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Choice of Tourist Destinations and Perceived Attractiveness in Benin: An Econometric and Predictive Model

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Abstract

This article highlights the main factors influencing the choice of tourist destinations in Benin, as well as perceptions of their attractiveness. It reveals that these decisions are based primarily on sociodemographic, economic, and environmental variables, including cost, safety, satisfaction, and cultural diversity. The study also emphasizes the importance of structural conditions and service quality in assessing tourist attractiveness. Finally, a comparative analysis of predictive models shows that the XGBoost model outperforms the random forest model, although the latter confirms the relevance of the identified variables.

Keywords

Tourist Destinations, Perceived Appeal, Satisfaction, Econometric and Predictive Model, Benin

1. Introduction

Tourism is now one of the most dynamic and resilient economic sectors worldwide. According to [1], international tourism is one of the sectors that has experienced rapid growth since the end of World War II. Before the health crisis, tourism was among the industries with the fastest growth rates, according to data from the World Tourism Organization. In 2023, international tourism had recovered to approximately 88% of its pre-pandemic level, with nearly 1.3 billion international arrivals and over 1.4 trillion in revenue generated. Its direct contribution to global GDP is estimated at 3.1%, and it accounts for approximately 7% of global service exports [2].

In addition to its macroeconomic impact, tourism plays a cross-cutting role by stimulating many related sectors, such as culture, crafts, agriculture, transportation, telecommunications, and digital services. In Africa, tourism potential is described as "exceptional" [3], due to the continent's wealth of natural and cultural resources [4]. However, despite this potential, tourism's contribution to GDP remains below the global average in several African countries [5].

In Benin, since the 1990s, interest in tourism development has increased, driven by public policies aimed at diversifying sources of economic growth. In 2019, tourism accounted for 6.23% of the national GDP, with approximately 337,000 tourists visiting the country.

Furthermore, although tourism is a valuable source of wealth creation, it is also subject to economic and social fluctuations and uncertainties. The COVID-19 pandemic led to a historic 74% decline in international arrivals in 2020 [6], illustrating the fragility of tourism in the face of global crises. This instability highlights the need for a thorough understanding of tourists' decision-making mechanisms, as their choice of destination results from a complex process influenced by cultural, social, economic, and psychological factors [7]. Tourists' sociodemographic characteristics, destination attributes (price, accessibility, quality of infrastructure), and the sociopolitical context are all variables that can influence the final decision [8] [9].

In the literature, the analysis of destination choice relies primarily on discrete choice models, such as multinomial logistic regression, which is framed within the theoretical framework of stochastic utility. These models make it possible to estimate the probability that a visitor will choose a particular destination from among a set of competing destinations, based on their personal characteristics and the attributes of the destinations. Although these approaches have been widely used internationally, their application to the Beninese context remains relatively unexplored.

With a view to strengthening Benin's international positioning as a destination, the rigorous identification of the factors determining destination choice as well as the perceived attractiveness of tourist sites is essential for guiding public policy and optimizing the tourism offering. A better understanding of visitor preferences not only allows for the effective targeting of tourist segments but also enables the prediction of their behavior in order to anticipate tourist flows and adapt infrastructure and services.

This study, whose primary objective is to identify the factors that determine the choice and perceived attractiveness of tourist destinations in Benin, and then to use tourists' sociodemographic and economic characteristics to predict their destination choices, will examine the study setting, the data, and the methods used for data analysis in Section 2 and 3. The results will be presented in Section 4, followed by a discussion in Section 5, and Section 6 will be devoted to the conclusion.

2. Materials and Methods

2.1. Study Area

This study was conducted in Benin (**Figure 1**), a West African country characterized by geographical and sociocultural diversity, across a range of representative sites covering the country's main tourist areas. It first covers the southern coastal and urban hub, centered on Cotonou, the country's economic capital, and its immediate surroundings, notably Ouidah, a coastal city with significant heritage value marked by the history of the slave trade, as well as Grand-Popo, a seaside

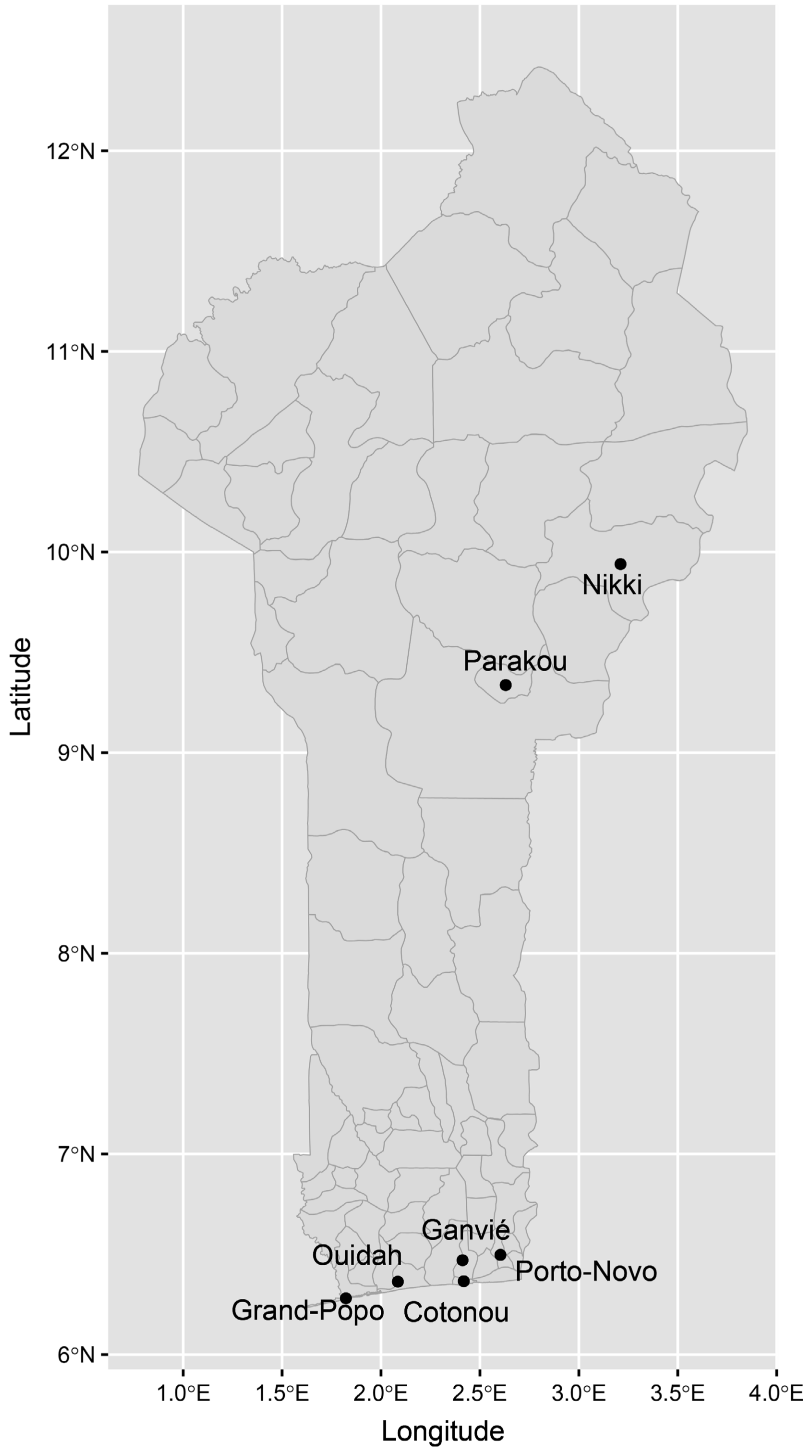

Figure 1. Geographic distribution and spatial representation of the study sites in Benin.

resort renowned for its beaches and biodiversity. The southeastern region is represented by Porto-Novo, the administrative capital with a rich cultural heritage, and by Ganvié, an iconic lakeside village for tourism. The study also extends to the north of the country, covering Parakou, the main urban center of the Borgou department, as well as the commune of Nikki, the cultural hub of the northeast.

2.2. Data Used

The data used comes from a survey of 430 tourists visiting several major sites in Benin between May and September 2025. The tourist sites surveyed include coastal areas such as Fidjrossè and Grand-Popo beaches, the lakeside town of Ganvié, and the royal palaces of Nikki and Parakou. It also includes major heritage and historical sites such as the Gate of No Return, the Slave Route, the open-air museum, Nonvitcha Square, and the Villa Karo Cultural Center in Grand-Popo. Sites of religious and traditional significance, such as the Zangbéto Temple, the Temple of the Pythons, the Abessan Honto Vodun Temple, and the Sacred Forest of Kpassè, have also been included.

3. Methodology

Our work is set within a probabilistic framework defined on a space $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω denotes the set of events, $\mathcal{F}$ a family on Ω, and $\mathbb{P}$ a probability measure. We consider a measurable random vector:

$$X : \Omega \to E,$$

where E is a separable seminormed space such that $E \subset \mathbb{R}^p$ with $p \in \mathbb{N}^*$. The vector X comprises the explanatory variables related to the individual characteristics of the tourists. The response variable is defined by

$$Y : \Omega \to \mathcal{Y},$$

We observe an independent and identically distributed sample with joint distribution $\mathbb{P}_{X,Y}$.

$$\mathcal{D}_n = \{(X_i, Y_i)\}_{i=1}^n, \quad (X_i, Y_i) \sim \text{i.i.d.}$$

We assume that, for all $x \in E$, the conditional distribution exists and characterizes the probabilistic mechanism generating the observed choices.

3.1. Multinomial Logistic Regression Model

To examine the relative probability of choosing a destination compared to a reference destination, we consider a multinomial logistic regression model. For $k = 1, \cdots, K-1$, where K denotes the number of different types of destinations. The model is written as:

$$\log\left(\frac{\pi_{i,k}}{\pi_{i,K}}\right) = \beta_{0,k} + \beta_{1,k} x_{i,1} + \cdots + \beta_{p,k} x_{i,p} = X_i^\top \beta_k, \tag{1}$$

where $X_i = (1, x_{i,1}, \cdots, x_{i,p})^\top$ et $\beta_k = (\beta_{0,k}, \cdots, \beta_{p,k})^\top$

$$\pi_k(x) = \mathbb{P}(Y = k \mid X = x) \tag{2}$$

s the parameter vector associated with destination k, and $\pi_{i,k}$ is the probability of choosing a given destination.

The predicted probabilities are given by:

$$\pi_{i,k} = \begin{cases} \dfrac{\exp\left(X_i^\top \beta_k\right)}{1 + \sum_{l=1}^{K-1} \exp\left(X_i^\top \beta_l\right)}, & k = 1, \cdots, K-1, \\ \dfrac{1}{1 + \sum_{l=1}^{K-1} \exp\left(X_i^\top \beta_l\right)}, & \text{for } k = K. \end{cases}$$

The full parameter vector is $\beta = \{\beta_1, \cdots, \beta_{K-1}\}$ and is estimated using the maximum likelihood method. The likelihood function is given by:

$$L(\beta) = \prod_{i=1}^{n} \prod_{k=1}^{K} \pi_{i,k}^{\mathbb{I}(Y_i = k)}, \tag{3}$$

and the corresponding log-likelihood:

$$\ell(\beta) = \sum_{i=1}^{n} \sum_{k=1}^{K} \mathbb{I}(Y_i = k) \log(\pi_{ik}). \tag{4}$$

Due to the nonlinearity of the model, the parameters are obtained through numerical optimization using the Newton-Raphson algorithm, which is based on iteration:

$$\beta^{(h+1)} = \beta^{(h)} - \left[\nabla^2 \ell\left(\beta^{(h)}\right)\right]^{-1} \nabla \ell\left(\beta^{(h)}\right), \tag{5}$$

where h denotes the iteration.

3.2. Ordinal Logistic Model

Since the perceived attractiveness of the destinations is ordered, we adopt an ordinal logistic model with proportional odds.

For $j = 1, \cdots, K-1$, the model is written as:

$$\log\left(\frac{\mathbb{P}(Y_i \le j \mid X_i)}{\mathbb{P}(Y_i > j \mid X_i)}\right) = \alpha_j + \beta^\top X_i, \tag{6}$$

We obtain the cumulative probabilities:

$$\mathbb{P}(Y_i \le j \mid X_i) = \frac{\exp\left(\alpha_j + \beta^\top X_i\right)}{1 + \exp\left(\alpha_j + \beta^\top X_i\right)}. \tag{7}$$

where α_j is the intercept associated with category j and β is the vector of coefficients common to all categories.

The central assumption of the model is that of proportional odds: the vector β is identical for all categories of the variable of interest; only the intercepts α_j vary.

This model allows us to identify the factors influencing the cumulative probability of belonging to an attractiveness level at most equal to j, while taking into account the natural order of the categories.

The full vector of parameters is estimated using the maximum likelihood method. The likelihood function is written as:

$$L(\theta) = \prod_{i=1}^{n} \prod_{k=1}^{K} \pi_{ik}^{\mathbb{I}(Y_i = k)}, \tag{8}$$

and the corresponding log-likelihood:

$$\ell(\theta) = \sum_{i=1}^{n} \sum_{k=1}^{K} \mathbb{I}(Y_i = k) \log(\pi_{ik}). \tag{9}$$

3.3. Random Forests

Random Forests are an ensemble model based on the aggregation of decision trees constructed independently using the bagging principle. Introduced by [10], this approach aims primarily to reduce the variance of a single tree while maintaining low correlation among the individual models.

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$ be a training sample. For each tree $b = 1, \cdots, B$, a bootstrap sample $\mathcal{D}^{(b)}$ is drawn with replacement from $\mathcal{D}$. At each node, a random selection of m variables from among p predictors ($m < p$) is considered to determine the best partition.

The aggregated predictor is given by:

$$\hat{y}_i = \frac{1}{B} \sum_{b=1}^{B} f_b(x_i) \tag{10}$$

In regression, where f_b denotes the b-th tree.

In classification, the prediction is based on a majority vote:

$$\hat{y}_i = \text{mode}\{f_b(x_i)\}_{b=1}^{B}. \tag{11}$$

Each tree is very deep, which results in low bias but high variance; aggregation then helps stabilize the predictions. Random selection of observations (bootstrapping) and explanatory variables ensures that the trees differ from one another, which improves the overall accuracy of the predictions.

The total variance of a prediction $\hat{f}_{RF}(x)$ can be formalized as follows:

$$\text{Var}\left(\hat{f}_{RF}(x)\right) = \rho\sigma^2 + \frac{1-\rho}{N}\sigma^2, \tag{12}$$

where ρ is the average correlation coefficient between two trees, σ^2 is the variance of a single tree, and N is the total number of trees in the forest. The method also allows for estimating the importance of explanatory variables using measures such as the **mean decrease in impurity** or the **mean decrease in accuracy**, and for evaluating the model's performance without explicit cross-validation using *Out-of-Bag* (OOB) observations.

3.4. Extreme Gradient Boosting

Boosting is an ensemble method that uses sequential aggregation to reduce the bias of a basic model with low bias and high variance. Each model uses information from previous models and seeks to improve the prediction.

[11] proposed *XGBoost*, a regularized and optimized version of gradient boosting. The model is additive and is written as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F}, \tag{13}$$

where each f_k is a decision tree belonging to the space $\mathcal{F}$.

The estimation is based on minimizing a penalized objective function:

$$\mathcal{L} = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \tag{14}$$

where ℓ denotes the loss function (mean squared error in regression or log-loss in classification) and introduces regularization on the complexity of the trees.

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_j w_j^2, \tag{15}$$

where T is the number of leaves and w_j are the weights associated with the leaves.

The optimization is performed sequentially using a second-order Taylor approximation of the loss function, utilizing the gradient and the Hessian. The trees are constructed by maximizing an analytical gain associated with the partitions, and the predictions are updated according to:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta w_{q(x_i)}^{*}, \tag{16}$$

where η is the learning rate and $q(x_i)$ denotes the leaf to which the observation x_i is associated.

4. Results

4.1. Descriptive Analysis

In this section, several variables were examined: the destination, the destination's perceived appeal among tourists, and the tourists' country of origin.

The breakdown of tourist destination types (**Figure 2**) reveals a marked predominance of cultural and historical destinations, which account for 44.2% of the sample. This high proportion suggests that a significant share of tourists are motivated by a desire to explore local heritage, history, and traditions. This result likely reflects the promotion of the national cultural offering and the particular appeal of most historical sites in the study area. Spiritual destinations (26.7%) reflect a growing interest in spiritual well-being. Community destinations (14.4%) and seaside destinations (14.7%) have similar shares, indicating a diversification of motivations between authentic encounters and coastal leisure activities.

The distribution of perceived destination attractiveness (**Figure 3**) shows that the "strong" category clearly dominates over the others. This result indicates that most destinations in the sample are considered particularly attractive, reflecting either a high quality of tourism offerings or a good match between tourists'

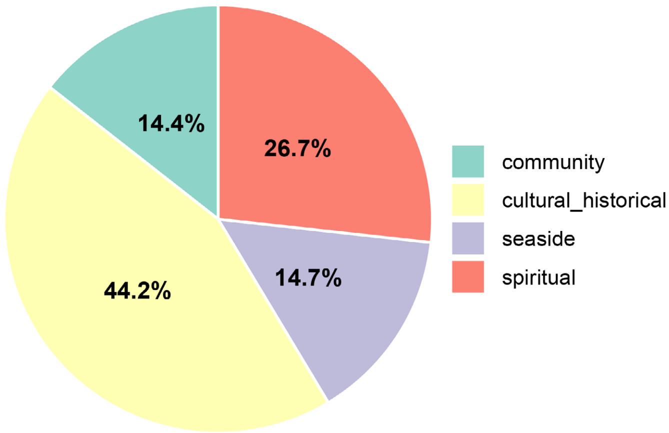

Figure 2. Breakdown of tourist destinations.

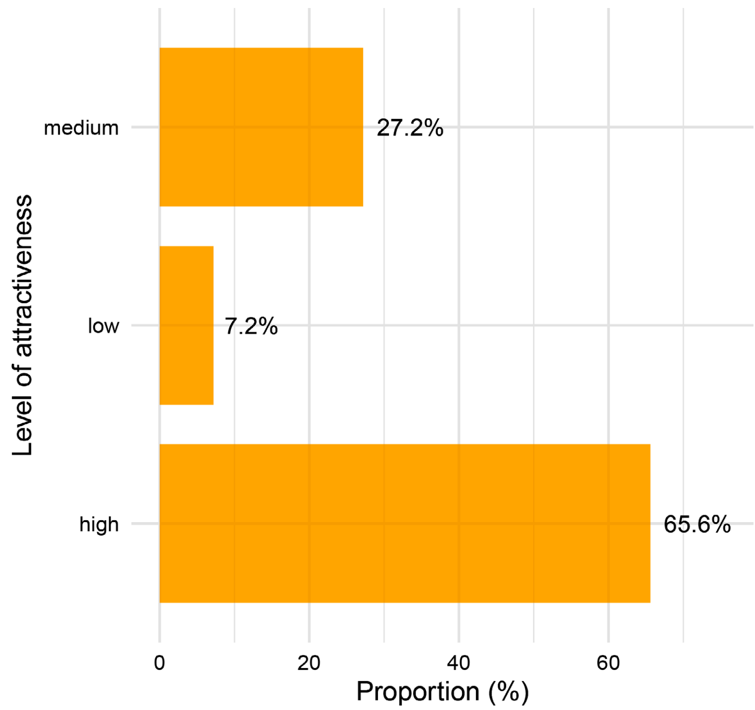

Figure 3. Distribution of the perceived attractiveness of destinations.

expectations and the destinations' characteristics. The low frequency of the "low" rating indicates an overall positive perception, while also identifying room for improvement for a small number of less attractive sites.

An analysis of tourist origins shows that Benin attracts visitors from several continents (**Figure 4**). The significant presence of tourists from Nigeria, Senegal, Togo, Gabon, and other countries underscores the importance of regional tourism, which is facilitated by easy access and cross-border exchanges. Benin thus emerges as a major regional tourism hub. The presence of visitors from Europe (France, Belgium, Germany) and the Americas (Canada, United States) attests to the international appeal of Benin's tourism offerings. This positive trend can be attributed to several government initiatives, notably: the modernization and

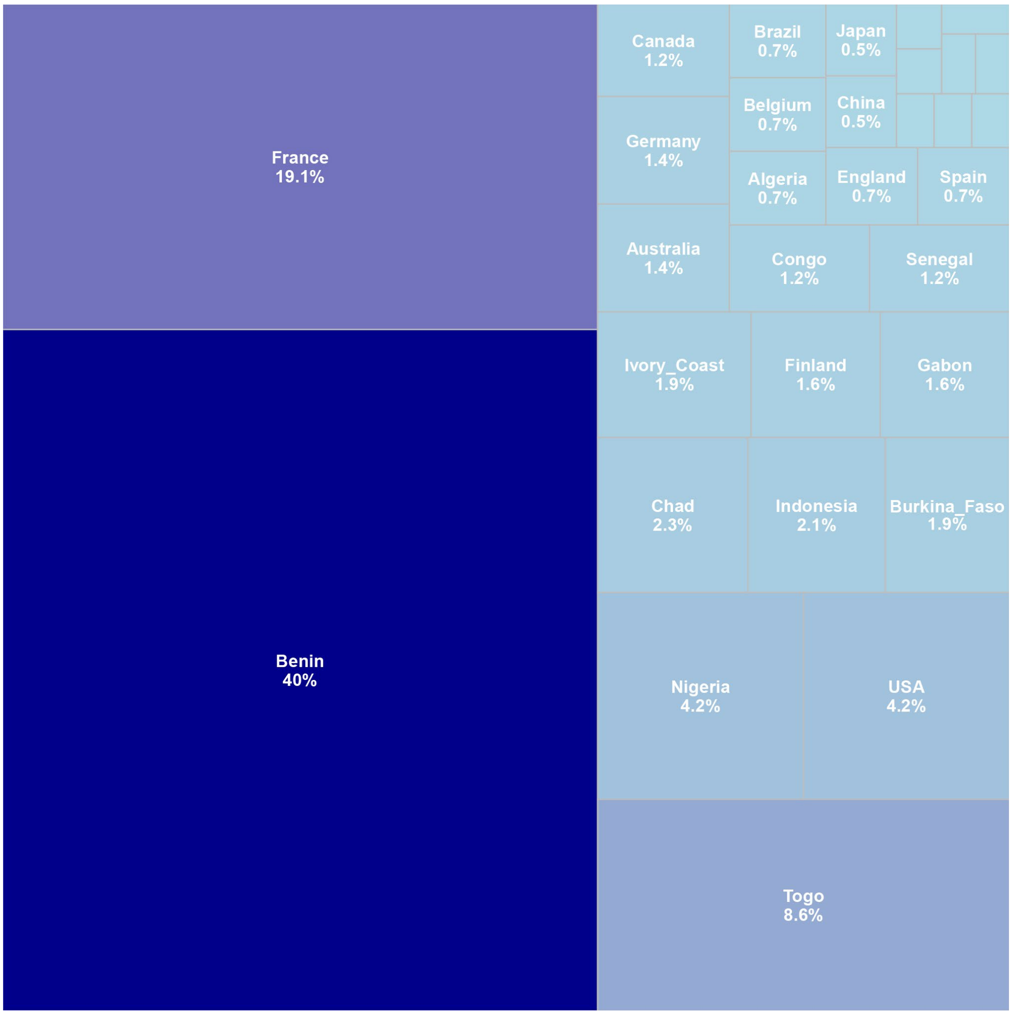

Figure 4. Breakdown of tourists by country of origin.

restoration of certain tourist sites, the implementation of the e-Visa, the promotion of intangible cultural heritage, and the enhancement of site security.

To deepen our analysis, we compared several variables using a graphical representation.

Figure 5 reveals marked differences in destination choices between men and women. Spiritual destinations attract 58.3% of female visitors, while other destinations attract more than 60% of men. We therefore conclude that women express a greater need for transformative experiences and personal development. This disparity suggests that certain tourism offerings specifically target a female audience, possibly for reasons of safety or thematic suitability.

The following box plot reveals significant differences in the distances traveled depending on the type of destination (Figure 6). The **spiritual** destination has the highest medians, indicating long-distance appeal. In contrast, community destinations primarily attract local or regional visitors. The variation in distances for cultural and historical sites contrasts with the consistency seen among beach destinations.

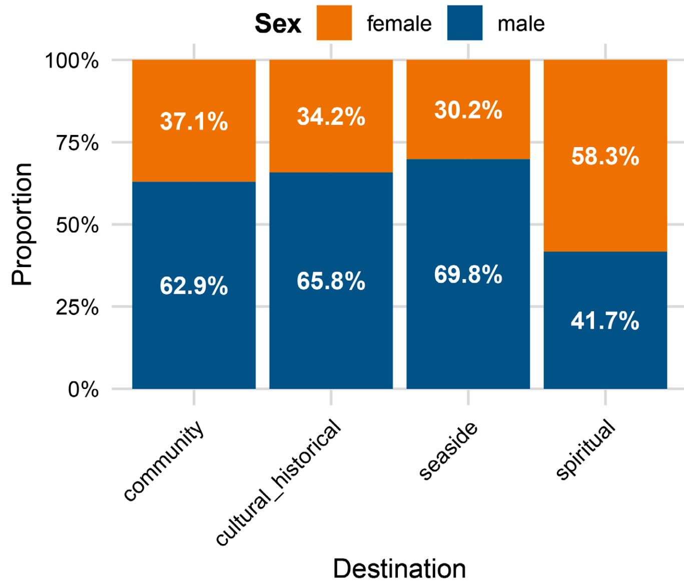

Figure 5. Visitor numbers by gender.

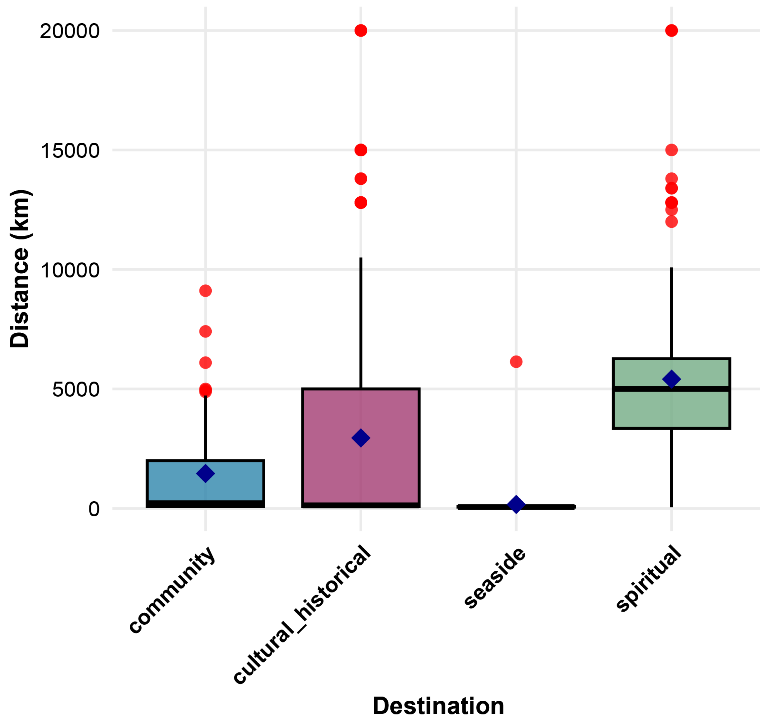

Figure 6. Distance traveled by destination.

4.2. Multivariate Analysis

4.2.1. Multinomial Logistic Regression

Backward selection based on the Akaike Information Criterion (AIC) reduced the initial model of 29 variables to a parsimony-based model of 19 explanatory variables, with a notable decrease in the AIC (from 845.02 to 796.64).

The multinomial logistic regression analysis shows that several variables are statistically significant, indicating that they influence the choice of tourist destination relative to the **community** reference. Among these variables are: age, gender, marital status, education level, monthly income, distance, reason for visit, average expenditure, cost of living at the destination, transportation costs, attractiveness, as well as certain satisfaction indicators such as facilities and accommodations, safety, and weather conditions.

Conversely, certain variables prove to be insignificant, such as length of stay, as well as certain aspects of marital status, educational level, reason for the visit, and perceived attractiveness. This suggests that, statistically speaking, these factors have no demonstrable influence on tourists' choice of seaside destination.

- **Seaside Destination**

Table 1 reveals that the probability of choosing a seaside destination over a

Table 1. Multinomial logistic regression (seaside vs community).

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
(Intercept)	6.279	24.823	0.253	0.800	533.055
age (ref.: 26_50)					
under_26	0.584	0.828	0.706	0.480	1.794
over_50	4.647	1.536	3.025	**0.002**	104.242
sex (ref.: female)					
male	−0.859	0.690	−1.245	0.213	0.423
education_level (ref.: others)					
primary	−6.017	2.329	−2.584	**0.010**	0.002
secondary	−3.748	2.135	−1.755	0.079	0.024
university	−4.056	2.127	−1.907	0.057	0.017
marital_status (ref.: single)					
divorced	−14.420	0.001	−20151.704	**0.000**	0.000
married	0.564	0.705	0.800	0.424	1.758
widowed	−8.893	110.579	−0.080	0.936	0.000
monthly_income (ref.: 500000_1000000)					
below_500000	−1.363	1.707	−0.798	0.425	0.256
above_1000000	3.908	2.279	1.715	0.086	49.820
average_expenditure (ref.: 200000_500000)					
below_200000	1.665	1.627	1.024	0.306	5.288
above_500000	−2.069	2.930	−0.706	0.480	0.126
cost_of_living (ref.: high)					
low	2.464	1.325	1.859	0.063	11.749
moderate	4.435	1.044	4.248	**0.000**	84.344
transport_cost (ref.: acceptable)					
cheap	−2.912	0.824	−3.533	**0.000**	0.054

Continued

expensive	−4.979	1.392	−3.578	**0.000**	0.007
transport_mode (ref.: other)					
plane	−4.086	2.676	−1.527	0.127	0.017
bus	−2.096	1.018	−2.059	**0.039**	0.123
taxi	−1.694	1.023	−1.656	0.098	0.184
private_car	−0.962	1.302	−0.739	0.460	0.382
distance	−0.747	1.762	−0.424	0.671	0.474
attractiveness (ref.: high)					
low	1.240	1.016	1.221	0.222	3.457
medium	−0.949	0.755	−1.258	0.209	0.387
cultural_event_participation (ref.: no)					
yes	2.280	0.817	2.790	**0.005**	9.780
facilities_and_accommodation (ref.: not satisfied)					
satisfied	−4.980	1.197	−4.159	**0.000**	0.007
tourism_infrastructure (ref.: not satisfied)					
satisfied	1.482	0.995	1.490	0.136	4.404
security (ref.: not satisfied)					
satisfied	−1.058	0.964	−1.098	0.272	0.347
weather_conditions (ref.: sunny)					
cloudy_no_rain	−4.083	1.613	−2.532	**0.011**	0.017
frequent_rain	−3.825	1.121	−3.413	**0.001**	0.022
variable_weather	−5.144	1.252	−4.108	**0.000**	0.006
visit_purpose (ref.: other)					
adventure	1.196	24.614	0.049	0.961	3.307
culture	3.420	24.591	0.139	0.889	30.557
relaxation	3.341	24.590	0.136	0.892	28.242
social_meetings	5.942	24.605	0.242	0.809	380.805
spirituality	−8.501	122.879	−0.069	0.945	0.000
length_of_stay	−1.373	0.777	−1.766	0.077	0.253
nearby_destination (ref.: no)					
yes	−0.939	0.753	−1.248	0.212	0.391

community-based destination is influenced by a range of socioeconomic, cultural, and contextual variables. The results show that, with a 5% margin of error, age, education level, marital status, cost of living and transportation, participation in cultural events, quality of facilities and accommodations, as well as weather conditions have a significant influence on the choice of this type of destination compared to tourists aged 26 to 50. In particular, tourists over the age of 50 are much more likely to choose a seaside destination. Conversely, those who are divorced are significantly less attracted to this type of destination.

The results also show that tourists who perceive the cost of living to be moderate and transportation costs to be affordable are more likely to prefer beach destinations over community-oriented ones. Furthermore, participation in cultural events increases the likelihood of choosing a beach destination by a factor of 9.78, reflecting the importance of cultural and social factors in visitors' motivations. Conversely, satisfaction with accommodations significantly reduces the likelihood of choosing this type of destination, which can be explained by a hospitality offering that is sometimes standardized and less focused on the authenticity sought by certain types of tourists. Similarly, tourists who visited the sites under unfavorable weather conditions notably characterized by cloudy skies without precipitation, frequent rain, or variable weather are significantly less likely to choose a seaside destination, highlighting this tourist destination's high sensitivity to weather fluctuations.

These findings suggest that the development of coastal tourism in Benin should be based on a strategy that combines improvements in the quality of hospitality infrastructure, the diversification of recreational and cultural activities, and the sustainable management of the coastline. By investing in the modernization of tourism facilities, the promotion of enriching experiences, and responsible environmental management, it would be possible to enhance the competitiveness and appeal of coastal areas.

- **Cultural & Historical Destination**

Table 2 reveals that the probability of choosing a cultural and historical destination over a community-based destination is influenced by several socioeconomic, cultural, and contextual variables. The results show that at the 5% significance level, age, marital status, monthly income, average spending, cost of living and transportation, distance, perceived attractiveness, participation in cultural events, quality of infrastructure, safety, weather conditions, and the reason for the visit have a significant influence on the choice of this type of destination. In particular, tourists over the age of 50 are much more likely to choose a cultural and historical destination (OR = 19.18), reflecting a preference for educational and heritage-focused travel. Conversely, divorced individuals or those with a monthly income below 500,000 CFA francs are significantly less likely to choose this type of destination, suggesting that social status and purchasing power influence tourism choices.

The results also indicate that tourists who perceive the cost of living at the destination to be moderate (OR = 18.66) and who spend less than 200,000 CFA francs (OR = 7.02) are more likely to prefer a cultural and historical destination, unlike those who consider transportation costs to be too low or too high. Furthermore, distance and perceived attractiveness play a decisive role: the more the destination is perceived as distant and attractive, the higher the probability of being drawn to it (OR = 11.88 and 8.41, respectively). Participation in cultural

Table 2. Multinomial logistic regression (cultural_historical vs community)

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
(Intercept)	6.566	2.922	2.247	**0.025**	710.212
age (ref.: 26_50)					
under_26	−0.192	0.725	−0.265	0.791	0.825
over_50	2.954	1.210	2.442	**0.015**	19.177
sex (ref.: female)					
male	−0.657	0.577	−1.140	0.254	0.518
education_level (ref.: others)					
primary	−1.979	2.227	−0.888	0.374	0.138
secondary	−0.148	2.081	−0.071	0.943	0.862
university	−0.820	2.114	−0.388	0.698	0.441
marital_status (ref.: single)					
divorced	−2.455	1.099	−2.234	**0.026**	0.086
married	0.675	0.600	1.126	0.260	1.965
widowed	1.763	58.595	0.030	0.976	5.827
monthly_income (ref.: 500000_1000000)					
less_500000	−2.323	1.042	−2.230	**0.026**	0.098
more_1000000	1.128	1.148	0.982	0.326	3.089
average_expenditure (ref.: 200000_500000)					
less_200000	1.949	0.991	1.967	**0.049**	7.022
more_500000	−1.651	1.009	−1.636	0.102	0.192
cost_of_living (ref.: high)					
low	0.377	0.938	0.402	0.688	1.457
moderate	2.927	0.870	3.364	**0.001**	18.662
transport_cost (ref.: acceptable)					
cheap	−2.100	0.679	−3.094	**0.002**	0.122
expensive	−3.067	1.004	−3.054	**0.002**	0.047
mode_of_transport (ref.: other)					
plane	−2.373	1.379	−1.721	0.085	0.093
bus	−1.615	0.907	−1.781	0.075	0.199
taxi	−1.608	0.952	−1.689	0.091	0.200
personal_car	−0.104	1.127	−0.092	0.927	0.901
distance	2.475	0.764	3.238	**0.001**	11.879
attractiveness (ref.: high)					
low	2.130	0.668	3.187	**0.001**	8.413

Continued

medium	−1.199	0.567	−2.114	**0.035**	0.302
cultural_event_participation (ref.: no)					
yes	1.885	0.684	2.754	**0.006**	6.585
facilities_and_accommodation (ref.: not satisfied)					
satisfied	−4.067	1.087	−3.741	**0.000**	0.017
tourism_infrastructure (ref.: not satisfied)					
satisfied	2.418	0.891	2.715	**0.007**	11.223
security (ref.: not satisfied)					
satisfied	−1.913	0.778	−2.460	**0.014**	0.148
weather_conditions (ref.: dominant sunshine)					
cloudy_no_rain	−2.163	1.064	−2.033	**0.042**	0.115
frequent_rain	−3.054	0.991	−3.081	**0.002**	0.047
variable_weather	−5.062	1.169	−4.328	**0.000**	0.006
purpose_of_visit (ref.: other)					
adventure	3.025	0.900	3.361	**0.001**	20.586
culture	3.783	0.762	4.967	**0.000**	43.936
relaxation	3.146	0.738	4.264	**0.000**	23.234
social_interactions	5.877	1.074	5.471	**0.000**	356.864
spirituality	1.085	1.236	0.878	0.380	2.960
length_of_stay	−0.373	0.307	−1.216	0.224	0.689
nearby_destination (ref.: no)					
yes	−1.756	0.608	−2.888	**0.004**	0.173

events is also associated with an increase in this probability (6.58 times higher odds), as is satisfaction with tourism infrastructure (OR = 11.22), confirming the importance of the cultural setting, facilities, and local atmosphere in the appeal of historic sites. Conversely, satisfaction with accommodations and safety significantly reduces the likelihood of choosing such a destination, which can be explained by tourists' higher expectations regarding comfort and safety.

Finally, travel motivations related to adventure, culture, relaxation, and social interaction have a very significant influence, increasing the likelihood of choosing a cultural and historical destination by factors ranging from 20 to over 350. Conversely, unfavorable weather conditions (cloudy skies without precipitation, frequent rain, and changeable weather) significantly reduce this probability, highlighting this tourism segment's dependence on favorable weather conditions.

These results suggest that the development of cultural and historical tourism in Benin should be based on the promotion of tangible and intangible heritage, the enhancement of cultural infrastructure, and improvements in the comfort and safety of sites. By investing in the creation of regular cultural events and the promotion of immersive experiences, it would be possible to enhance the appeal of this segment while contributing to the preservation of the national heritage and the sustainable diversification of Benin's tourism offerings.

- **Spiritual Destination**

Table 3 shows that the likelihood of choosing a spiritual destination over a community destination is influenced by several variables, such as age, gender, monthly income, average spending, cost of living and transportation, distance,

Table 3. Multinomial logistic regression (spiritual vs community).

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
(Intercept)	6.798	53.555	0.127	0.899	896.501
age (ref.: 26_50)					
under_26	0.790	0.830	0.952	0.341	2.204
over_50	3.288	1.279	2.571	**0.010**	26.788
sex (ref.: female)					
male	−1.723	0.601	−2.867	**0.004**	0.178
education_level (ref.: others)					
primary	1.259	67.057	0.019	0.985	3.521
secondary	5.240	67.042	0.078	0.938	188.760
university	5.439	67.042	0.081	0.935	230.301
marital_status (ref.: single)					
divorced	−1.599	1.105	−1.447	0.148	0.202
married	0.669	0.689	0.970	0.332	1.951
widowed	7.363	58.604	0.126	0.900	1576.663
monthly_income (ref.: 500000_1000000)					
under_500000	−3.193	1.067	−2.991	**0.003**	0.041
over_1000000	−0.308	1.142	−0.270	0.787	0.735
average_expenditure (ref.: 200000_500000)					
under_200000	2.173	1.088	1.996	**0.046**	8.782
over_500000	−0.030	1.008	−0.030	0.976	0.970
cost_of_living (ref.: high)					
low	1.477	1.110	1.330	0.183	4.378
moderate	3.056	1.018	3.002	**0.003**	21.252
transport_cost (ref.: acceptable)					
cheap	−1.988	0.772	−2.576	**0.010**	0.137
expensive	−2.842	1.080	−2.631	**0.009**	0.058

Continued

mode_of_transport (ref.: other)					
plane	0.182	1.620	0.112	0.911	1.199
bus	2.455	1.424	1.724	0.085	11.645
taxi	0.970	1.453	0.667	0.504	2.637
personal_car	2.205	1.568	1.407	0.159	9.073
distance	2.932	0.771	3.806	**0.000**	18.771
attractiveness (ref.: high)					
low	2.865	0.792	3.616	**0.000**	17.543
medium	−1.280	0.653	−1.962	**0.050**	0.278
participation_in_cultural_events (ref.: no)					
yes	2.735	0.726	3.767	**0.000**	15.404
facilities_and_accommodation (ref.: not satisfied)					
satisfied	−4.048	1.127	−3.592	**0.000**	0.017
tourism_infrastructure (ref.: not satisfied)					
satisfied	2.248	0.973	2.311	**0.021**	9.464
security (ref.: not satisfied)					
satisfied	0.103	0.947	0.109	0.913	1.109
weather_conditions (ref.: predominantly sunny)					
cloudy_no_rain	−2.267	1.198	−1.893	0.058	0.104
frequent_rain	−3.971	1.064	−3.734	**0.000**	0.019
variable_weather	−6.468	1.255	−5.153	**0.000**	0.002
purpose_of_visit (ref.: other)					
adventure	−6.417	13.573	−0.473	0.636	0.002
culture	−7.461	13.566	−0.550	0.582	0.001
relaxation	−8.943	13.565	−0.659	0.510	0.000
social_interactions	−8.058	13.603	−0.592	0.554	0.000
spirituality	−6.973	13.588	−0.513	0.608	0.001
length_of_stay	0.078	0.315	0.247	0.805	1.081
nearby_destination (ref.: no)					
yes	−1.021	0.649	−1.572	0.116	0.360

perceived attractiveness, participation in cultural events, quality of tourism infrastructure, facilities and accommodations, as well as weather conditions. In particular, tourists over the age of 50 are significantly more likely to choose a spiritual destination (OR = 26.79), reflecting a heightened interest in introspective and symbolic experiences. In contrast, men and individuals with a monthly income below 500,000 CFA francs are significantly less likely to choose this type of destination, suggesting that spiritual tourism appeals more to women and individuals with a higher income level.

The results also show that tourists with low average spending (less than 200,000 CFA francs) who perceive the cost of living to be moderate are more likely to choose a spiritual destination, reflecting a preference for accessible environments that offer a setting conducive to tranquility and meditation. Furthermore, participation in cultural events (OR = 15.40) and a positive perception of tourism infrastructure (OR = 9.46) significantly increase this likelihood, reflecting the close link between spirituality, culture, and regional ties. Conversely, satisfaction with accommodations significantly reduces the likelihood of choosing this type of destination (OR = 0.017), likely because spiritual experiences are often had in simple, unadorned settings. The positive coefficients associated with distance (OR = 18.77) and perceived attractiveness (OR = 17.54) also suggest that tourists are willing to travel longer distances to experience spiritual encounters deemed unique and meaningful.

Finally, adverse weather conditions such as frequent rain (OR = 0.019), changeable weather (OR = 0.002), or cloudy skies significantly reduce the likelihood of choosing a spiritual destination, highlighting the vulnerability of spiritual tourism to weather fluctuations.

These results therefore suggest that the development of spiritual tourism in Benin should be based on a strategy aimed at promoting sacred sites and places of worship with strong symbolic significance, while improving access, basic infrastructure, the integration of cultural activities, and the preservation of the natural environment, it would be possible to enhance the attractiveness and sustainability of this rapidly emerging tourism segment.

4.2.2. Ordinal Regression

To analyze the perceived attractiveness of destinations, an ordinal logistic regression was estimated. The top-down selection procedure based on the AIC criterion led to the selection of a parsimony-based ordered logistic model, reducing the number of explanatory variables from sixteen (16) to nine (9), while significantly improving the model fit, as indicated by the decrease in the AIC from 630.12 to 617.7965.

- **Seaside Destination**

Analysis of the ordered logistic regression model (**Table 4**) reveals that several variables have a significant impact on the perceived attractiveness of seaside destinations in Benin.

The distance variable, which is significant at the 5% threshold, indicates that the more accessible or closer a destination is, the more attractive it is perceived to be by tourists. A cost of living perceived as low or moderate has a negative effect, suggesting that tourists prefer destinations where the relative cost is reasonable but not excessively low. The quality of the environment, which received a level of satisfaction deemed positive by tourists, and political and social stability enhance attractiveness, indicating that tourists value safety and the environmental setting.

Table 4. Ordinal regression for seaside destination.

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
low|medium	−30.960	9.989	−3.099	**0.002**	0.00
medium|high	−25.733	9.985	−2.577	**0.010**	0.00
distance	39.980	14.478	2.761	**0.006**	2.31e17
low_cost_of_living	−4.709	0.657	−7.163	**0.000**	0.009
moderate_cost_of_living	−0.739	0.260	−2.841	**0.004**	0.477
environment_quality_satisfied	2.472	0.273	9.048	**0.000**	11.85
stable_political_social_situation	0.938	0.219	4.285	**0.000**	2.555
visit_purpose_culture	2.609	0.573	4.556	**0.000**	13.584
visit_purpose_relaxation	4.986	0.579	8.610	**0.000**	146.42
visit_purpose_social_meetings	4.978	0.616	8.078	**0.000**	145.234
tourism_infrastructure_satisfied	−0.759	0.280	−2.708	**0.007**	0.468
security_satisfied	−2.918	0.349	−8.365	**0.000**	0.054
welcome_and_information_satisfied	−0.851	0.720	−1.181	0.238	0.427
cultural_diversity_satisfied	0.230	0.215	1.074	0.283	1.259

Furthermore, the reasons for visiting whether for culture, relaxation, or social interaction are highly significant and have a marked positive effect, reflecting the diversity of tourist expectations and the importance of tailoring the tourism offering to these different motivations. Conversely, the variables hospitality and information and cultural diversity are not significant, suggesting that they have a limited influence on the immediate perception of the attractiveness of seaside destinations.

The *low|medium* and *medium|high* thresholds indicate that there are perceptible differences between levels of attractiveness, although these differences are not uniform across all categories of variables.

Overall, it is primarily factors related to distance, cost of living, environmental quality, socio-political stability, and reasons for visiting that determine how attractive seaside destinations are perceived to be. This shows that tourists do not judge destinations solely on material or logistical criteria, but also on qualitative and contextual criteria that influence their perceived experience.

- **Community Destination**

As shown in Table 5, several variables significantly influence the perceived attractiveness of EU destinations, while others have no notable effect.

Significant variables include the cost of living at the destination, the socio-political situation, reasons for visiting, tourist infrastructure, safety, hospitality and information, and cultural diversity. The positive effect of low and moderate cost of living at the destination suggests that tourists prefer EU destinations where the relative cost is affordable but perceived as offering good value for money.

Table 5. Ordinal regression for community destination.

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
low|medium	4.603	0.368	12.491	**0.000**	99.738
medium|high	6.833	0.398	17.182	**0.000**	927.968
distance	−0.514	0.132	−3.880	**0.000**	0.598
low_cost_of_living	3.036	0.193	15.722	**0.000**	20.830
moderate_cost_of_living	1.685	0.162	10.430	**0.000**	5.392
satisfied_environmental_quality	−1.588	0.172	−9.227	**0.000**	0.204
stable_political_social_situation	1.733	0.129	13.465	**0.000**	5.658
visit_purpose_culture	1.554	0.270	5.759	**0.000**	4.729
visit_purpose_relaxation	1.406	0.281	4.994	**0.000**	4.078
visit_purpose_social_meetings	0.007	0.320	0.023	0.982	1.007
visit_purpose_spirituality	1.031	0.329	3.128	**0.002**	2.803
satisfied_tourism_infrastructure	1.630	0.149	10.907	**0.000**	5.103
satisfied_security	2.485	0.176	14.145	**0.000**	12.002
satisfied_reception_and_information	−0.449	0.146	−3.076	**0.002**	0.638
satisfied_cultural_diversity	0.899	0.162	5.550	**0.000**	2.457

A stable political and social situation and safety significantly enhance attractiveness, underscoring the importance visitors place on a safe and stable environment. The reasons for visiting, whether related to culture, relaxation, or spirituality, are also significant and positive, reflecting the diversity of tourist expectations and the influence of personal motivation on the perception of attractiveness. Conversely, distance has a negative and significant effect, while certain reasons for visiting, such as social gatherings and the quality of the environment, have less influence on perceived attractiveness.

- **Historic and Cultural Destination**

Analysis of the ordered logistic regression model (Table 6) reveals that the perceived attractiveness of cultural-historical destinations is influenced by a combination of logistic, contextual, and motivational factors.

Distance has a marked negative effect ($\beta = -0.50$), indicating that the distance from a cultural-historical destination reduces the likelihood of it being perceived as attractive. Cost of living has a positive effect at low and moderate levels, suggesting that tourists value affordable cultural and historical sites. A satisfactory environmental quality and a stable socio-political situation enhance perceived attractiveness, underscoring the importance of a safe and pleasant setting.

The reasons for visiting show contrasting effects: culture, relaxation, and social interaction significantly increase attractiveness, while spirituality reduces the likelihood that the destination will be perceived as attractive, reflecting the diversity of tourists' expectations. Furthermore, variables such as tourism infrastructure,

Table 6. Ordinal regression for cultural_historical destination.

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
low|medium	2.210	0.238	9.270	**0.000**	9.117
medium|high	5.047	0.251	20.095	**0.000**	155.548
distance	−0.503	0.035	−14.430	**0.000**	0.604
low_cost_of_living	0.669	0.153	4.375	**0.000**	1.953
moderate_cost_of_living	0.223	0.102	2.190	**0.029**	1.250
satisfied_environmental_quality	1.308	0.121	10.821	**0.000**	3.699
stable_political_social_situation	0.653	0.108	6.055	**0.000**	1.921
cultural_visit_purpose	0.673	0.178	3.776	**0.000**	1.960
leisure_visit_purpose	1.515	0.175	8.678	**0.000**	4.549
social_meetings_visit_purpose	2.849	0.241	11.845	**0.000**	17.271
spiritual_visit_purpose	−2.289	0.343	−6.665	**0.000**	0.101
satisfied_tourism_infrastructure	0.725	0.119	6.094	**0.000**	2.064
satisfied_security	0.531	0.117	4.529	**0.000**	1.700
satisfied_welcome_and_information	0.749	0.111	6.740	**0.000**	2.114
satisfied_cultural_diversity	1.112	0.092	12.050	**0.000**	3.040

safety, hospitality and information, and cultural diversity are all significant and contribute positively, reflecting the importance of the quality of service and the experience offered to visitors.

- **Spiritual Destination**

Table 7 shows that several variables significantly influence perceptions of the attractiveness of spiritual destinations. The positive effects of low or moderate cost of living, political and social stability, safety, cultural diversity, as well as motives for visiting focused on culture, relaxation, and social interaction suggest that spiritual attractiveness is not limited to the religious or symbolic dimension of the place. It also depends on a favorable material and social environment. In other words, a spiritual space perceived as safe, culturally diverse, and economically accessible attracts more visitors. Conversely, the *quality of the environment*, *tourist infrastructure*, *hospitality*, and the *motive of spirituality* itself do not prove to be decisive factors, indicating that the spiritual quest in Benin seems to be guided more by conviviality and the social atmosphere than by the physical quality of the setting.

The negative effect of distance indicates that the farther away the destination is, the less attractive it is perceived to be, confirming that spiritual tourists are sensitive to accessibility. This finding reflects the local roots of spiritual tourism, which is often linked to community, family, or cultural practices close to home. Furthermore, the motives of relaxation and social interaction reinforce the idea that a spiritual visit is perceived not only as an experience of contemplation but also as an opportunity for socializing and cultural exchange. Furthermore, socio-political

Table 7. Ordinal regression for spiritual destination.

Variable	*Estimate*	*Standard error*	*Test statistic*	*p-value*	*Odds ratio*
low|medium	−0.045	0.370	−0.123	0.902	0.956
medium|high	2.226	0.370	6.020	**0.000**	9.262
distance	−0.444	0.042	−10.451	**0.000**	0.642
low_cost_of_living	1.611	0.170	9.467	**0.000**	5.007
moderate_cost_of_living	1.350	0.151	8.953	**0.000**	3.858
satisfied_environmental_quality	−0.477	0.151	−3.159	**0.002**	0.621
stable_political_social_situation	0.528	0.120	4.400	**0.000**	1.695
visit_purpose_adventure	0.300	0.237	1.266	0.205	1.349
visit_purpose_culture	0.699	0.222	3.147	**0.002**	2.012
visit_purpose_relaxation	1.261	0.218	5.772	**0.000**	3.528
visit_purpose_social_meetings	0.822	0.317	2.592	**0.010**	2.276
visit_purpose_spirituality	−0.090	0.235	−0.383	0.701	0.914
satisfied_tourism_infrastructure	−0.050	0.131	−0.379	0.705	0.952
satisfied_security	1.018	0.183	5.575	**0.000**	2.766
satisfied_welcome_and_information	−0.412	0.120	−3.440	**0.001**	0.662
satisfied_cultural_diversity	0.857	0.113	7.574	**0.000**	2.357

stability and cultural diversity appear to be essential conditions for the expression of the sense of trust and harmony that visitors seek in this type of destination. These results thus reveal a form of hybridization between spirituality and well-being, where the religious dimension coexists with a quest for security, peace, and an enriching human experience.

4.3. Predictive Analysis

To prepare for model training, the dataset was first divided into training and test sets (80% versus 20%), stratified by the response variable "destination" to ensure that the distributions remained consistent between the two samples.

4.3.1. Random Forest Model

The random forest model incorporates a wider range of variables, including factors related to tourists' characteristics and satisfaction levels. In particular, the model takes into account the variable that determines why a tourist chooses a particular destination.

Figure 7 presents the evolution of the Out-Of-Bag (OOB) error according to the number of trees in the random forest model. The error decreases rapidly during the first iterations before stabilizing around 300 trees, indicating convergence of the model. The final OOB error is approximately 0.35, corresponding to an overall accuracy close to 65%. Differences between class-specific error curves reveal that some tourist destination categories are more difficult to predict than others, highlighting heterogeneity in tourist profiles and destination characteristics.

Figure 8 presents the most influential variables driving tourists' destination choices. The results reveal that cost_of_living, country_of_origin, and average_expense are among the most important determinants of destination selection. These variables capture key economic and socio-demographic dimensions of tourist behavior, highlighting the central role of financial considerations and travelers' backgrounds in shaping destination preferences.

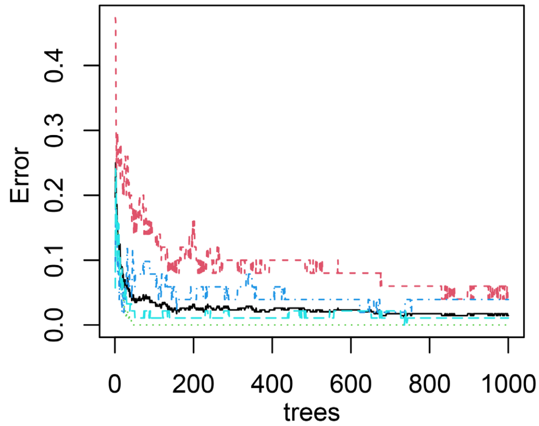

Figure 7. Error OOB.

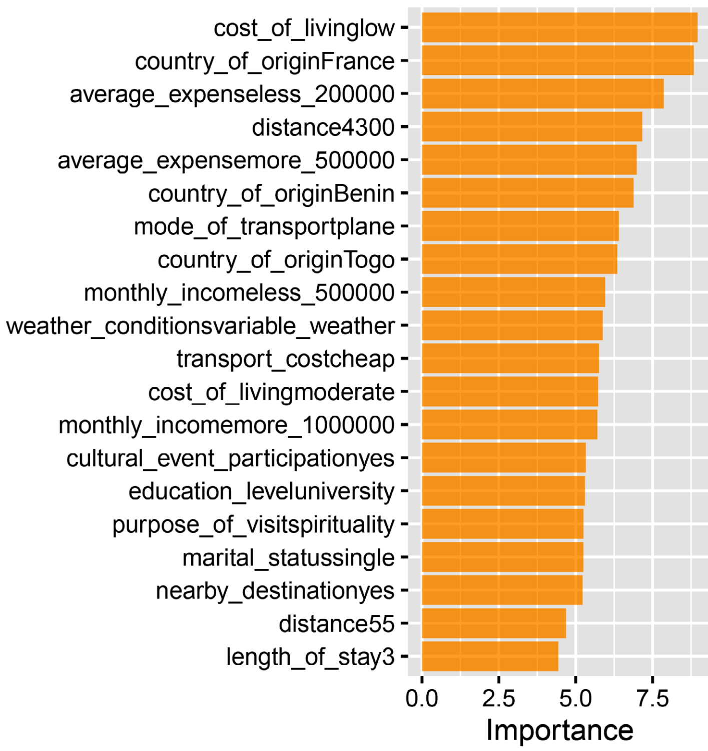

Figure 8. Relevance of variables—Random forest.

In addition, distance, mode_of_transportation, monthly_income, and weather_ conditions exert heterogeneous effects on decision-making across individuals and contexts. This observed heterogeneity reflects the diversity of tourist profiles and suggests that destination choice is driven by the joint interaction of economic, geographic, and environmental determinants.

Furthermore, the algorithm provides an estimated overall error rate of 40% for the resulting forest. This indicates that, on average, 40% of destination predictions are incorrect. With an accuracy of 60% and an average F1 score of 57.3%, the model demonstrates moderate predictive capability, where the gap between these two metrics reveals significant inter-class performance disparities. The following graph shows the confusion matrix.

Analysis of the confusion matrix **Figure 9** indicates that the cultural-historical category is predicted with 29 correctly classified observations. This performance highlights that the model is able to effectively identify tourist profiles motivated by cultural and historical exploration, reflecting the relevance of explanatory variables such as participation in cultural events, level of education, and length of stay.

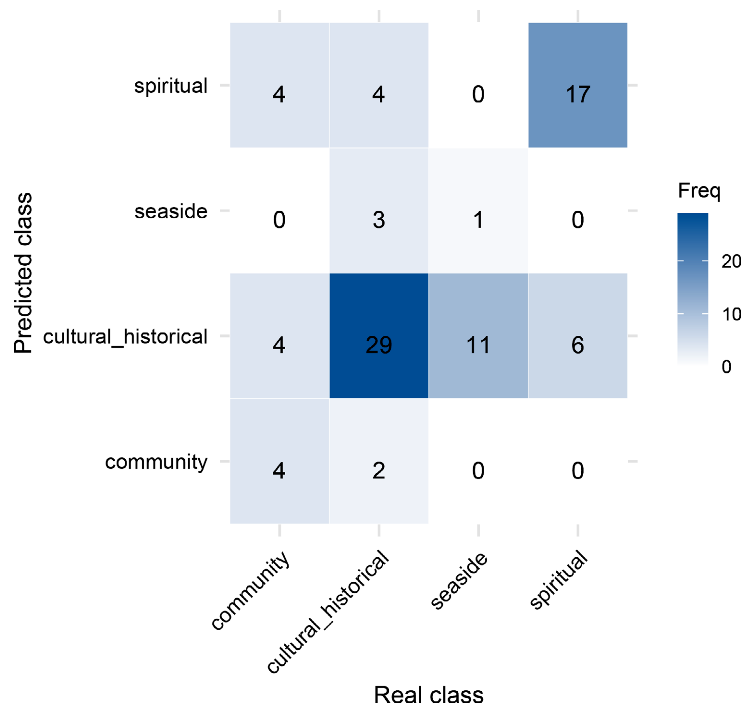

Figure 9. Confusion matrix—Random forest.

In contrast, the spiritual, community, and seaside destinations exhibit much lower classification rates, with 17, 4, and 1 correctly predicted observations, respectively, highlighting the model's difficulty in distinguishing certain classes whose socio-economic or behavioral characteristics overlap.

These results show that, despite its ability to capture certain implicit structures in the data, the model has limitations when it comes to making subtle distinctions between destinations with similar profiles.

4.3.2. Extreme Gradient Boosting (XGBoost) Model

Figure 10 shows the relative importance of the explanatory variables in the XGBoost model. An examination of the figure reveals that the cost of living variable emerges by a wide margin as the most influential predictive factor, with an importance level far exceeding that of all other variables. This dominance indicates that the cost of living constitutes the primary discriminating factor in the classification of destinations. Next, weather conditions, country_of_origin, and length of stay exhibit relatively high importance, reflecting tourists' sensitivity to climatic and logistical constraints associated with travel.

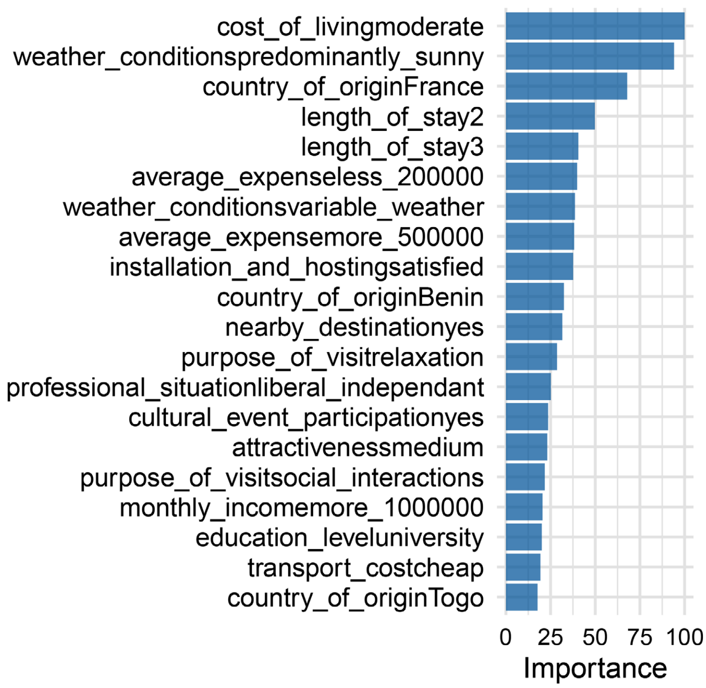

Figure 10. Significance of the variables—XGBoost.

A comparison between the Random Forest and XGBoost models highlights differences in variable importance patterns. Random Forest spreads importance across several economic, socio-demographic, and travel-related factors, indicating a multidimensional structure of destination choice determinants. In contrast, XGBoost concentrates importance on a limited set of key predictors, with cost_of_living as the dominant variable, followed by weather_conditions, country_of_origin, and length_of_stay, indicating a more selective and hierarchical structure.

Furthermore, the algorithm estimates the overall error rate of the XGBoost model at 37.65%, indicating that, on average, 37.65% of destination predictions are incorrect. With an accuracy of 62.35% and an average F1-score of 58.41%, the model exhibits moderate predictive performance. The discrepancy between these two metrics, however, suggests marked differences in performance across classes, revealing that some destinations are predicted better than others.

Analysis of the confusion matrix Figure 11 indicates that the cultural_historical and spiritual categories correctly predicted 29 and 17 observations, respectively. This performance highlights that the model is able to effectively identify tourist profiles motivated by heritage and historical exploration, as well as spiritual experiences.

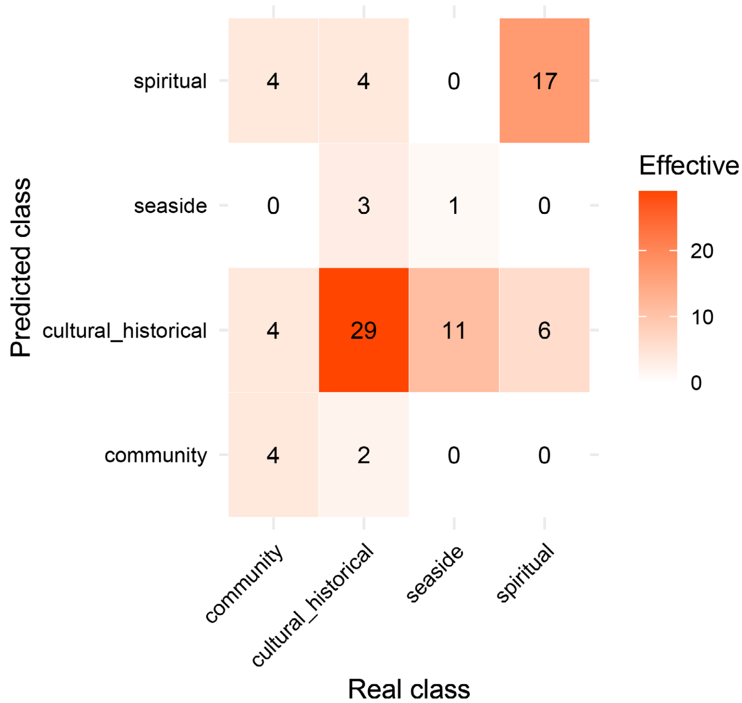

Figure 11. Confusion matrix—XGBoost.

In contrast, the community and seaside destinations show much lower classification rates, with 4 and 1 correctly predicted observations, respectively, highlighting the model's difficulty in distinguishing certain classes whose socioeconomic or behavioral characteristics overlap.

The XGBoost model performs slightly better than the Random Forest model, with an error rate of 37.65%, an accuracy of 62.35%, and an F1-score of 58.41%. It classifies well the cultural_historical and spiritual categories, but struggles with community and seaside destinations.

In comparison, the Random Forest model shows slightly lower performance, with an error rate of 40%, an accuracy of 60%, and an F1-score of 57.3%. It is also effective for cultural_historical destinations but faces similar difficulties for the other categories.

Overall, XGBoost is more suitable for this task because it achieves a better balance between accuracy and F1-score and better captures key patterns in the data.

5. Discussion

The results of this study reveal a marked preference for cultural and historical destinations, followed by spiritual, seaside, and community-based destinations, reflecting a growing desire for experiences that foster identity and learning. This ranking can be explained by the significant influence of socioeconomic and contextual factors such as age, income, level of education, and distance, confirming that tourism choices depend not only on the availability of offerings but also on individual motivations, accessibility, and local characteristics, as highlighted by [12] and [13].

Estimates from the multinomial logistic model confirm the central role of sociodemographic, economic, and environmental variables particularly income, age, safety, and weather conditions, in the choice of tourist destinations, consistent with the results of [14] and [15], which highlight the influence of weather conditions and the security context on tourist visitation and visitor satisfaction.

Furthermore, ordered logistic models highlight the importance of factors related to service quality, cost of living, and infrastructure in perceptions of a destination's attractiveness, thereby supporting the conclusions of [16] regarding the decisive role of contextual factors in assessing tourism attractiveness.

Finally, the XGBoost approach confirms the relevance of these determinants for prediction, while outperforming the Random Forest model in terms of overall predictive performance. Both models reveal heterogeneity in classification accuracy across destination types, particularly for less frequent categories, which remain more difficult to distinguish. These results highlight the value of a methodological framework combining machine learning models to achieve both explanatory and predictive insights into tourist destination choice in Benin.

6. Conclusions

This study identified the key determinants of choice and perceived attractiveness of tourist destinations in Benin based on a sample of 430 tourists.

The results of the econometric models show that sociodemographic and economic factors, combined with dimensions related to security, sociopolitical stability, environmental quality, and cultural diversity, significantly influence destination choices as well as the perception of their attractiveness, with varying effects depending on the type of destination. Machine learning approaches highlight the relevance of key structural and contextual factors, including cost of living, weather conditions, length of stay, and country of origin, while also revealing variations in variable importance across models.

These findings highlight the value of a methodological approach that combines econometrics and machine learning to better understand and predict tourist behavior, and provide valuable support for the development of targeted tourism development policies in Benin.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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