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Forecasting Sustainable Mega-Event Host Cities Using a Random-Forest Composite Index

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Abstract. Large-scale sporting events such as the Super Bowl and the NBA All-Star Weekend generate substantial social and economic value, but they also impose significant environmental pressures through energy consumption, transportation emissions, and urban infrastructure demands. As sustainability becomes an increasingly important criterion in event planning, host-city evaluation requires data-driven, multi-factor analysis rather than reliance on economic indicators alone. This study develops a quantitative sustainability assessment framework based on a Random Forest model, using multi-dimensional data from U.S. cities between 2019 and 2023. The model predicts 2029 environmental indicators and computes feature-importance weights for key sustainability determinants, including climate conditions, transportation capacity, carbon emissions, energy structure, economic strength, and urban density. These results are integrated into a composite sustainability index to evaluate host-city suitability. The dataset incorporates official statistics on climate, emissions, energy use, transportation infrastructure, and socioeconomic conditions. Results indicate that transportation systems, economic capacity, and emissions intensity are the dominant drivers of sustainable hosting potential. Application to NBA All-Star host-city analysis further reveals event-specific differences in factor importance. Overall, the framework provides an interpretable and scalable tool for sustainable mega-event planning.

Keywords: Sustainable event planning; Random Forest; Host-city evaluation; Environmental indicators; Feature importance.

1. Introduction

1.1. Background

With the continuous advancement of human society, environmental pollution problems are becoming increasingly severe. Among these problems, the carbon emissions of sports mega-events in particular pose a serious challenge to global environmental sustainability. Studies have found that the largest proportion of these greenhouse gas emissions originates from spectator travels (Pereira et al., 2017).

For example, the sustainability report of VfL Wolfsburg shows that spectator travel alone contributes to over 60% of total event-related emissions. In another case, the 2010 FIFA World Cup 2010 in South Africa found that international air travel accounted for about 67 % of the tournament's carbon footprint (Sonjica, 2009). Furthermore, the 2014 FIFA World Cup 2014 in Brazil reported that transportation accounted for 83.7 % of its total greenhouse gas emissions, with international flights alone contributing more than 50 % (FIFA, 2014).

As a result, carbon emission control and energy-efficiency strategies for large-scale sports events have become a central focus for governments, sports associations, and international environmental organizations (Su, X.-z., Chen, L., & Xu, X. L., 2025).

The Super Bowl, as the most-watched single-day sporting event in the United States, generates enormous social and economic value but also produces an unavoidable environmental footprint (National Football League [NFL], 2024; Green Sports Alliance, 2022). These environmental impacts arise primarily from:

(1) stadium energy demand (U.S. Environmental Protection Agency [eGRID], 2023);

(2) temporary operational facilities (Green Sports Alliance, 2022);

(3) broadcasting infrastructure (U.S. Department of Energy, 2021);

(4) food and material logistics (Green Sports Alliance, 2022); and most critically,

(5) spectator transportation (EPA SmartWay, 2023; NFL Green, 2024).

In response, the NFL has implemented the league-wide sustainability initiative "NFL Green," which coordinates mitigation and legacy projects with host committees, public agencies, and non-governmental organizations to reduce environmental impacts and promote long-term ecological benefits (NFL Green, 2024).

Existing sustainability scorecards, such as the Super Bowl 50 Sustainability Report (Super Bowl 50 Host Committee, 2016), reveal substantial differences among candidate host cities. These differences are driven by factors including local climate, urban energy structure, transportation capacity, population density, and waste management systems (Super Bowl 50 Host Committee, 2016; Green Sports Alliance, 2022). However, these indicators rarely influence the actual host-city selection process, which continues to be dominated by economic considerations and logistical constraints (Arizona State University W. P. Carey School of Business, 2024).

Given that environmental performance is strongly shaped by city-specific characteristics and that future Super Bowl sustainability will increasingly rely on data-driven planning, there is an urgent need for a location-aware quantitative model capable of integrating multi-dimensional urban indicators, evaluating their relative importance, and predicting long-term trends in sustainability. This need motivates the present study, which aims to formalize the host-city selection problem as a multi-factor modeling task and to develop predictive and interpretable tools for identifying the most environmentally sustainable host city in future years.

1.2. Problem Restatement

This project focuses on three core objectives: First, collect and process multi-dimensional data of specified cities; Second, use random forest model for training and prediction; Third, expand the model to analyze Olympic Games and NBA events, and compare factor weights.

This project focuses on three core objectives:

(1) Collect and process multi-dimensional data from selected U.S. cities,

(2) Apply Random Forest model for prediction, feature-importance evaluation, and sustainability scoring,

(3) Extend the model to analyze other mega-events including the Olympic Games and the NBA All-Star Weekend.

Following the need for a location-aware quantitative model introduced in Section 1.1, this study formulates the Super Bowl host-city selection problem as a **multi-factor predictive evaluation task**, which integrates climate conditions, energy structure, transportation networks, carbon emissions, and socioeconomic capacity (Super Bowl 50 Host Committee, 2016; Green Sports Alliance, 2022). Because these indicators vary significantly across regions and evolve over time, a model capable of incorporating **multi-year, multi-city, multi-dimensional data** is required (Arizona State University W. P. Carey School of Business, 2024).

To achieve this, the study undertakes the following components:

2. Multi-Dimensional City Data Collection and Processing

We collected and cleaned a five-year dataset (2019–2023) for 22 U.S. cities that either have NFL teams or have historically served as Super Bowl hosts. The dataset contains approximately twenty variables covering geography, climate (NOAA, 2024), transportation infrastructure (U.S. DOT, 2023), carbon emissions (U.S. EPA, 2023), local energy structure (U.S. EIA, 2024), and socioeconomic indicators (U.S. Census Bureau, 2024). Preprocessing steps ensured data completeness, consistency, and comparability across cities.

3. Assumptions and Justifications

We relied on assumptions to limit the scope of the problem and form reasonable predictions. We included assumptions in our sustainability analysis that were both justified and necessary to guarantee that the modeling frame was accurate.

The first assumption is that the selection of host cities was based on all of our factors, and the considerations remained the same throughout 2019-2023. This assumption is justified because historical data have shown consistent factor interaction patterns over the past decade. Without fundamental changes in economic development or energy policy, these factors are expected to remain considered equally for our prediction tools to analyze.

Second, we assume that the effects of extreme events, such as pandemics, serious natural disasters, or geopolitical crises, are not considered. These events can heavily alter carbon emissions, transportation patterns, and local economies, but they do not reflect the normal trend. Excluding accidental factors is justified because we needed to focus on long-term trend prediction. Our purpose is to model sustainability outcomes under ordinary conditions. This aligns with how cities and the NFL prepare for major events.

Third, we assume that each city's current environmental policy framework will remain consistent over the prediction period. We assume that existing sustainability strategies will continue without major changes. While policy shifts are possible, we base our model on the published commitments as they stand now, as these provide a stable baseline for prediction. This assumption helps us predict environmental outcomes using established plans instead of hypothetical policy changes.

Fourth, we believe the involvement of the Super Bowl still costs the same as that of the very recent years. The capacity of the stadium used during the game and the waste generated during the event have minimized changes over the last couple of years of the early 2010s. There have been no changes announced with regard to the nature of the game that could increase the waste generated during this event.

Another detail worth mentioning was that data from 2024 were not considered for the prediction. This was due to time limitations in the data collection process and incompleteness of data from official sources. A large proportion of data for our indicators was not available or made public yet for the year 2024, so it had to be excluded to eliminate null values.

Finally, our plan was to use data from 2023 as the primary basis for predicting conditions in 2029. Data from 2023 were more recent and contemporary, which would give better continuation in predicting future selections.

These assumptions clarified the conditions required for our model and would ensure that our results were effective for analyzing environmental sustainability through 2029

4. Identification of Factors

1. **Longitude (°W) and Latitude (°N)** - These coordinates identify the city's geographic location, which influences climate, weather, and terrain. They help compare cities in terms of regional suitability for hosting large outdoor events like the Super Bowl.

2. **Average Day Temperature (°F)** - These measures typical daytime conditions in the city. Moderate temperatures reduce the risk of weather-related disruptions and improve comfort for players and spectators.

3. **Average Night Temperature (°F)** - Nighttime temperature affects overall climate stability and impacts fan experience during late events.

4. **Air Humidity (%)** - Humidity influences how comfortable the environment feels and can affect field conditions. Lower or moderate humidity generally contributes to better play conditions and spectator comfort.

5. **Wind Speed (mph) -** Wind levels can affect game performance, especially in open stadiums. Lower wind speeds are optimal because they cause less interference and decrease the possibility of weather delays.

6. **Number of Rainy Days (days)** - This indicator reflects weather reliability in a given year. Fewer rainy days mean a lower probability of event disruption, making a city a more attractive host.

7. **Number of Sunny Days (days) -** Number of sunny days is a positive indicator of stable weather conditions. Cities with more sunshine offer a more predictable environment for scheduling major sporting events.

8. **GDP (billion dollars) -** GDP measures the overall economic strength of the city's state. Higher GDP usually indicates better infrastructure, stronger government support, and more capacity to host major events.

9. **Yearly Average Income (dollars) -** Higher average income suggests a stronger local consumer base and greater spending capacity. This supports tourism and the event economy surrounding the Super Bowl.

10. **Population (people) -** Population shows the size of the local market and its ability to support event operations. A larger population usually correlates with more available services, labor, and spectators.

11. **Area (km^2) -** The geographic area provides context on how densely a region is arranged. It also relates to infrastructure planning, transportation systems, and available space for major events.

12. **Population Density (ppl/km^2) -** Density indicates how crowded a region is, which affects transportation and congestion. Moderate density is generally ideal because it is high enough to support attendance but not so high that transportation becomes difficult.

13. **Length of Expressway (mile) -** This measures the extent of major road infrastructure. Longer expressways can support the large influx of visitors during the Super Bowl with less traffic congestion.

14. **Sale of Electricity (Thousand Megawatthours) -** Electricity consumption is an indicator for urban development and economic activity. Higher electricity sales often correlate with developed infrastructure and energy reliability for large events.

15. **Emission of Carbon Dioxide (Thousand Metric Tons) -** CO_2 emissions indicate the city's environmental footprint. Lower emissions suggest cleaner operations and contribute to sustainability objectives for major sports events.

5. Model

5.1. Random Forest and Feature Importance

Random Forest (RF) is an ensemble learning framework in which a large number of decision trees are constructed on bootstrap samples of the original dataset (Breiman, 2001). Each tree is grown using the CART methodology, and at each internal node only a randomly selected subset of predictors is evaluated (Ho, 1998). This dual randomization reduces correlation among trees, stabilizes predictions, and improves generalization performance. Although Random Forest adopts the Gini impurity as its splitting criterion, it is useful to outline the major impurity measures employed in decision tree algorithms—Information Entropy, Information Gain, Gain Ratio, and Gini impurity—as they represent different formalizations of node purity.

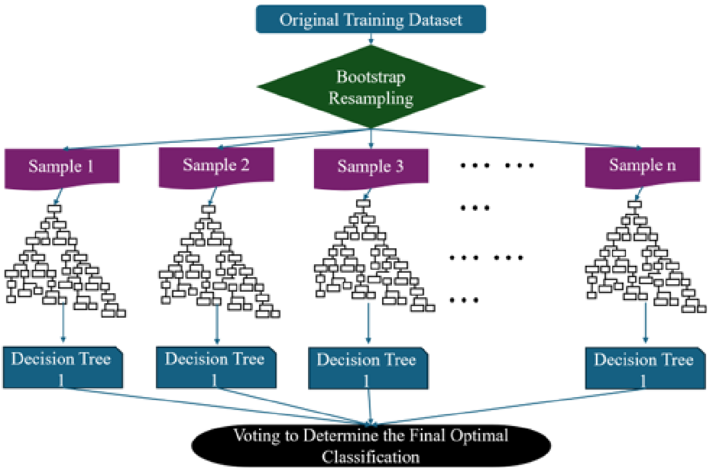

Figure3: The steps of classification of random forest.

5.1.1. Information Entropy and Information Gain (ID3)

Information entropy provides a quantitative measure of class impurity.

Given a node D containing $|Y|$ classes with class proportion p_k:

$$Ent(D)=-\sum_{k=1}^{Y} p_k \log_2 p_k \tag{1}$$

A feature a with V distinct values partitions Dinto subsets $D^{(1)},\ldots,D^{(V)}$.

The expected post-split entropy is:

$$\sum_{v=1}^{V} \frac{|D^{(v)}|}{|D|} Ent(D^{(v)}) \tag{2}$$

The Information Gain of feature a is defined as:

$$Gain(D,a)=Ent(D)-\sum_{v=1}^{V} \frac{|D^{(v)}|}{|D|} Ent(D^{(v)}) \tag{3}$$

5.1.2. Gain Ratio

Information Gain systematically favors attributes with many distinct values.

C4.5 compensates for this by normalizing gain with the intrinsic value (IV):

$$IV(a)=-\sum_{v=1}^{V} \frac{|D^{(v)}|}{|D|} \log_2 \frac{|D^{(v)}|}{|D|} \tag{4}$$

The Gain Ratio is defined as:

$$Gain\_ratio\ (D,a)=\frac{Gain\ (D,a)}{IV(a)} \tag{5}$$

5.1.3. Gini Impurity (CART, Used in Random Forest)

Gini impurity is selected as its splitting criterion. For node D with class proportions p_k:

$$Gini(D)=1-\sum_{k=1}^{Y} p_k^2 \tag{6}$$

If attribute a partitions D into $D^{(1)},\dots,D^{(V)}$, the Gini index of a is calculated by the formula $Gini\_index\ (D,a)=\sum_{v=1}^{V}\frac{|D^{(v)}|}{|D|}Gini(D^{(v)})$. Then we select the attribute minimizing this weighted impurity:

$$a^*=\underset{a\in A}{\operatorname{argmin}}\ Gini\_index(D,a). \tag{7}$$

This is equivalent to maximizing the reduction in Gini impurity.

5.2. Gini Method

5.2.1. Calculated Result for The Weight of Index

Table 1 below shows **the** calculated result for the weight of characteristic by analyzing the data with Gini method in several years.

Table 2: Result for Calculating the Weight of Characteristic with Gini Method.

Factor	Ranking of importance	Weight
Density of population(ppl/km²)	1	0.096546
GDP (billion)	2	0.079851
Air humidity (%)	3	0.074262
Yearly average income(dollar)	4	0.073588
population(person)	5	0.073553
Average day temperature(°F)	6	0.073093
Number of sunny days(day)	7	0.071884
average night temperature(°F)	8	0.06609
Wind speed(mph)	9	0.054347
Emission of carbon dioxide (Thousand Metric Tons)	10	0.051366
Sale of electricity (Thousand Megawatt hours)	11	0.047099
latitude(°N)	12	0.044516
Size of area(km²)	13	0.042559
Number of rainy days(day)	14	0.041428
Emission of nitrogen oxide (Thousand Metric Tons)	15	0.030903
Emission of sulfur oxide (Thousand Metric Tons)	16	0.029409
longitude(°W)	17	0.026464
Length of expressway(mile)	18	0.023042

5.2.2. Application of Model Among Host Cities

First of all, we applied Gini method to demonstrate which of cities that has hosted Super Bowl before should host again. The list of cities has been mentioned above in section2.1 According to the calculated weight for each characteristic, we can use the formula to calculate the specific score each cities get at 2024. Because we use the data of 2019 to train the data of 2020, use the data of 2020 to train the data of 2021, the rest can be done in same manner. Therefore, we got the data of 2024 by using the data of 2023 to train it. Next, according to the calculated weight for each characteristic, we applied the weighted sum model to calculate the specific score for each host city get at 2024.

$$S = \sum_{i=1}^{n} w_i \cdot x_i \tag{8}$$

In the formula, S represents the total score, w_i represents the corresponding weight, x_i represents the original score of one specific element.

This formula is in charge of calculating the sum of total scores that is calculated by multiplying the value of each element by its corresponding importance of weight. Then add all of the individual cal culated product together that represents the score of each element.

The table below shows the calculated result for the ranking and score of host cities in 2024

Table 3: Result for Calculating the Ranking and Score of Host Cities in 2024

Ranking	City	Score
1	Dallas–Fort Worth Metro (Arlington)	626091.5823
2	Houston	582979.3562
3	Miami / Miami Gardens	492687.9434
4	Atlanta	477913.8979
5	Detroit	462944.4537
6	Los Angeles	305929.1676
7	Minneapolis	284858.8465
8	Tampa	267537.4873
9	Indianapolis	171023.9798
10	Jacksonville	152135.5693
11	San Diego	126514.4331
12	East Rutherford (Bergen County)	81981.69414
13	New Orleans	81466.01471
14	Irvine	60025.15615
15	Palo Alto	41239.77358
16	Pasadena	41004.34021
17	Santa Clara	39387.81965
18	Glendale	28698.81079
19	Inglewood	27742.48035

5.2.3. Application of Model Among Potential Host Cities

As we mentioned before, the set of potential host cities we chose are Kansas City (Missouri), Nashville (Tennessee), and Seattle (Washington). And **we applied Gini method to choose the most environmentally sustainable city among the set of potential host cities within the United States. The selected cities in potential host list are Missouri, Tennessee, and Washington.** Similarly, we also applied the weighted sum model to calculate the specific score for each potential host city in 2024.

5.3. Entropy Method

5.3.1. Calculated Result for the Weight of Index

Table 6 below shows the calculated result for the characteristics of characteristic by analyzing the data with Entropy method in several years.

Table 4: Result for Calculating the Weight of Characteristic with Gini Method.

Factor	Ranking of importance	Weight
Density of population(ppl/km^2)	1	0.090966
average night temperature(°F)	2	0.087653
Average day temperature(°F)	3	0.077206
population(person)	4	0.072386
Air humidity (%)	5	0.072149
GDP (billion)	6	0.069115
Number of sunny days(day)	7	0.065353
Yearly average income(dollar)	8	0.053037
Wind speed(mph)	9	0.052133
Emission of carbon dioxide (Thousand Metric Tons)	10	0.049455
Sale of electricity (Thousand Megawatt hours)	11	0.048511
latitude(°N)	12	0.047537
Number of rainy days(day)	13	0.045377
longitude(°W)	14	0.044108
Size of area(km^2)	15	0.043871
Emission of nitrogen oxide (Thousand Metric Tons)	16	0.032898
Length of expressway(mile)	17	0.026661
Emission of sulfur oxide (Thousand Metric Tons)	18	0.021585

5.3.2. Application of Model Among Host Cities

Similarly, we also applied the weighted sum model to calculate the specific score for each host city at 2024.

Table 7 below shows the calculated result for the ranking and score of host cities in 2024.

Table 5: Result for Calculating the Ranking and Score of Potential Host Cities in 2024

Ranking	City	Score
1	Dallas–Fort Worth Metro (Arlington)	615717.542
2	Houston	573319.8724
3	Miami / Miami Gardens	483854.8339
4	Atlanta	469271.92
5	Detroit	454544.2864
6	Los Angeles	299157.1638
7	Minneapolis	278961.4107
8	Tampa	260556.085
9	Indianapolis	167074.3446
10	Jacksonville	149080.9466
11	San Diego	122291.6024
12	New Orleans	79046.93214
13	East Rutherford (Bergen County)	78841.90595
14	Irvine	53455.06399
15	Pasadena	38204.16636
16	Palo Alto	35062.29608
17	Santa Clara	34967.82502
18	Glendale	27235.8372
19	Inglewood	26027.11528

Therefore, we can conclude the top three citites in sustainability, Dellas-Fort Worth Metro (Arlington) is at leading position, followed by Houston and Miami/Miami Gardens respectively.

5.3.3. Application of Model Among Potential Host Cities

Similarly, we also applied the weighted sum model to calculate the specific score for each potential host city in 2024.

The table below shows the calculated result for the ranking and score of potential host cities in 2024.

Table 6: Result for Calculating the Ranking and Score of Potential Host Cities in 2024.

Ranking	City	Score
1	Kansas City	70006.62612
2	Nashville	60037.35732
3	Seattle	14304.25916

This table represents the combined results of the Gini and entropy methods. The top three cities are still Dallas–Fort Worth Metro (Arlington) Houston, Miami / Miami Gardens. Among them, the top one city is Dallas–Fort Worth Metro (Arlington). And the most potential city to host the Super Bowl is Kansas City.

6. Evaluation

This paper builds a clear, data-driven pathway from "sustainability matters" to a practical host-city screening tool. By training a Random Forest on multi-dimensional indicators (climate, transportation, emissions, energy structure, and socioeconomic capacity) from 22 U.S. cities over 2019–2023, the study aims to forecast future environmental indicators (e.g., for 2029) and translate model outputs into interpretable factor weights.

The strongest contribution is the attempt to connect predictive modeling with decision-making: feature-importance results are combined into a composite index, making it easier for planners to compare cities instead of juggling dozens of raw variables.

That said, the conclusions should be treated as "directional" rather than definitive. The analysis depends on several simplifying assumptions—stable policy environments, no extreme disruptions, and reliance on recent years as a baseline—which are reasonable for a first model but can weaken long-horizon forecasts.

Methodologically, Random Forest importance can be sensitive to correlated predictors and scaling choices, so the paper would benefit from robustness checks (e.g., permutation importance or SHAP-style explanations) and clear validation metrics. In addition, the final weighted sum scoring step is easy to communicate, but it can hide trade-offs: a city may score well overall while performing poorly on a critical sustainability dimension.

Overall, the framework is a promising starting point for sustainable event planning, especially if future revisions add uncertainty estimates, stronger validation, and more explicit treatment of event-specific emissions (notably travel).

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