Descriptive Analysis

After obtaining the ranking above, we divide the 19 candidate cities into five regions (West Coast, Southwest, Midwest, South, Northeast) and summarize the within-region ranks in Table 4.

Table 4. City ranking by region.

Region	City	Ranking
West Coast	Stanford	1
	Santa Clara	2
	San Francisco	3
	San Diego	5
	Los Angeles	6
Southwest	Phoenix	11
	Las Vegas	12
Midwest	Minneapolis	7
	Pontiac	10
	Detroit	16
	Indianapolis	19
South	Tampa	8
	Atlanta	9
	Jacksonville	13
	Miami	14
	New Orleans	15
	Houston	17
	Arlington	18
Northeast	East Rutherford	4

The regional summary helps interpret the ranking. It is not a validation of predictive accuracy. The model is a proxy-based screening tool with simplified boundaries.

4.4. Additional Candidates (NFL-Team Cities Without Hosting History)

In addition to evaluating the 19 candidate cities above, we also evaluate nine additional cities that host National Football League (NFL) teams but have not previously hosted this event. Green Bay has the highest rank among these nine cities under our method. Because a full set of normalized proxy data is not available for all nine cities in the compiled database, we summarize these findings qualitatively.

5. Discussion

5.1. Case Study II (Generalization): 2029 Copa América

We computed the expanded weights shown in Table 5.

Table 5. Weight of indicators (expanded model).

Indicator	Unit	Weight
W_e	megawatt hour	18.7%
W_c	tons of CO_2 eq.	20.8%
W_v	tons	17%
W_w	thousands of gal.	14%
W_p	population	22.4%
W_g	government expenditure	7%

We normalized the country-level indicators. Table 6 reports the normalized values.

Table 6. Environmental and infrastructure indicators by country (normalized).

Country	R_d^n	R_e^n	R_a^n	R_w^n	R_c^n	R_t^n
Argentina	0.485714	0.069409	0.077395	0.212766	0.333333	0.254845
Bolivia	1.000000	0.168380	0.259764	0.574468	0.000000	0.321668
Brazil	0.171429	0.344473	0.521623	0.446809	0.600000	0.385969
Canada	0.571429	0.601542	1.000000	0.723404	0.466667	0.671544
Chile	0.571429	0.388175	0.014664	0.000000	0.800000	0.293842
Colombia	0.428571	0.673522	0.165495	0.297872	0.466667	0.419122
Ecuador	0.771429	0.724936	0.259764	0.361702	0.200000	0.396505
Mexico	0.085714	0.000000	0.077395	1.000000	0.333333	0.274779
Paraguay	0.714286	1.000000	0.102649	0.243243	0.133333	0.530589
Peru	0.942857	0.433162	0.081700	0.148936	0.400000	0.283613
United States	0.228571	0.005141	0.806870	0.837838	1.000000	0.505207
Uruguay	0.571429	0.892031	0.000000	0.378378	0.600000	0.498470
Venezuela	0.000000	0.592545	0.102649	0.234043	0.133333	0.254265

Using Eq. (8), we computed the ranking shown in Table 7.

Table 7. Overall ranking of candidate countries (2029 Copa América scenario).

Rank	Country
1	Canada
2	United States
3	Uruguay
4	Paraguay
5	Brazil
6	Colombia
7	Ecuador
8	Chile
9	Peru
10	Mexico
11	Argentina
12	Bolivia
13	Venezuela

5.2. Policy Implications

Cities receive substantial scores for waste and energy use at venues. To enhance venue sustainability scores, cities need to take steps to minimize the amount of waste created, improve recycling rates, reduce reliance on electricity-generated emissions, and use cleaner sources of electricity. A city's ability to accomplish these tasks will affect the city's overall sustainability score. In order to minimize waste generated at venues, cities should implement a more efficient recycling program and reduce the amount of single-use materials used at venues. Cleaner electricity will help improve the energy proxy score, as will using energy-efficient equipment, including efficient lighting, heating, ventilation, and air conditioning (HVAC) controls.

5.3. Limitations and Future Work

EWM cannot be used as a stand-alone method. The EWM depends on the variability of the dataset. Low variability across measures will often result in smaller EWM weights because the indicators provide limited discriminative information.

Using proxy indicators to represent event impact, this system allows a ranking to be created. This ranking is intended for shortlisting or screening purposes and does not represent a causal relationship. This also means that changing the boundary parameters can affect results. An example is the Delta water-demand assumption [7–9], coupled with the Delta energy boundary.

Using a mean-value replacement for years affected by COVID in the EWM might reduce variability in the dataset and affect the weights calculated based on entropy. Future research should use more precise data and provide robustness checks to validate results.

6. Conclusion

This paper proposes a proxy-based, entropy-weighted scoring framework for environment-focused host selection for sports mega-events. We use the EWM to compute data-driven weights for four burden categories: energy, carbon, waste, and water. We then rank candidates using matched city-level proxies and a weighted-sum score. In the 2029 Super Bowl scenario, Stanford ranks first among 19 candidate cities under the stated boundary conditions and proxy assumptions. We also adapt the same pipeline to the 2029 Copa América. Under the expanded proxy set, Canada ranks first among candidate countries. The framework is intended for screening and shortlisting. It relies on proxy indicators and simplified boundaries. Results can change with data sources, preprocessing choices, and boundary settings. Future work can add finer-grained event accounting and basic robustness checks when additional data become available.

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