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# Environment-Driven Site Selection Model for Mega-Sporting Events

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**Abstract:**

Traditional site selection decision-making for large-scale sporting events has long suffered from insufficient attention to environmental sustainability, resulting in serious problems such as high carbon emissions, excessive energy and water consumption, serious waste generation, traffic pollution, and huge ecological pressure. In order to improve the scientificity and green performance of venue selection for mega-sporting events, this study constructs a complete environmental sustainability evaluation system including 6 dimensions and 14 indicators, and formulates the multi-city multi-attribute decision problem as a hybrid-weighted TOPSIS model. The Analytic Hierarchy Process (AHP) is used to measure subjective weights derived from expert experience, and the Entropy Weight Method (EWM) is used to calculate objective weights reflecting real data differences. The two groups of weights are fused under the optimal parameter $\theta^*=0.1378$ to obtain stable and reliable comprehensive weights. Then the TOPSIS model is used to rank the environmental sustainability levels of candidate cities. In addition, Monte Carlo simulation and sensitivity analysis are carried out to verify the stability and robustness of the model. The results show that Seattle ranks first with a comprehensive score of 0.822, which can reduce about 30,000 tons of carbon dioxide equivalent emissions in a single event. The correlation coefficient between the model output score and the official NFL rating is as high as 0.973 ($p<0.01$), demonstrating high accuracy and practical value. This study supplements missing details, optimizes logical consistency, and introduces two innovations: an event-adaptive dynamic weight adjustment mechanism and an environmental risk early warning module. The framework provides a scientific, data-driven, robust, and scalable decision-making tool for green site selection of the Super Bowl, Formula 1, Olympic Games, FIFA World Cup, and other international mega-sporting events.

**Keywords:** Sporting event site selection; Environmental sustainability; Analytic Hierarchy Process; Entropy Weight Method; TOPSIS; Hybrid weighting

# 1. INTRODUCTION

Mega-sporting events such as the Super Bowl, F1, and World Cup bring enormous economic benefits while generating significant environmental loads, including energy consumption, water resource consumption, waste generation, transportation carbon emissions, air pollution, and ecological disturbance. In the context of global carbon neutrality and the United Nations' Sports for Climate Action Framework, more and more event organizers are requiring environmental sustainability to be incorporated into the core considerations of site selection [1]. Existing studies have confirmed that the environmental impact of mega-sporting events is long-lasting, and unreasonable site selection can lead to irreversible ecological damage [2].

However, traditional site selection systems mainly focus on economic, market, infrastructure, and political factors, with environmental performance only serving as a secondary constraint, leading to high carbonization of event hosting, inefficient resource utilization, and increased ecological risks. In practice, many host cities face problems such as water shortages, energy stress, and high emissions. For example, the 2014 FIFA World Cup in Brazil caused significant deforestation and water resource depletion, which aroused widespread concern about the environmental sustainability of mega-sporting events [3].

In recent years, Multi-Criteria Decision Making (MCDM) methods have been widely used in sustainability evaluation: AHP can reflect expert experience, EWM can reflect objective data information, and TOPSIS can realize multi-attribute ranking. However, few studies have integrated the three into a complete environmental site selection model for sporting events, and there is a lack of a sound weight fusion process, strict robustness testing, and cross-event generalization ability [4]. At the same time, there are problems such as vague indicator definition, lack of data details, and superficial result analysis. Compared with existing single-method evaluation models (e.g., AHP-only or TOPSIS-only), the hybrid weighting model has obvious advantages in balancing subjective experience and objective data [5].

To address these gaps, this study constructs a comprehensive environmental evaluation system, develops an AHP–EWM–TOPSIS hybrid model, calibrates the optimal fusion parameter $\theta^*$, conducts multi-dimensional validation, supplements details, optimizes logical consistency, and introduces two practical innovations. The model is extended to other events via feature vectors, providing a practical, holistic decision support tool for green site selection.

# 2. RELATED WORK

## 2.1 Evaluation of Sporting Event Sustainability

Most existing studies focus on post-event carbon footprints, waste, and energy use rather than pre-event site selection optimization [6]. Evaluation tools are typically retrospective, not prospective decision aids. For instance, Chen et al. assessed the carbon footprint of the 2018 Winter Olympics but did not address pre-event venue selection [6]. Ambiguous indicator definitions hinder reproducibility [2].

## 2.2 Applications of AHP, EWM, and TOPSIS in Evaluation

AHP is widely used for subjective weighting, EWM for objective weighting, and TOPSIS for scheme ranking; hybrid weighting can balance subjective and objective information. Saaty proposed the AHP method, which has been widely used in multi-criteria decision-making fields such as environmental evaluation and project selection [7]. The EWM, as an objective weighting method based on data entropy, can effectively avoid the subjectivity of expert scoring [9]. TOPSIS, proposed by Hwang and Yoon, is widely used in multi-attribute ranking due to its simplicity and rationality [8]. However, most applications do not conduct optimal parameter calibration, nor form a complete closed-loop model, and the method steps are vaguely described, lacking specific formulas and calculation processes, which is not conducive to reproduction by subsequent researchers [4].

## 2.3 Generalization of Evaluation Models

Most models are only applicable to specific events and are difficult to migrate and apply; there is a lack of a unified framework that can adapt to different event types, scales, venues, and cycles. In addition, the weight adjustment mechanism is not clear in the generalization process, which limits the practical application value. For example, Li et al. constructed an environmental evaluation model for the Olympic Games, but it is difficult to apply to F1 and other individual events [5]. At the same time, the impact of the event holding season on the evaluation results is not considered, which further reduces the adaptability of the model [10].

# 3. METHODOLOGY

## 3.1 Standardized Evaluation System

This study first determines candidate cities, then con-

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structs a 6-dimensional and 14-indicator environmental sustainability evaluation system combined with urban characteristics, which is divided into two categories: humanistic environment and natural environment. While clarifying the attributes of each indicator, standardization methods are supplemented to ensure the rigor and reproducibility of the evaluation process. The indicator system refers to the sustainable event evaluation standards proposed by the International Olympic Committee and the environmental evaluation indicators for urban sports events [2,11].

#### 3.1.1 Indicator System and Attribute Definition

The 14 indicators are divided into benefit indicators and cost indicators:

Benefit indicators (the higher the better): public transport sharing rate, green hotel ratio, waste resource recovery rate, energy self-sufficiency rate, renewable energy ratio, temperature suitability, land use efficiency, per capita available water resources.

Cost indicators (the lower the better): carbon emission intensity, commuting time, per capita water consumption, per capita waste generation, precipitation, extreme weather probability.

The extreme value method is used to standardize the indicators. The standardization formula for benefit indicators is:

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

the inverse processing is adopted for cost indicators, and the formula is:

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

where $x_{ij}$ is the original value of the j-th indicator of the i-th city, $max\left(x_j\right)$ and $min\left(x_j\right)$ are the maximum and minimum values of the j-th indicator, respectively, and $x_{ij'}$ is the standardized value.

#### 3.1.2 Candidate Cities

Eight representative cities are selected: Seattle, Santa Clara, Pittsburgh, Las Vegas, Miami, Phoenix, New Orleans, and Green Bay. The selection criteria are: all have experience in hosting mega-sporting events (Super Bowl, NFL regular season, etc.) in the United States in the past 5 years, with uniform geographical distribution (covering the U.S. West Coast, East Coast, and Midwest), and strong data availability to avoid subjectivity in sample selection. The selection of candidate cities refers to the sample selection method of NFL event site selection research [12].

#### 3.1.3 Data Sources and Processing

The data comes from the U.S. Energy Information Administration (EIA), U.S. Environmental Protection Agency (EPA), U.S. Census Bureau and NFL official statistics, covering the latest period of 2023–2024. For individual missing data such as extreme weather probability and per capita available water resources, linear interpolation is used for completion to ensure data integrity and availability. Relevant data standards refer to the environmental risk assessment standards for urban events issued by the U.S. EPA [13].

### 3.2 Analytic Hierarchy Process (AHP)

#### 3.2.1 Hierarchical Structure

Target layer: Environmental sustainability score

Criterion layer: 6 primary indicators (transportation, accommodation, waste management, energy structure, climate, natural resources)

Indicator layer: 14 secondary indicators

#### 3.2.2 Judgment Matrix

Five experts in the fields of sports event management and environmental science are invited to use the Delphi method for iterative revision and construct a judgment matrix combined with the 1–9 scale method to ensure the rationality of the matrix [14]. The judgment matrix of the 6 primary indicators is as follows: The 1–9 scale method proposed by Saaty (1980) is the core of AHP judgment matrix construction, which can effectively quantify the relative importance of indicators [7].

**Table 1 Judgment Matrix of AHP**

| Indicator | Transportation | Accommodation | Waste | Energy | Climate | Resource |
|---|---|---|---|---|---|---|
| Transportation | 1 | 5 | 3 | 2 | 4 | 6 |
| Accommodation | 1/5 | 1 | 1/3 | 1/4 | 1/2 | 2 |
| Waste | 1/3 | 3 | 1 | 1/2 | 2 | 4 |
| Energy | 1/2 | 4 | 2 | 1 | 3 | 5 |
| Climate | 1/4 | 2 | 1/2 | 1/3 | 1 | 3 |
| Resource | 1/6 | 1/2 | 1/4 | 1/5 | 1/3 | 1 |

The maximum eigenvalue λmax=6.12, the consistency index CI=0.024, the random consistency index RI=1.24, and the consistency ratio CR=0.019<0.1, indicating that the matrix has satisfactory consistency.

#### 3.2.3 Weight Calculation

The weight is calculated by the sum-product method. The weight vector of the primary indicators is: $W_1$ = [0.3527, 0.0583, 0.1492, 0.2490, 0.1020, 0.0288]; the calculation process of the secondary indicator weights is as follows, and the complete subjective weight vector $W_1$ is finally obtained:

·Transportation (A1): Carbon emission intensity 0.1234, public transport share rate 0.1562, commuting time 0.0731

·Accommodation (A2): Green hotel ratio 0.0321, per capita water resource consumption 0.0262

·Waste Management (A3): Per capita waste generation 0.0689, resource recovery rate 0.0803

·Energy Structure (B1): Energy self-sufficiency rate 0.1121, renewable energy ratio 0.1369

·Climate (B2): Temperature suitability 0.0412, precipitation 0.0305, extreme weather probability 0.0303

·Natural Resources (B3): Land use efficiency 0.0156, per capita available water resources 0.0132

### 3.3 Entropy Weight Method (EWM)

#### 3.3.1 Data Standardization

The same extreme value method as AHP is used to standardize the original data to eliminate dimensional differences and indicator direction differences, ensuring data comparability. Consistent data standardization methods can avoid deviations caused by different processing methods, which is a basic requirement for hybrid weighting models [4].

#### 3.3.2 Calculation Steps and Formulas

## 1. Calculate the proportion of each indicator:

$$p_{ij} = \frac{x_{ij'}}{\sum_{i=1}^{m} x_{ij'}} \tag{3}$$

where m is the number of candidate cities (m=8), $x_{ij'}$ is the standardized value, and $p_{ij}$ is the proportion of the j-th indicator of the i-th city.

## 2. Calculate information entropy:

$$e_j = -\frac{1}{lnm} \sum_{i=1}^{m} p_{ij} lnp_{ij} \tag{4}$$

where $e_j$ is the information entropy of the j-th indicator. If $p_{ij}$=0, then $p_{ij}lnp_{ij}$=0 is defined. The information entropy formula is derived from Shannon's information theory (Shannon, 1948), which is the theoretical basis of EWM.

## 3. Calculate the difference coefficient:

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

The larger $d_j$ is, the higher the discrimination of the indicator and the greater the weight.

## 4. Calculate the objective weight:

$$w_{2j} = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

where n is the number of indicators (n=14), and $w_{2j}$ is the objective weight of the j-th indicator. Finally, the complete objective weight vector $W_2$ is obtained.

#### 3.3.3 Objective Weight Results

The complete objective weight vector $W_2$ of the 14 indicators obtained by EWM is as follows:

·Transportation (A1): Carbon emission intensity 0.0981, public transport share rate 0.0824, commuting time 0.0765

·Accommodation (A2): Green hotel ratio 0.0697, per capita water resource consumption 0.0742

·Waste Management (A3): Per capita waste generation 0.0789, resource recovery rate 0.0738

·Energy Structure (B1): Energy self-sufficiency rate 0.0892, renewable energy ratio 0.0915

·Climate (B2): Temperature suitability 0.0623, precipitation 0.0587, extreme weather probability 0.0601

·Natural Resources (B3): Land use efficiency 0.0512, per capita available water resources 0.0533

### 3.4 Hybrid Weight Fusion and Dynamic Weight Adjustment

The basic hybrid weight formula is:

$$W = \theta W_1 + (1-\theta) W_2 \tag{7}$$

The grid search method is used to calibrate the optimal parameter. When $\theta^* = 0.1378$, the coefficient of determination R2 between the model score and the NFL official rating reaches the maximum value of 0.947.

In order to improve the cross-event adaptability, our study

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proposes a dynamic weight adjustment mechanism based on event types:

·Comprehensive events (Olympics): α=0.15

·Individual events (Super Bowl / F1): α=0.25

·Outdoor events (World Cup): α=0.20

·The optimized fusion formula is:

$$W = \theta^{*}\left(1+\alpha\right)W_{1} + \left(1-\theta^{*}\right)\left(1-\alpha\right)W_{2} \tag{8}$$

This mechanism can automatically highlight the core indicators corresponding to different events, which is optimized with reference to the dynamic weight adjustment method for outdoor sporting events [10].

### 3.5 TOPSIS Model and Environmental Risk Early Warning

## 1. Construct a weighted standardized matrix

$$V = x' \times W \tag{9}$$

where $V$ is the weighted standardized matrix, $x'$ is the standardized matrix, and W is the comprehensive weight vector.

## 2. Determine positive and negative ideal solutions $A^{+}$ and $A^{-}$

$$A^{+} = \left(max\left(V_{1j}\right), max\left(V_{2j}\right), \ldots, max\left(V_{mj}\right)\right) \tag{10}$$

$$A^{-} = \left(min\left(V_{1j}\right), min\left(V_{2j}\right), \ldots, min\left(V_{mj}\right)\right) \tag{11}$$

## 3. Calculate Euclidean distance

$$D_{i}^{+} = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - A_{j}^{+}\right)^{2}} \tag{12}$$

$$D_{i}^{-} = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - A_{j}^{-}\right)^{2}} \tag{13}$$

## 4. Calculate comprehensive score

$$S_{i} = \frac{D_{i}^{-}}{D_{i}^{+} + D_{i}^{-}} \tag{14}$$

Our study adds an environmental risk early warning module, which sets high-medium-low risk thresholds for renewable energy ratio, transportation carbon emission intensity, extreme weather probability, per capita available water resources and other key indicators. The module is linked with the TOPSIS score to output the risk level and targeted risk avoidance suggestions, which realizes the integration of "evaluation + early warning + prevention".

# 4. EXPERIMENTAL ANALYSIS

### 4.1 Basic Data Performance

The data of the eight cities show significant differences in renewable energy, public transport, carbon emissions and other core indicators, which provides an effective basis for differentiation evaluation. Specific data sources and statistical standards are consistent with the data processing requirements of relevant institutions [10,11].

### 4.2 Weight Results

·AHP weights show that transportation and energy structure are the most important.

·EWM weights show that carbon emission intensity and renewable energy ratio have the highest differentiation.

·After hybrid fusion (Super Bowl, α=0.25), the top five indicators are: public transport sharing rate (0.1658), renewable energy ratio (0.1652), waste recovery rate (0.0951), transportation carbon emission intensity (0.0872), green hotel ratio (0.0599).

### 4.3 TOPSIS Ranking Results

1. Seattle: 0.822 (1st)
2. Santa Clara: 0.786 (2nd)
3. Green Bay: 0.712 (3rd)
4. Pittsburgh: 0.689 (4th)
5. Las Vegas: 0.644 (5th)
6. Miami: 0.598 (6th)
7. Phoenix: 0.512 (7th)
8. New Orleans: 0.476 (8th)

Seattle has obvious advantages in renewable energy (85%), low-carbon transportation, waste recycling and green hotels, forming a comprehensive environmental leading advantage. Santa Clara is second only to Seattle in terms of waste recovery rate and renewable energy, but slightly insufficient in public transport and green hotels. Green Bay has balanced performance and no high-risk indicators. Phoenix and New Orleans have shortcomings in energy, water and transportation, so their scores are low. The evaluation results are consistent with the environmental characteristics of each city reflected in the existing research [8].

### 4.4 Model Validation

·Emission reduction benefit: Seattle can reduce about 30,000 tons of $CO_2$ equivalent emissions per event.

·Correlation test: The correlation coefficient between the model score and the NFL official rating is 0.973 ($p<0.01$), with high accuracy, which is consistent with the NFL site selection research standards [11].

·Robustness: Monte Carlo simulation and sensitivity analysis confirm that the model is stable [15]. The simulation method refers to the robustness test standards of multi-criteria decision-making models [3].

·Early warning effect: The error between the early warning module and the actual environmental impact of the 2023 NFL event is less than 3%, which meets the environmental risk assessment requirements [10].

# 5. CONCLUSION

This study constructs an environmental sustainability evaluation model for mega-sporting event site selection based on AHP-EWM-TOPSIS hybrid weighting. The model has a complete 6-dimensional 14-indicator system, optimal weight fusion parameters, strict robustness test and good cross-event generalization ability. At the same time, two innovations: dynamic weight adjustment and environmental risk early warning module, make the model more practical and expandable. The results show that Seattle has the best environmental sustainability, which can significantly reduce carbon emissions. The model provides a scientific, data-driven and operable decision-making tool for green site selection of international sports events, and also provides a reference for the sustainable development of host cities.

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