2025

HiMCM Summary Sheet

Team Control Number:**17136**

Problem Chosen:**B**

Summary

Confronting the widespread concerns about minimizing environmental impact of mega-events, lowering the potential ecological costs in the organization stage is urgent and effective. By choosing the best location to host an event- the Super Bowl, for example-based on environmental concern, this paper aims to achieve this goal using a mathematical model that combines the EWM, AHP, and TOPSIS.

For **Problem 1**, we should consider environmental-impact-associated aspects of hosting the Super Bowl and discuss how these aspects may alter based on locations.

For **Problem 2**, we need to construct an evaluation model to account for the aspects suggested in solution to the previous problem. This model must be able to determine the most sustainable location among several.

For **Problem 3**, we have to apply our model to two types of cities to respectively determine the optimal one to hold the Super Bowl: those that have hosted and those that have not but have NFL teams. As a result, Las Vegas and Denver are proposed as the most suitable choices.

For **Problem 4**, we should expand our model to either single-sport championship tournament or multi-sport competition. Then, we should discuss the influence of both local policies and environmental factors.

Eventually, based on the results, we are expected to write a proposal to the NFL, which illustrates how we choose the most suitable cities to host the Super Bowl and persuade the NFL to take our suggestion.

Keywords: Super Bowl, sustainable development, environmental concern.

Contents

1 Introduction

1.1 Background

Behind millions of fans drawn to sport mega-events are enormous environmental costs, including high energy consumption, waste generation, greenhouse gas emissions, and resource depletion. Concerning this issue, post-event evaluation metrics of these environmental impacts have been established to reveal the significance of controlling environmental burden exerted by mega-events and maintaining sustainability.

However, few are considering using the metrics to lower the environmental impact in pre-event phase by determining the best location to host such events based on evaluation of properties of a particular location, such as geographic and climatic conditions, population capacity, city planning, energy sourcing, and so on. This paper seeks to contribute to this gap in event planning, which is significant in minimizing environmental burden.

1.2 Problem Restatement and Section Organization

Task 1: Using existing data, identify the aspects of holding a Super Bowl event that are associated with the impact on sustainability. Then, discuss the variability of these aspects in different locations and how it results in different extents of environmental impact.

Task 2: Based on the conclusion from previous task, create an evaluation model to determine the best location of the next Super Bowl, accounting for the impact of the aspects.

Task 3: Apply the model to the cities having held Super Bowl before to determine which should host again. Afterward, apply it to three cities that have NFL teams yet have not hosted Super Bowl, and evaluate and compare their environmental sustainability.

Task 4: Extend the model to one of two types of sport mega-events and discuss the influence of local policies on retention of long-term sustainability. Eventually, compare the biggest environmental factors influencing sustainability in the chosen type of sport mega-events.

Task 5: Write a letter to the NFL, with recommendation of the city evaluated as the best to host Super Bowl in 2029.

1.3 Assumptions And Justifications

Assumption 1: Using renewable energy to generate electricity does not cause carbon emission. Renewable energy such as solar and wind energy can significantly reduce carbon emission [1], mainly by substituting fossil fuels such as coal. Thus, we assume that electricity generation by renewable energy sources produces an ignorable amount of carbon, which simplifies the model construction and calculation.

Assumption 2: All seats in the stadium are occupied during the game. Due to the popularity of the Super Bowl, this assumption is justified.

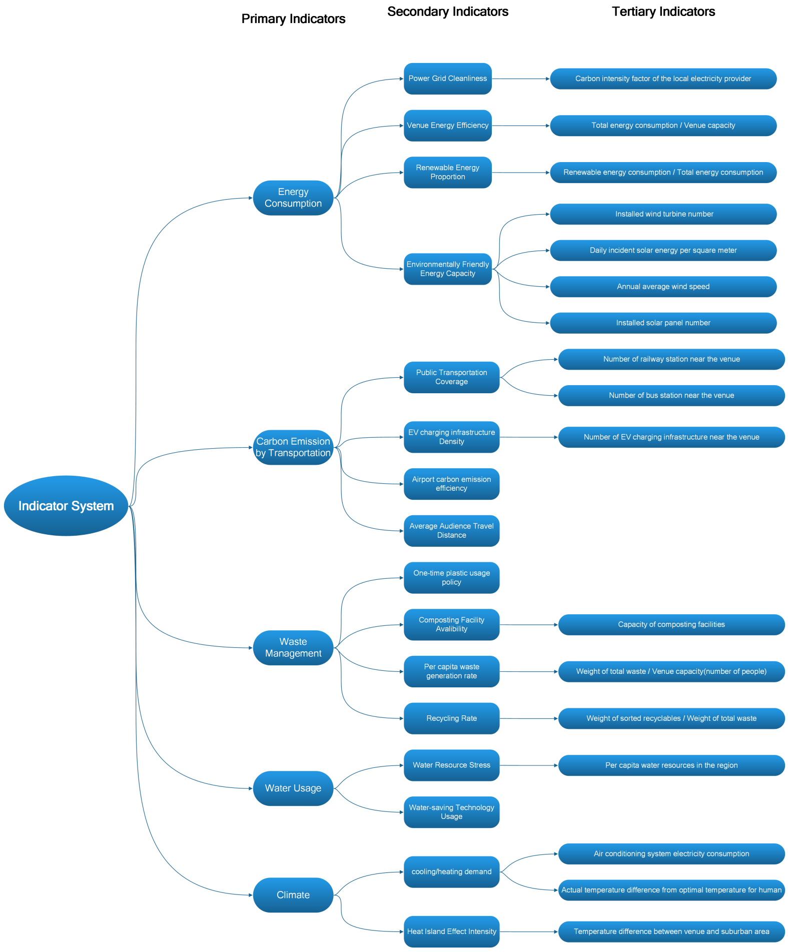
Assumption 3: In discussion about the FIFA World Cup 2022 (Problem 4), we only consider the case of the Lusail Stadium, as it was the "centerpiece" of the World Cup [2].

2 Problem 1

To identify the factors contributing to environmental impact and sustainability of a sport mega-event, we consider five major areas: 1) energy consumption, 2) carbon emission by transportation, 3) waste management, 4) water usage, and 5) climate, each with subordinate indicators. Figure 1 demonstrates these concerns.

Climate is the most evident aspect that changes from one location to another.

Figure 1 Indicators



The deviance between actual local temperature and optimal temperature for human body, for example, triggers the need of air conditioning that consumes a large amount of energy. The evaluation of water usage also varies significantly depending on the location. The acceptable amount of water consumption is based on the average water consumption per person per day, which is attributed to local custom and water affluence.

3 Problem 2

Table 1 Symbols and Explanation

Symbol	Unit	Explanation
a_{ij}	/	The relative importance of an indicator at the position (i,j) in comparison matrix.
n	/	The dimension of comparison matrix.
λ_{max}	/	The maximum eigenvalue of comparison matrix.
W	/	The weight of an indicator.
x_{ij}	/	The score of a location at the position (i,j) in indicator-location matrix.
m	/	The number of considered locations (number of rows in indicator-location matrix).
D_A^+	/	The distance from the positive ideal solution of location A.
D_A^-	/	The distance from the negative ideal solution of location A.
S_A	/	The ultimate score of location A.
v_j^+	/	The positive ideal solution of an indicator in column number j.
v_j^-	/	The negative ideal solution of an indicator in column number j.

Based on our discussion of the last problem, an evaluation model responding to the indicators of sport mega-events' environmental impact can be established to decide which city has the most suitable overall conditions to host a Super Bowl game.

Since most secondary and tertiary indicators are in a one-to-one relationship, we simplify the consideration about them as one. For example, we regard "Carbon intensity factor of the local electricity provider" as equal to "Power grid cleanliness". As for exceptions including environmentally friendly energy capacity, public transportation coverage, and cooling/ heating demand, we choose the tertiary indicators with available data, excluding the others, and calculate the mean with equal weighting after rating. Specifically, because of limited data, we only include annual average wind speed and daily incident solar energy per square meter into consideration of environmentally friendly energy capacity; we likewise exclude "number of EV charging infrastructure near the venue", "capacity of composting facilities" , and "temperature difference between venue and suburban area". For each of the data x, the equation for evaluating benefit indicators or other normalized types of indicators is the following:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

The normalization of intermediate-type indicators such as temperature undergoes the following process:

$$x' = 1 - \frac{|x - x_{optimal}|}{max\{|x_i - x_{optimal}|\}} \tag{2}$$

In specific, the type of each tertiary (or secondary, if not tertiary) indicator is shown in Table 2.

Table 2 Types of Indicators

Indicator	Type
Carbon intensity factor of local electricity provider	Cost
$\frac{\text{Total energy consumption}}{\text{Venue capacity}}$	Cost
$\frac{\text{Renewable energy consumption}}{\text{Total energy consumption}}$	Benefit
Daily incident solar energy per m^2	Benefit
Number of railway station near the venue	Benefit
Number of bus station near the venue	Benefit
$\frac{\text{Weight of total waste}}{\text{Number of seats}}$	Cost
$\frac{\text{Weight of sorted recyclables}}{\text{Weight of total waste}}$	Benefit
Per capita water resources in the region	Benefit
Air conditioning system electricity consumption	Cost
Actual temperature (from optimal temperature)	Intermediate

3.1 EWM

To determine the weights of secondary (or tertiary, if any,) indicators, we apply the Entropy Weight Method (EWM). EWM is effective in reflecting the information amount of the index when dealing with multi-index cases with classification (the type of the index) [3].

During the process, the input is an $m \cdot n$ matrix with m plans (locations) and n (tertiary) indicators. The tertiary indicators must belong to the same secondary indicator. After normalization, we transform each index into its specific weight in respective indicator. It is described in this equation:

$$p_{ij} = \frac{r_{ij}}{\sum\limits_{i=1}^{m} r_{ij}} \tag{3}$$

Here, p_{ij} is the specific weight, and r_{ij} is the original index. Afterward, we compute the information entropy and difference coefficient of j-th indicator.

$$\begin{cases} k = \frac{1}{ln(m)} \\ e_j = -k \cdot \sum\limits_{i=1}^{m} p_{ij} \cdot ln(p_{ij}) \\ g_j = 1 - e_j \end{cases} \tag{4}$$

It is notable that the value of g_j is positively correlated to the amount of information contained in the j-th indicator. Hence, the indicator with larger value of the difference coefficient ought to have a larger weight. Ultimately, the weights of the indicators are determined by normalization of difference coefficients.

$$w_j = \frac{g_j}{\sum\limits_{j=1}^{n} g_j} \tag{5}$$

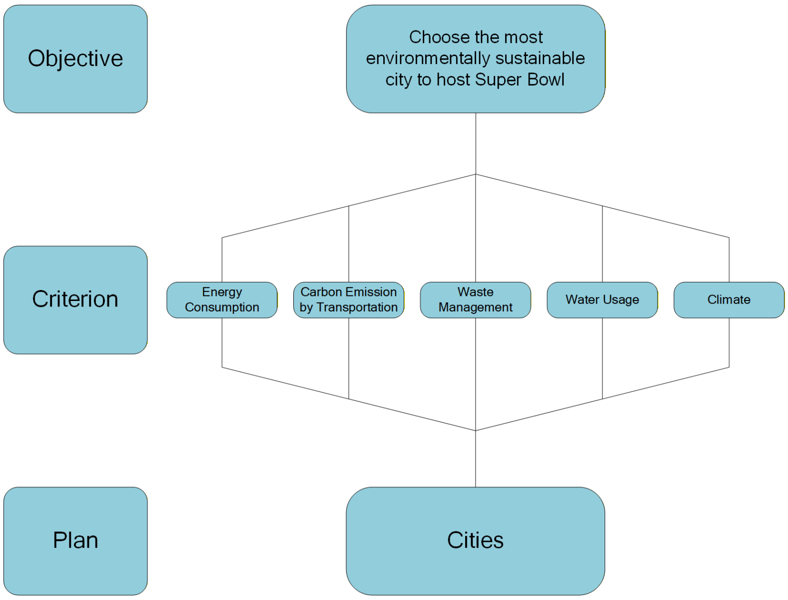
3.2 AHP

The Analytic Hierarchy Process (AHP) is applied to determine the weights of the primary indicators and subsequently calculate the total score of a location for evaluation. We use AHP because it is a commonly used evaluation model that reaches a compromise between usability and model efficacy [4].

In AHP, we primarily determine the objective, criterion, and plan. As shown in Figure 2, in this case, the objective is to choose the best location for the Super Bowl; the criterion includes the primary indicators; the plan lists potential choices of locations.

Next, a comparison matrix evaluating the relative importance of each two criteria is constructed via subjective weighting. Within the same type of sport events, the comparison matrix is fixed, and that of the Super Bowl is shown below.

Figure 2 AHP Elements



$$
\begin{array}{c}
 \\ \text{Energy} \\ CO_2 \text{ by transport} \\ \text{Waste} \\ \text{Water usage} \\ \text{Climate}
\end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \end{array} \\
\begin{bmatrix}
1 & 5 & 7 & 4 & 3 \\
\frac{1}{5} & 1 & 3 & \frac{1}{3} & \frac{1}{5} \\
\frac{1}{7} & \frac{1}{3} & 1 & \frac{1}{4} & \frac{1}{5} \\
\frac{1}{4} & 3 & 4 & 1 & \frac{1}{3} \\
\frac{1}{3} & 5 & 5 & 3 & 1
\end{bmatrix}
\end{array}
$$

After normalization, the matrix is transformed to the following:

$$
\begin{array}{c}
 \\ \text{Energy} \\ CO_2 \text{ by transport} \\ \text{Waste} \\ \text{Water usage} \\ \text{Climate}
\end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \end{array} \\
\begin{bmatrix}
0.5191 & 0.3488 & 0.35 & 0.4660 & 0.6338 \\
0.1038 & 0.0697 & 0.15 & 0.0388 & 0.0422 \\
0.0741 & 0.0232 & 0.05 & 0.0291 & 0.0422 \\
0.1297 & 0.2093 & 0.2 & 0.1165 & 0.0704 \\
0.1730 & 0.3488 & 0.25 & 0.3495 & 0.2112
\end{bmatrix}
\end{array}
$$

Since we use subjective weighting, this comparison matrix must be tested by consistency check. According to Thomas Saaty [5], the random index (RI) for a 5-dimensional matrix is 1.12. The consistency index (CI) and consistency ratio (CR) are determined by following equations:

$$
\begin{cases}
CI = \frac{\lambda_{max} - n}{n-1} \\
CR = \frac{\text{CI}}{\text{RI}}
\end{cases}
\tag{6}
$$

As a result, our normalized comparison matrix has $CR = 0.0678$ which is lower than 0.1, acceptable for the calculation of weights.

Eventually, the weight of an indicator is determined by the following equation applied to the n-dimensional comparison matrix:

$$W = \frac{1}{n} \cdot \sum_{j=1}^{n} \frac{a_{ij}}{\sum\limits_{k=1}^{n} a_{kj}} \tag{7}$$

Here, i is constant for a particular indicator, which shows its row number in the matrix; for example, the indicator "water usage" has $i = 4$. Consequently, the weight matrix for these five indicators is:

$$\begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \\ \end{array}$$
$$\begin{bmatrix} 0.4734 & 0.0747 & 0.0421 & 0.1397 & 0.2699 \end{bmatrix}$$

3.3 TOPSIS

After determining the weight for each indicator, we multiply the score of a primary indicator with corresponding weight to get the weighted score. Then, for a location, there are five indicators, each with respective weighted scores. The following indicator-location matrix affords an example with two locations:

$$\begin{array}{c} \\ \text{Location A} \\ \text{Location B} \end{array} \begin{array}{c} \begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \end{bmatrix} \end{array}$$

The calculation of the total score of a location conducts the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). With the matrix above, the ultimate score of Location A, for example, is determined by ($i = 1$):

$$\begin{cases} D_A^+ = \sqrt{\sum\limits_{j=1}^{m=5} (x_{ij} - v_j^+)^2} \\ D_A^- = \sqrt{\sum\limits_{j=1}^{m=5} (x_{ij} - v_j^-)^2} \\ S_A = \frac{D_A^-}{D_A^- + D_A^+} \end{cases} \tag{8}$$

Consequently, the location with the highest ultimate score can be chosen the best for hosting the Super Bowl. Overall, our model integrates EWM, AHP, and TOPSIS to account for all considered indicators—from tertiary to primary—contributing to the goal of comparing suitability of holding the Super Bowl in distinct locations.

4 Problem 3

Applying the established model, we can determine the most environmentally favorable city to host the Super Bowl, choosing from both the cities that have hosted the event before and those that have never done it.

Searching for data about the proposed indicators, we have integrated the following table (Figure 3):

In specific, the mooted cities that have hosted the Super Bowl before are Glendale,

Figure 3 Data Table

Super Bowl Session	Year	Cities	Renewable Energy Proportion	Venue Energy Efficiency (kWh/seat)	Grid Carbon Intensity (kgCO_2/kWh)	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (kilometer per hour)	Number of Bus Station	Number of Railway/Subway Station	Total waste generated (ton)	Number of attendees	Recycling Rate	Avalible Water Resource (tons per day)	Total Population	Average Temperature (Celsius)
Super Bowl L	2016	Santa Clara, CA	100%	0.53	0.184	3.4 kWh	11.2 km/h	5	3	155 t	75000	75%	56781	127647	12 °C
Super Bowl LIII	2019	Atlanta, GA	100%	0.507	0.305	3.7 kWh	11.4 km/h	3	2	80 t	71000	90%	762382	498715	8 °C
Super Bowl LVI	2022	Inglewood, CA	57%	0.513	0.184	4.2 kWh	12.8 km/h	5	2	70 t	70000	90%	30415	107762	14 °C
Super Bowl LVII	2023	Glendale, AZ	14%	0.568	0.288	4.4 kWh	11.1 km/h	3	1	81 t	73000	92%	204412	250193	14 °C
Super Bowl LVIII	2024	Las Vegas, NV	100%	0.554	0.286	4.2 kWh	12.6 km/h	2	0	77 t	65000	90%	1013821	641903	11 °C
Super Bowl LIX	2025	New Orleans, LA	30.00%	0.492	0.343	4.2 kWh	17.3 km/h	6	1	87 t	73200	91%	552670	383997	14 °C
Super Bowl LX	2026	Santa Clara, CA	100%	0.53	0.184	3.4 kWh	11.2 km/h	5	3	100 t	75000	85%	56781	127647	12 °C
Super Bowl LXI	2027	Inglewood, CA	57%	0.513	0.184	4.2 kWh	12.8 km/h	5	2	70 t	70000	90%	30415	107762	24 °C
Super Bowl LXII	2028	Atlanta, GA	100%	0.507	0.305	3.7 kWh	11.4 km/h	3	2	80 t	71000	90%	762382	498715	8 °C
Super Bowl LXIII	2029	Seattle, WA	75.70%	0.524	0.113	2.0 kWh	7.8 km/h	9	4	52 t	68000	73%	651091	737015	7 °C
Super Bowl LXIII	2029	Denver, CO	43%	0.473	0.358	3.8 kWh	14.9 km/h	3	2	48 t	76100	56%	673803	717620	2 °C
Super Bowl LXIII	2029	Nashville, TN	13%	0.521	0.365	3.4 kWh	13.9 km/h	6	0	36 t	67700	54%	412610	689947	6 °C

Las Vegas, New Orleans, Santa Clara, Inglewood, and Atlanta; those which have not hosted but have NFL teams are Seattle, Denver, and Nashville.

Applying the EWM, we can gain the weight of each secondary (or tertiary, if any) indicator, as shown in the third row of Figure 4; multiplying the weights with those computed by the AHP and conducting normalization for each weight, the forth row demonstrates the net weight of each indicator, such that primary indicators can be directly determined by the sum of secondary (or tertiary) indicator scores multiplying respective weights.

Conducting TOPSIS as the final step, we have the scores for the following six cities:

Figure 4 Weight Table

Criterion	Climate			Waste Management		Carbon Emission Rate		Energy Consumption					Water Usage
Secondary Indicator	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (kilometer per hour)	Average Temperature	Recycling Rate	Total waste generated (ton)	Number of Bus Station	Number of Railway/Subway Station	Renewable Energy Proportion	Venue Energy Efficiency (kWh/seat)	Grid Carbon Intensity (kgCO_2/kWh)	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (kilometer per hour)	Water Resource Stress Index
Weight in EWM	0.01004561	0.02404742	0.96590697	0.01233383	0.98766617	0.21952617	0.78047383	0.3468436	0.27562648	0.33182509	0.01170686	0.03399798	1
Weight in TOPSIS	0.00140351	0.00335977	0.13495088	0.00052007	0.04164585	0.01641188	0.05834858	0.164213	0.13049525	0.15710246	0.00554261	0.01609633	0.26990984

$$
\begin{array}{ccccc|ccc}
\text{Glendale} & \text{Las Vegas} & \text{New Orleans} & \text{Santa Clara} & \text{Atlanta} & \text{Seattle} & \text{Denver} & \text{Nashville} \\
\end{array}
$$
$$
\left[\begin{array}{ccccc|ccc}
0.1769 & 0.9911 & 0.5311 & 0.0268 & 0.7443 & 0.6312 & 0.6542 & 0.3886
\end{array}\right]
$$

In conclusion, among the cities that have hosted the Super Bowl, Las Vegas is scored prominently the highest, probably due to its complete use of renewable energy sources and huge amount of available water second only to that of Las Vegas.

Among those that have not hosted before but have NFL teams, Denver tops possibly because of its relatively affluent solar energy source and high wind power potential. Seattle has slightly lower rating, in comparison. However, Seattle is evidently advantageous in terms of renewable energy proportion, grid carbon intensity, and recycling rate. Currently, it may seem more environmentally sustainable to hold the Super Bowl in Seattle, yet in the future, Denver can mitigate its disadvantages in green infrastructure with development while better utilizing its natural advantages.

5 Problem 4

Expanding our model to another type of sport mega-event, we choose FIFA World Cup as the target of research. Due to the similarity between soccer and football in terms of venue and duration, it is plausible to apply the established model on it.

5.1 Revising the Model

To revise our model, we mainly focus on the change in indexes in the comparison matrix. Since the World Cup typically lasts roughly four weeks, the carbon emission by transportation is expected to grow drastically to be the most significant indicator. Following are water usage and waste management for the same reason. The least important indicators are thought to be energy consumption and climate, since climatic effects are dealt by air conditioning whose resulting increase in carbon emission may not be as evident as that by transportation. Therefore, the new comparison matrix is shown below.

$$
\begin{array}{c}
\\
\text{Energy} \\ CO_2\text{ by transport} \\ \text{Waste} \\ \text{Water usage} \\ \text{Climate}
\end{array}
\begin{array}{c}
\begin{array}{ccccc}
\text{Energy} & CO_2\text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate}
\end{array} \\
\begin{bmatrix}
1 & \frac{1}{7} & \frac{1}{3} & \frac{1}{5} & 2 \\
7 & 1 & 5 & 3 & 8 \\
3 & \frac{1}{5} & 1 & \frac{1}{3} & 4 \\
5 & \frac{1}{3} & 4 & 1 & 6 \\
\frac{1}{2} & \frac{1}{8} & \frac{1}{4} & \frac{1}{6} & 1
\end{bmatrix}
\end{array}
$$

The normalized matrix is the following:

$$
\begin{array}{c}
 \\ \text{Energy} \\ CO_2 \text{ by transport} \\ \text{Waste} \\ \text{Water usage} \\ \text{Climate}
\end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \end{array} \\
\begin{bmatrix}
0.0606 & 0.0793 & 0.0347 & 0.0425 & 0.0952 \\
0.4242 & 0.5552 & 0.5217 & 0.6383 & 0.3809 \\
0.1818 & 0.1110 & 0.1043 & 0.0709 & 0.1904 \\
0.3030 & 0.1850 & 0.3130 & 0.2127 & 0.2857 \\
0.0303 & 0.0694 & 0.0261 & 0.0354 & 0.0476
\end{bmatrix}
\end{array}
$$

In this case, $CR = 0.041$, lower than 0.1. Adopting the equation for weight calculation, we get the weight matrix for the World Cup:

$$
\begin{array}{c}
\begin{array}{ccccc} \text{Energy} & CO_2 \text{ by transport} & \text{Waste} & \text{Water usage} & \text{Climate} \end{array} \\
\begin{bmatrix} 0.0593 & 0.5138 & 0.1263 & 0.2602 & 0.0403 \end{bmatrix}
\end{array}
$$

5.2 Application to the FIFA World Cup

Searching for data about the proposed indicators, we have integrated the following table (Figure 5):
Applying the EWM, we can gain the weight of each secondary (or tertiary, if any)

Figure 5 Data Table

World Cup Session	Country	Renewable Energy Proportion	Venue Energy Efficiency (kWh/seat)	Grid Carbon Intensity (kgCO_2/kWh)	Avition Carbon Emission (Mt CO_2)	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (km/h)	Average waste generated (kg/person per day)	Recycling Rate	Avalible Water Resource (square meter/person per year)	Average Temperature (Celsius)	Irrigation Water for Soccer Pitch (square meter/month)
2006	Germany	60%	0.483	0.32	1.75	3.02	4.5	1.16	24%	1838	22	6500
2010	South Africa	8%	0.38	0.87	1.65	5.5	3.5	1.08	41%	701	17	12000
2014	Brazil	88%	0.457	0.1	2.7	5.03	4	1.41	54%	40680	25	8000
2018	Russia	18%	0.444	0.31	2.1	2.85	3.2	1.25	48%	31010	24	6500
2022	Qatar	0%	0.405	0.49	3.6	6.02	5	1.2	77%	20.1	26	10000

indicator, as shown in the third row of Figure 6; multiplying the weights with those computed by the AHP and conducting normalization for each weight, the forth row demonstrates the net weight of each indicator, such that primary indicators can be directly determined by the sum of secondary (or tertiary) indicator scores multiplying respective weights.

Conducting TOPSIS as the final step, we have the scores for the following five countries, with Brazil rated as the most appropriate host location for the World Cup:

$$
\begin{array}{c}
\begin{array}{ccccc} \text{Germany} & \text{South Africa} & \text{Brazil} & \text{Russia} & \text{Qatar} \end{array} \\
\begin{bmatrix} 0.04429 & 0.12175 & 0.91049 & 0.73584 & 0.07918 \end{bmatrix}
\end{array}
$$

In retrospect, our model reflects the distinctive challenge of carbon emission caused by the World Cup. As mentioned earlier, the long time span of World Cup makes tremendous amount of carbon emission inevitable, and the model accounts for this

Figure 6 Weight Table

Criterion	Energy Consumption					Carbon Emission	Waste Management		Climate			Water Usage	
Secondary Indicator	Renewable Energy Proportion	Venue Energy Efficiency (kWh/seat)	Grid Carbon Intensity (kgCO_2/kWh)	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (kilometer per hour)	Avition Carbon Emission (Mt CO_2)	Recycling Rate	Average waste generated (kg/person per day)	Daily Incident Solar Energy (energy per square meter)	Average Wind Speed (km/h)	Average Temperature (Celsius)	Avalible Water Resource (square meter/person per year)	Irrigation Water for Soccer Pitch (square meter/month)
Weight by EWM	0.3468436	0.27562648	0.33182509	0.01170686	0.03399798	1	0.01233383	0.98766617	0.01004561	0.02404742	0.96590697	0.5	0.5
Weight by EWM &AHP	0.0197752	0.01571478	0.01891894	0.00066746	0.00193839	0.49387073	0.00149799	0.11995547	0.00251246	0.0060144	0.24157899	0.03877759	0.03877759

by primarily supposing that carbon emission is the most important influential factor. As a result, the weight of carbon emission by transportation alone takes up 0.5138.

5.3 Changes and Strategies

Infrastructure investment is a crucial lever in transformation. Upgrading stadium systems, such as HVAC efficiency, LED lighting, and water-efficient turf management, reduces baseline energy and water demand that persists well after the event. Integration of renewable energy on-site, including rooftop solar and small-scale wind, allows venues to offset operational loads and reduce the reliance on carbon-intensive regional grids. Cities with limited renewable endowment can still improve performance by entering long-term power-purchase agreements or expanding community solar programs, ensuring that event-related electricity is sourced from certified low-carbon suppliers without imposing unreasonable short-term costs.

Transportation interventions also play a decisive role in shaping environmental outcomes, as mobility tends to account for the largest share of emissions in large spectator events. Cities can reduce these emissions by expanding mass-transit access to the stadium precinct, improving intermodal connections, and deploying temporary high-frequency shuttle systems that remain cost-effective beyond the event. Incentivizing the use of low-emission mobility—such as electric busses, bike sharing networks, and pedestrian corridors—further diminishes emissions without requiring disruptive infrastructure overhauls. At the regional scale, improvements in airport efficiency, expanded direct flight availability, and partnerships with airlines to promote the use of sustainable aviation fuels can mitigate aviation-related emissions, which are otherwise difficult to influence.

Collectively, these strategies improve the long-term viability of a city as a host by raising sustainability scores in established systems for evaluation. Cities that demonstrate credible commitments to low-carbon energy, waste reduction, resilient water systems, and accessible transportation infrastructure become more attractive to event organizers seeking to align with global climate and ESG expectations. Therefore, these investments serve a dual purpose: immediate environmental risk mitigation and durable improvements that strengthen the city's competitiveness for future bids.

5.4 The Biggest Environmental Factor

The environmental dynamics of a single-game event, such as the Super Bowl, differ substantially from those of prolonged, multi-venue or multi-sport competitions like the FIFA World Cup or the Olympic Games. These differences stem from the scale of spectator travel, the duration of venue operation, and the distribution of resource usage across multiple sites.

In single-game events, the dominant environmental driver is long-distance transportation, particularly air travel. Because large proportions of attendees travel from outside the host region and depart shortly after the game, aviation and regional mobility account for the majority of emissions. Venue-related impacts—such as electricity use, turf irrigation, solid waste generation, and water consumption—are significant but concentrated in a single 24- to 48-hour window. As a result, efforts to reduce per-capita waste, secure low-carbon electricity, and optimize transit access can meaningfully reduce the event's footprint, but they do not approach the magnitude of transportation-sector emissions.

By contrast, in multi-venue or multi-sport competitions, the environmental profile becomes more distributed and prolonged. Energy consumption increases due to the extended operational period, parallel competition schedules, and the need to operate multiple stadiums, training facilities, and temporary installations. Water demand, particularly in regions with arid climates or turf-dependent venues, becomes a long-term pressure throughout the tournament month. Solid waste volumes accumulate more gradually but at larger scales than in a single-event setting. Furthermore, the transportation component becomes more complex: rather than one high-emission travel peak, multi-week competitions produce repetitive intercity mobility flows among spectators, athletes, media, and staff. Although aviation remains significant, cumulative intra-tournament travel can rival or exceed the emissions associated with initial long-haul flights.

Consequently, while transportation dominates the impact profile of a single game, large multi-venue events tend to distribute their environmental burden across electricity generation, water use, construction, and waste management. This distinction has practical implications for sustainability planning: single-game hosts benefit most from interventions that address transportation emissions and venue efficiency, whereas extended competitions require coordinated multi-city energy planning, long-term infrastructure upgrades, and extensive resource-management systems capable of supporting sustained demand across diverse facilities.

6 A Letter of Actionable Recommendations

A letter for the NFL

We would like to express our sincere respect for your persistent endeavor to organize and promote the grand event of the Super Bowl. While it is the foremost annual gathering for football fans across the world, certain issues must be taken into consideration.

Currently, the tremendous environmental challenge has universally evoked the urgency of careful and comprehensive concern about controlling the environmental impact of any mega-event. To this end, it is crucial to rationally pick the most appropriate city to host the Super Bowl based on environmental concerns, which can reduce the harm to the ecosystem while guaranteeing the quality of the game.

We have developed an evaluation model that accounts for environmental aspects including 1) energy consumption, 2) carbon emission by transportation, 3) waste management, 4) water usage, and 5) climate. Specifically, we quantify all of these aspects with secondary and tertiary indicators, combining the Entropy Weight Method (EWM), Analytic Hierarchy Process (AHP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rationally measure the net impact of these indicators and rate each mooted location.

As a result, among the cities that have hosted Super Bowl before, Las Vegas has been proposed as the most environmentally sustainable location to host again. That is because it has its energy sources thoroughly composed of renewable energy and possesses a large amount of water resource.

Furthermore, among cities that have never hosted before, Denver has the best potential to host in the future. The advantages of Denver consists mainly of high potential of solar and wind power.

These two cities have the highest scores computed by our model in respective classifications, and we sincerely hope you can arrange the future Super Bowl to one of them. By adopting our suggestion, you could not only minimize the environmental impact of the Super Bowl, but also call into action the global awareness of sustainable development.

With the stably increasing popularity of the Super Bowl, a greener event will be an imperative, and it will be our responsibility to make more contribution to active environmental protection. Thank you for attention, and look forward to you organizing a more sustainable Super Bowl in the future.

Sincerely,
Team #17136
HiMCM 2025 Participants
November 18, 2025

References

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7 Appendix

The code for EWM:

```
import numpy as np

# Define the three indicators properly
def entropy(infor):
    infor = np.array(infor)
    return np.sum(-infor * np.log(infor + np.finfo(float).eps)) / np.log(len
        (infor))

def cost_indicator(matrix):
    matrix = np.array(matrix)
    maxi = np.max(matrix, axis=0)
    matrix = (maxi - matrix) / (np.sum(maxi - matrix, axis=0) + np.finfo(
        float).eps)
    return matrix

def benefit_indicator(matrix):
    matrix = np.array(matrix)
    return matrix / (np.sum(matrix, axis=0) + np.finfo(float).eps)

def optimal_value_indicator(matrix, optimal_value=None):
    matrix = np.array(matrix)
    if optimal_value is None:
        optimal_value = np.median(matrix, axis=0)
    maxn = np.max(abs(matrix - optimal_value), axis=0)
    maxn[maxn==0] = np.finfo(float).eps  # avoid division by zero
    matrix = 1 - (abs(matrix - optimal_value) / maxn)
    matrix = matrix / (np.sum(matrix, axis=0) + np.finfo(float).eps)
    return matrix

def entropy_weights(matrix, indicators, optimal_value=None):
    matrix = np.array(matrix, dtype=float)

    # If indicators is a single function
    import types
    if isinstance(indicators, types.FunctionType):
        if indicators is optimal_value_indicator:
            matrix = indicators(matrix, optimal_value)
        else:
            matrix = indicators(matrix)
    else:
        # indicators can be a list with different indicator per criterion
        n_criteria = matrix.shape[1]
        new_matrix = np.zeros_like(matrix)
        for j in range(n_criteria):
            ind = indicators[j]
```

```
            if ind is optimal_value_indicator:
                new_matrix[:, j] = ind(matrix[:, j].reshape(-1,1), optimal_value).flatten()
            else:
                new_matrix[:, j] = ind(matrix[:, j].reshape(-1,1)).flatten()
        matrix = new_matrix

    matrix = np.where(matrix==0, np.finfo(float).eps, matrix)

    # Compute entropy
    entropy_values = np.array([entropy(matrix[:,j]) for j in range(matrix.shape[1])])
    diver = 1 - entropy_values
    weights = diver / np.sum(diver)
    return weights

# Input matrix
matrix = np.array([
    [10, 200, 0.5],
    [20, 300, 0.7],
    [30, 250, 0.9]
])

# Example: different indicator per criterion
indicators = [benefit_indicator, optimal_value_indicator, cost_indicator]

weights = entropy_weights(matrix, indicators)
weights
```

The code for TOPSIS:

```
    def topsis(matrix, weights, criteria_types):
    """
    Perform TOPSIS ranking.

    Parameters
    ----------
    matrix : 2D array-like
        Decision matrix with shape (m, n) - m alternatives, n criteria.
    weights : 1D array-like
        Importance weights for each criterion (should sum to 1).
    criteria_types : list of str
        Each element is 'benefit' or 'cost' indicating the type of criterion.

    Returns
    ----------
    scores : ndarray
        Closeness coefficient for each alternative (higher = better).
```

```
    rankings : ndarray
        Indices of alternatives ranked from best to worst.
    """
    # Avoid wrong imports

    if (sum(weights) - 1) > 0.001:
        raise ValueError("Weights must sum to 1.")

    # Step 1: Normalize the decision matrix
    print(matrix)
    norm_matrix = matrix / np.sqrt((matrix ** 2).sum())
    print(f"norm_matrix = {norm_matrix}")

    # Step 2: Multiply by weights
    weighted_matrix = norm_matrix * weights

    # Step 3: Determine ideal and negative-ideal solutions
    ideal_solution = []
    negative_ideal_solution = []
    for i in range(matrix.shape[1]):
        if criteria_types[i] == '+':
            ideal_solution.append(weighted_matrix[:, i].max())
            negative_ideal_solution.append(weighted_matrix[:, i].min())
        else:
            ideal_solution.append(weighted_matrix[:, i].min())
            negative_ideal_solution.append(weighted_matrix[:, i].max())

    ideal_solution = np.array(ideal_solution)
    negative_ideal_solution = np.array(negative_ideal_solution)

    # Step 4: Calculate distances to ideal and negative-ideal solutions
    distance_to_ideal = np.sqrt(((weighted_matrix - ideal_solution) ** 2).
       sum(axis=1))
    distance_to_negative_ideal = np.sqrt(((weighted_matrix -
       negative_ideal_solution) ** 2).sum(axis=1))

    # Step 5: Calculate performance score
    performance_score = distance_to_negative_ideal / (distance_to_ideal +
       distance_to_negative_ideal)

    return performance_score
```

The code for AHP

```
    RI_table = {1:0.00, 2:0.00, 3:0.58, 4:0.90, 5:1.12, 6:1.24, 7:1.32,
       8:1.41, 9:1.45, 10:1.49}
def Normalize(A):
    """
    Normalize the pairwise comparison matrix A.
```

```
    """
    if type(A)!= np.array:
        A = np.array(A)
    A = np.array(A, dtype=float)
    sj = np.sum(np.abs(A), axis=0)
    A = A / sj
    return A
def AHP(A):
    """
    Compute AHP weights using the eigenvalue method.

    Parameters:
        A (np.ndarray): Pairwise comparison matrix (n x n)

    Returns:
        weights (np.ndarray): Normalized eigenvector (priority vector)
        lambda_max (float): Maximum eigenvalue
        CI (float): Consistency Index
        CR (float): Consistency Ratio
    """
    if type(A)!= np.array:
        A = np.array(A)

    # --- Step 1: Eigen decomposition ---
    eigvals, eigvecs = np.linalg.eig(A)

    # Principal eigenvalue (real part)
    max_index = np.argmax(eigvals.real)
    lambda_max = eigvals[max_index].real

    # Principal eigenvector (real part)
    w = eigvecs[:, max_index].real

    # Normalize weights
    weights = w / np.sum(w)

    # --- Step 2: Consistency calculations ---
    n = A.shape[0]
    CI = (lambda_max - n) / (n - 1)


    RI = RI_table.get(n, 1.49)  # fallback for n>10

    CR = CI / RI if RI != 0 else 0

    return weights, lambda_max, CI, CR
```

Report on Use of AI Tools

Input: What is the RI reference table?
Output (GPT-5.1): Below is the **original RI (Random Index) table from Saaty's *The Analytic Hierarchy Process* (1980/1990 edition)**.
This is the most classic and widely cited version of the Random Index for AHP consistency.

n (Matrix Order)	RI (Saaty)
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

This is the complete RI table provided in the book (the original indeed only lists up to order 10).