A rolling-origin ensemble forecasting framework for tourism revenue: elastic net and CatBoost – the case of Türkiye (2002–2024)

İbrahim Budak and İsa Yayla

Abstract

Purpose – *This study develops and evaluates a multivariate ensemble forecasting framework for tourism revenue that combines Elastic Net and CatBoost under rolling-origin validation, using Türkiye (2002–2024) as an illustrative case to generate medium-term reference scenarios.*

Design/methodology/approach – *Tourism revenue was the dependent variable, with international visitors, Blue Flag beaches, ministry-certified facilities, travel agencies, museums/historical sites, and museum-site visitors as explanatory indicators. The multicollinear multivariate structure was modeled using Elastic Net and CatBoost and evaluated via rolling-origin (expanding-window) cross-validation using RMSE, MAE, and* R^2*. A benchmark ARIMA model was also tested under the same evaluation scheme for comparison.*

Findings – *Elastic Net delivered the best out-of-sample accuracy (*$R^2 = 0.894$*; RMSE = 4.02; MAE = 2.80), while CatBoost produced a smoother, more conservative trajectory. Standardized Elastic Net coefficients and CatBoost SHAP values consistently identify visitor volume (VIS) and museum visitors (MV) as the dominant drivers. The equal-weight ensemble yields a balanced 2025–2027 nominal reference path with a modest post-pandemic increase. The benchmark ARIMA (2,1,2) performs substantially worse across error metrics, supporting the superiority of the proposed multivariate ML framework.*

Originality/value – *The study contributes a generalizable forecasting workflow that (1) benchmarks regularized linear and gradient-boosted models under a common rolling-origin design and (2) shows that a transparent simple-average ensemble yields more robust medium-term reference scenarios under shocks and structural breaks. Türkiye is used as a demonstration case.*

Keywords *Tourism revenue, Elastic Net, CatBoost, Ensemble method*

Paper type *Research article*

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1. Introduction

The tourism sector is considered a strategic economic area due to its ability to generate foreign exchange revenue on a global scale, support employment, and accelerate regional development. However, the rise of digital platforms, the increasing complexity of online booking and search behavior, sudden shocks such as the COVID-19 pandemic, and geopolitical fluctuations have made forecasting tourism demand in terms of both level and volatility more difficult than ever. This complex structure has called into question not only traditional time series models based on linear trend assumptions, but also single model approaches that cannot flexibly capture relationships within the data, accelerating the shift towards advanced machine learning and deep learning methods for forecasting tourism demand and revenues (Hall and Rasheed, 2025).

Recent tourism demand and revenue forecasting has expanded beyond classical ARIMA/SARIMA and exponential smoothing toward gradient-boosted trees and deep learning architectures, including LSTM/GRU and Transformer-based models (Sun *et al*., 2022; Xie *et al*., 2020; Dong *et al*., 2023; Yi *et al*., 2025; Li *et al*., 2024). Evidence indicates that attention-based and Transformer-style designs can better capture long-range dependencies and regime shifts, while decomposition–ensemble and other hybrid formulations improve robustness under volatility (Sun *et al*., 2022; Xie *et al*., 2020). In parallel, ensemble learning and forecast-combination strategies (e.g. bagging, stacking, weighted aggregation) increasingly integrate complementary model families and report measurable accuracy gains in tourism settings (Zhang *et al*., 2025; Chang *et al*., 2024; Diao *et al*., 2025). A detailed and critical synthesis of this methodological trajectory is provided in the Literature Review.

Türkiye-focused studies confirm the relevance of tourism revenues for macroeconomic balances and suggest that AI-based approaches can outperform classical benchmarks under certain conditions (Gülay, 2024; Bilek, 2025; Alioglu, 2022; Cankurt, 2016). However, comparative designs that jointly benchmark regularized linear, gradient-boosted, and ensemble strategies within a unified rolling-origin framework using multivariate tourism indicators and crisis-related regime shifts remain limited.

Recent work also highlights that forecast accuracy under concept drift and regime shifts can be improved via adaptive deep learning and ensemble designs (Bi *et al*., 2024). These findings indicate that destinations such as Türkiye, which are exposed to both geopolitical risks and global economic fluctuations, require flexible and robust frameworks that combine rolling-origin cross-validation, forecast-combination/ensemble averaging, regularization (e.g. Elastic Net), and gradient-boosted models such as CatBoost, rather than static approaches based on a single model.

This study addresses this gap by developing and evaluating a method-first, destination-level forecasting framework for tourism revenue. The framework benchmarks a regularized linear model (Elastic Net) and a non-linear gradient boosting model (CatBoost) using a rolling-origin (expanding-window) validation design, and then combines them via a transparent simple-averaging ensemble to produce robust medium-term reference scenarios. The model is specified in a multivariate setting using demand- and supply-side tourism indicators (e.g. international visitors, Blue Flag beaches, ministry-certified facilities, travel agencies, and museum/site-related indicators). Türkiye is used solely as an empirical demonstration case to illustrate the workflow and to generate 2025–2027 nominal revenue reference projections. From a tourism futures perspective, the study fits within the field of Tourism Futures by advancing a forward-looking, uncertainty-aware approach that supports destinations in anticipating alternative development paths rather than merely explaining past performance. By translating multivariate tourism indicators into transparent medium-term reference scenarios, the paper contributes to tourism futures research by offering a replicable forecasting workflow for scenario-informed destination planning under shocks, volatility, and structural change. Finally, benchmarking against a univariate ARIMA baseline confirms that the proposed multivariate ML/ensemble framework provides superior out-of-sample forecast accuracy under volatility and structural breaks.

2. Literature review

Tourism revenue and demand forecasting has historically progressed from conventional econometric and time-series models toward more flexible data-driven approaches. Early work relied heavily on ARIMA-type specifications and econometric causal models to capture trend and seasonality, providing interpretable baselines but often struggling under structural breaks and regime changes that are common in tourism systems. Large-scale reviews document this evolution and emphasize that no single model dominates across contexts, motivating comparative and multi-method designs in tourism forecasting research (Song *et al*., 2019; Abdou *et al*., 2021; Cró and Martins, 2017).

More recently, machine learning (ML) approaches have been adopted to address non-linearity, complex interactions, and multicollinearity among tourism-related predictors. Compared with purely univariate time-series benchmarks, ML models can exploit multi-dimensional indicators (e.g. demand, capacity, and quality signals) to improve predictive accuracy, particularly when the data-generating process is non-linear or unstable. However, ML methods require careful validation designs to avoid optimistic estimates and to ensure robust out-of-sample performance under realistic forecasting settings (Abdou *et al*., 2021; OECD, 2025).

Deep learning (DL) methods especially recurrent architectures such as LSTM/GRU and hybrid neural models represent a further step in modeling complex temporal dependencies, offering automated representation learning and improved capacity to capture non-linear dynamics. Evidence from tourism applications suggests DL can outperform traditional statistical baselines in many cases, but performance gains are sensitive to data volume, frequency, and the presence of high-dimensional auxiliary signals; in small-sample annual settings, parsimonious regularized models and carefully tuned ML models often remain competitive (Law *et al*., 2019; Hsieh, 2021; Dowlut and Gobin-Rahimbux, 2023).

A complementary line of research highlights ensemble learning and forecast combination as a practical strategy to improve robustness under uncertainty. By aggregating models with different inductive biases (e.g. linear regularized vs non-linear tree boosting), ensembles can reduce variance and mitigate model misspecification risk, which becomes especially important during crisis periods (e.g. COVID-19) when volatility and structural breaks undermine single-model stability. Recent tourism forecasting studies demonstrate the value of ensemble frameworks such as stacking or other combination schemes particularly when demand patterns shift rapidly and the future resembles neither the distant past nor a stable regime (Cankurt and Subasi, 2022; Wang *et al*., 2024; Liu *et al*., 2025; Cró and Martins, 2017).

Finally, tourism futures are increasingly shaped by systemic shocks beyond pandemics, including climate-related disruptions that alter destination attractiveness and seasonality. This expands the forecasting agenda from point prediction toward resilience-aware scenario design, where methods must remain adaptive under changing regimes and external drivers. Accordingly, forecasting frameworks that benchmark complementary model classes and provide transparent ensemble reference scenarios are well aligned with future-oriented tourism planning under volatility (Barrutiabengoa *et al*., 2024; Hamilton *et al*., 2005; OECD, 2025).

Building on this trajectory, the present study positions Türkiye as an illustrative testbed and contributes a method-first framework that jointly benchmarks a regularized linear model (Elastic Net) and a non-linear gradient boosting model (CatBoost) under rolling-origin validation, and then combines them via a transparent simple-averaging ensemble to produce robust medium-term reference scenarios.

3. Data and variables

3.1 Dataset and sources

Empirical analysis uses annual data for the Türkiye case covering 2002–2024. The main variable of the study is tourism revenue, which is used as the target series in the estimation models. Auxiliary variables include the number of international visitors, the number of Blue Flag beaches, the number of ministry-certified tourism facilities, the number of registered travel agencies, the number of museums and archaeological sites, and the number of visitors to these museums and sites. Tourism revenue (TR) was obtained from TurkStat’s official tourism statistics. The remaining structural indicators were compiled from the Ministry of Culture and Tourism to ensure consistency in definitions and classification across years.

3.2 Definition of variables

Table 1 provides an overview of the variables used in the study, including their symbols, definitions, units of measurement, frequency and data sources. Tourism revenue (TR) is

Table 1 Key indicators and variables used in the study (Türkiye, 2002–2024)			
Variable	*Symbol*	*Definition*	*Unit*
Tourism Revenue	TR	International tourism receipts of Türkiye	Billion USD
Number of Visitors	VIS	Number of international visitors (arrivals)	Million/pax
Blue Flag Beaches	BF	Number of Blue Flag certified beaches	Count
Certified Facilities	CF	Number of ministry-certified tourism facilities	Count
Travel Agencies	TA	Number of officially registered travel agencies	Count
Museums and Sites	MS	Number of museums and archaeological sites	Count
Museum Visitors	MV	Number of visitors to museums and archaeological sites	Million/pax

Source(s): TurkStat (TR); Ministry of Culture and Tourism (other indicators)

measured in billion US dollars and represents the total international tourism receipts of Türkiye. The number of visitors (VIS) captures the annual number of international tourist arrivals. The remaining variables (BF, CF, TA, MS and MV) reflect different dimensions of Türkiye's tourism infrastructure and cultural supply, such as beach quality, accommodation capacity, distribution channels and cultural heritage.

In the empirical strategy, TR is modelled as the dependent variable in both the benchmark univariate ARIMA specification and the multivariate ML models (Elastic Net and CatBoost). The auxiliary indicators are also used in descriptive and correlation analyses to contextualize the revenue forecasts.

4. Methods

4.1 Forecasting models used

4.1.1 Elastic net regression. Elastic Net is a regression approach that combines L1 (Lasso) and L2 (Ridge) penalty terms, performing variable selection while regularizing the model by shrinking the coefficients. This structure reduces the multicollinearity problem often seen in multivariate datasets with high correlations and produces more stable estimates compared to the classical least squares method. Current statistical learning literature emphasizes that Elastic Net can retain variables with significant effects in the model while limiting the effect of variables that contribute weakly or carry redundant information, thereby preventing overfitting (Hong and Chen, 2015; Rauschenberger *et al.*, 2021). In the empirical implementation, the variables entering the Elastic Net model were standardized to have zero mean and unit variance (z-scores) so that the estimates and regularization would not be affected by scale differences across predictors.

This approach is particularly meaningful in the context of tourism economics, as tourism revenues are often determined simultaneously by many variables that move together, such as visitor numbers, facility capacity, transportation, and cultural attractiveness indicators. In studies examining the determinants of tourist spending and tourism demand, the use of advanced regularization techniques such as SCAD–Elastic Net instead of classical regression provides flexibility in variable selection and higher prediction accuracy (Abbruzzo *et al.*, 2014). Similarly, Elastic Net's ability to overcome multicollinearity and select important variables has been validated in the fields of education and social sciences; adaptive Elastic Net approaches have been shown to be successful in terms of variable selection and model generalizability (Topal, 2021). In the demand forecasting literature, Elastic Net has been used as a component of hybrid models in some studies and has been preferred, along with methods such as K-means clustering and Gaussian process regression, to create more flexible and robust forecasting frameworks in volatile and uncertain environments (Al-Jawarneh *et al.*, 2021; Chung *et al.*, 2023). The main rationale for selecting Elastic Net in this study is its ability to statistically manage the strong correlation structure observed among Türkiye's tourism indicators and to provide a flexible, interpretable, and overfitting-free forecasting framework even with a relatively limited number of annual observations.

4.1.2 CatBoost regression. CatBoost is a modern machine learning algorithm based on gradient boosting that operates on decision trees. It stands out for its advantages in handling categorical variables, its “ordered boosting” structure, and its special design aimed at reducing bias. The algorithm demonstrates strong performance in terms of both computational efficiency and prediction accuracy on high-dimensional and complex datasets, thanks to its symmetric (oblivious) tree structures and training strategies that reduce target leakage (Hancock and Khoshgoftaar, 2020). In recent comprehensive comparative studies, CatBoost has been tested alongside other gradient boosting algorithms in classification and regression problems. It has been reported to consistently deliver the best or near-best results, particularly in scenarios with a high density of categorical features and limited sample size (Florek and Zagdański, 2023).

The applied literature shows that CatBoost can be used not only in technology or finance but also in modeling tourism-related consumption decisions. For example, in a recent study modeling students’ tourism consumption behavior, factors influencing tourism spending and travel decisions were evaluated using various ensemble and feature learning methods, including CatBoost; and it was shown that high accuracy was achieved with the appropriate selection of model parameters (such as learning rate, number of iterations, depth) (Xu, 2025). Similarly, studies optimizing CatBoost with multiple algorithms to improve its prediction performance in different engineering and environmental problems reveal that the algorithm can strongly capture non-linear relationships and provide generalizable solutions even in noisy data environments (Qiu *et al*., 2025). The reason for choosing CatBoost in this study is its ability to flexibly model the potential nonlinear and interactive relationships between Türkiye’s tourism revenues and visitor numbers, tourism infrastructure, and cultural attractiveness indicators. Furthermore, even with a limited number of annual observations, when used in conjunction with Elastic Net, it can create a comparative prediction framework that encompasses both linear and nonlinear components. However, the high flexibility and capacity of tree-based gradient boosting models such as CatBoost also make them more prone to overfitting in very small samples; therefore, in this study, model complexity is deliberately constrained and evaluated within a rolling-origin cross-validation framework to control this risk.

4.1.3 Rolling-origin (expanding window) cross-validation. Classic k-fold cross-validation approaches used to evaluate model performance in time series often lead to biased or overly optimistic error estimates because they neglect the temporal dependence between observations. Therefore, methods that preserve the time dimension and perform training–testing separation based on chronological order are considered more appropriate, especially in predictive applications. The rolling-origin or expanding window cross-validation approach provides a structure that addresses precisely this need: in each iteration, the training set is expanded starting from the initial year, while the test set is separated for the next period (or a fixed horizon); thus the model is both re-estimated on an increasingly larger information set and tested in a realistic “forward-looking” prediction scenario (Bergmeir and Benítez, 2012; Cerqueira *et al*., 2020).

In recent years, in evaluation frameworks developed for time series forecasting, the rolling-origin approach has been proposed as a standard method for measuring the generalizability of linear and nonlinear models under the headings of “time series cross-validation” or “prequential evaluation.” Because it naturally reflects structural changes between observations, regime shifts, and new information added to the dataset over time, multiple rolling-origin evaluations are recommended over a single train–test split based on a fixed training set, especially for series that include crisis and shock periods (Hewamalage *et al*., 2023). In this study, the predictive performance of Elastic Net and CatBoost models is evaluated using training windows that gradually expand from 2002 onwards and a one-period forecast horizon at each step; the error metrics obtained in each iteration are combined to calculate the overall success level. Thus, for tourism series with a limited number of annual observations, both the time dependency of the data process is preserved and consistency across different sample portions is tested.

Given the sharp COVID-19-related drop in 2020, we augment the multivariate ML models with two engineered covariates: a deterministic time index (Trend) and a COVID-19 indicator (dummy = 1 for 2020, 0 otherwise). No additional robust loss functions are introduced; the benchmark ARIMA model remains purely univariate, and the pandemic year enters the rolling-origin evaluation as an ordinary observation.

The benchmark ARIMA model is embedded in the same evaluation scheme: the (p,d,q) order is fixed at (2,1,2) based on the full-sample AIC, while the model parameters are re-estimated on each expanding window and used to generate a one-step-ahead forecast for the subsequent year.

4.1.4 Ensemble (combined) forecasting approach. It has long been recognized in forecasting literature that predictions based on a single model can be sensitive to factors such as model specification errors, parameter uncertainty, and structural breaks. Therefore, combining forecasts obtained from different model families—that is, the ensemble or forecast combination approach—is a powerful strategy recommended especially in areas of high uncertainty. Recent studies have shown that, in both macroeconomic indicators and demand forecasting applications, appropriately weighted or simply averaged combined forecasts often yield lower error rates than even the best individual model (Atiya, 2020; Petropoulos *et al*., 2022).

Empirical studies examining the performance of forecast combination techniques in the context of tourism demand and revenues have revealed that the results obtained for short, medium, and long-term horizons are systematically more accurate than those from individual models. A comparative study on tourism demand shows that combining forecasts from different statistical and artificial intelligence-based models using various methods significantly reduces the mean absolute error and root mean square error measures across all horizons. This finding demonstrates that the ensemble approach is particularly useful in areas such as tourism, which are prone to shocks and structural uncertainty (Song *et al*., 2009). Within the scope of this study, the Elastic Net and CatBoost models were considered as complementary structures; the former was used as a component capturing linear and regularized relationships, while the latter was used as a component capturing nonlinear and interactive structures. The predictions obtained from the models were combined using a simple equal-weighted (i.e. unweighted) average, thus yielding a more balanced and flexible tourism revenue prediction framework that is sensitive to both linear and nonlinear data generation processes. More complex weighted-average or dynamic combination schemes were not pursued, because the small sample size ($n = 23$) makes stable weight estimation difficult and the historical performance gap between Elastic Net and CatBoost is not very large (both models capture the underlying trend reasonably well); in this context, a simple equal-weighted average was preferred as a transparent and robust combination rule.

4.1.5 Hyperparameter selection. In this study, the hyperparameter settings for the Elastic Net and CatBoost models were determined using a rolling-origin (expanding window) cross-validation approach to suit the time series structure. At each expanding window layer, the current training set (for example, 2002–2015) was used in an inner cross-validation procedure to evaluate different hyperparameter combinations; hyperparameters were optimized based solely on this inner evaluation, after which the final model was re-estimated on the full training window with the selected settings and used to generate a one-step-ahead forecast for the next year. Thus, hyperparameter selection was dynamically evaluated not only through a single fixed split but also through expanding training samples over time.

For the Elastic Net model, the fundamental hyperparameters α, which determines the regularization strength, and l1_ratio, which controls the L1–L2 combination, were tested in various combinations. In this context, a grid search was performed for α between 0.01 and 1 and for l1_ratio between 0.2 and 0.8; each combination was tested within a rolling-origin cross-validation structure. The results obtained showed that the combination of $\alpha = 0.1$ and l1_ratio = 0.5, which provided the lowest average RMSE, was the most suitable hyperparameter set for the final model. This choice allowed the model to avoid overfitting and flexibly capture the dynamics of tourism revenues, which vary from year to year.

For the CatBoost model, the main hyperparameters determining performance, namely learning rate, tree depth, and number of trees (iterations), were again evaluated within the rolling-origin cross-validation framework. Comparing different combinations revealed that iterations = 400, learning_rate = 0.05, and depth = 6 yielded the best results in terms of overall error metrics, and these settings were used in the final analyses. This hyperparameter configuration contributed to the model capturing short-term fluctuations, the trend component, and structural breaks in a more balanced manner.

The hyperparameters selected for both models were optimized to be consistent with the RMSE, MAE, and R^2 values reported in the study. In addition, given the small sample size ($n = 23$), hyperparameter choices—particularly for CatBoost (moderate tree depth, limited number of iterations and a relatively low learning rate)—were intentionally kept conservative so as to avoid overly complex models and reduce the risk of overfitting. Therefore, all performance findings presented in the results section are based on the best model configurations obtained at the end of the rolling-origin-based hyperparameter selection process.

For interpretability, predictors are z-score standardized; therefore, Elastic Net coefficients are reported as standardized coefficients and can be compared across variables. For CatBoost, we compute SHAP values and summarize global importance using mean absolute SHAP values.

4.2 Model comparison criteria

In this study, three fundamental error metrics were used to evaluate the relative performance of Elastic Net, CatBoost, and the combined (ensemble) predictions derived from them: root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). RMSE is calculated by taking the square root of the average of the squares of the prediction errors and, due to its structure that penalizes large errors more heavily, reveals the model's performance, particularly in the face of outliers and high deviations. MAE, on the other hand, is based on the average of the absolute differences between the actual values and the predicted values; thanks to its linear and easily interpretable structure, it directly shows the average "number of units" by which the predictions deviate. The R^2 coefficient measures how much of the total variance in the dependent variable is explained by the model, thus allowing for a comparison of the explanatory power of models. The combined use of error measures allows for a more balanced assessment in terms of both scale unit (RMSE, MAE) and explained variance ratio (R^2); in this respect, it constitutes an approach commonly recommended in regression-based forecasting studies (Chai and Draxler, 2014).

5. Results

5.1 Descriptive statistics and correlation analysis

The sample consists of 23 annual observations for the period 2002–2024. Over this horizon, both tourism revenue and the number of international visitors exhibit a strong upward trend, with noticeable slowdowns around 2015–2016 and a sharp decline in 2020 associated with the COVID-19 shock. Supply-side indicators such as Blue Flag beaches, certified facilities, travel agencies and museums also increase steadily, reflecting a broad quantitative expansion of Türkiye's tourism sector.

Table 2 reports descriptive statistics for all variables. Tourism revenue is expressed in billion USD, while the number of visitors and museum visitors are expressed in millions; the remaining indicators are counts.

Table 2 Descriptive statistics for Türkiye's tourism indicators (2002–2024)

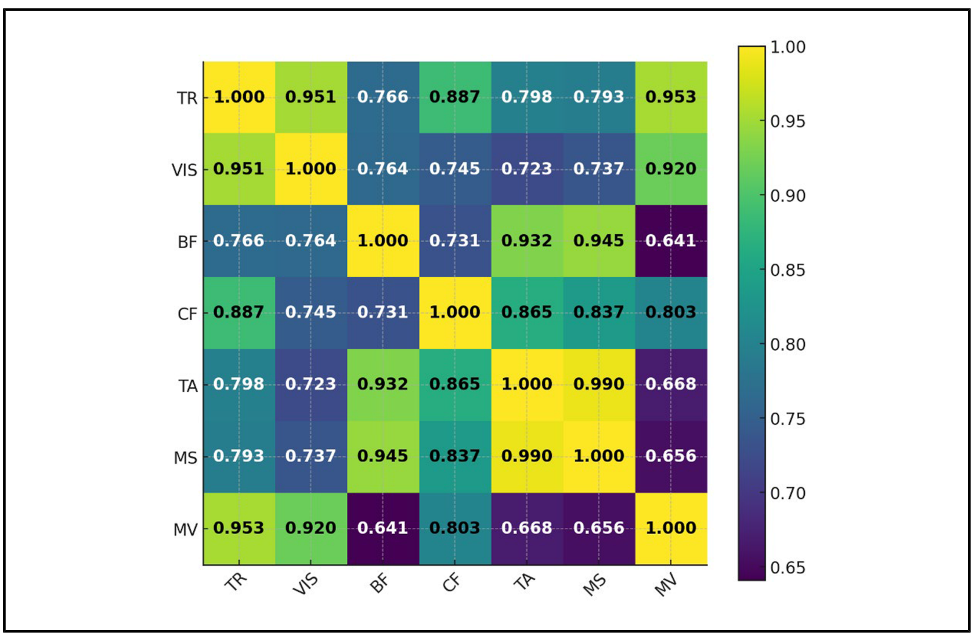
Variable	*Mean*	*Std. dev*	*Min*	*Max*
Tourism Revenue (billion USD)	28.93	12.51	12.42	61.10
Number of Visitors (million)	34.79	13.00	15.21	62.27
Museum Visitors (million)	24.98	13.00	7.42	61.69
Blue Flag Beaches (count)	386.65	152.80	139	621
Certified Tourism Facilities (count)	12373.65	3710.98	8,847	22216
Travel Agencies (count)	8,510.22	3737.12	4,344	16258
Museums and Sites (count)	328.78	16.85	309	363

The mean tourism revenue over the sample is about 29 billion USD in the recorded units, with the maximum almost five times the minimum value, which points to a substantial scaling-up of the sector over 2 decades. The average number of international visitors is close to 35 million, again with a wide range between the early 2000s and the most recent years. The supply-side variables show similar patterns: the number of Blue Flag beaches roughly quadruples, the stock of certified facilities and travel agencies more than doubles, and the number of museums and sites increases from 309 to 363. Museum visitors also grow strongly, indicating rising interest in cultural and heritage-based tourism.

To examine the joint dynamics of these indicators, Figure 1 presents the Pearson correlation matrix.

Tourism revenue is very strongly correlated with the number of international visitors (0.95) and with museum visitors (0.95), highlighting the close link between total inflows, cultural tourism intensity and revenue performance. Revenue is also highly correlated with the number of certified facilities (0.89), and strongly associated with travel agencies (0.80) and museums (0.79), suggesting that expansions in tourism infrastructure and distribution capacity move broadly in line with revenue growth. The supply-side indicators are themselves tightly interrelated—for example, the correlation between agencies and museums is 0.99 and between Blue Flag beaches and

Figure 1 Pearson correlations between tourism variables (2002–2024)



museums 0.95—indicating a coordinated and mutually reinforcing development of different components of the tourism system.

Taken together, the descriptive statistics and correlation patterns confirm that Türkiye's tourism sector has undergone sustained quantitative expansion, punctuated by a few crisis-related setbacks, and that demand- and supply-side variables co-evolve closely with tourism revenues. This provides a coherent empirical background for the forecasting results presented in the following subsections.

5.2 Model performance and predictions

The predictive performance of the models was evaluated using the described rolling-origin (expanding window) cross-validation framework. Accordingly, the rolling-origin results obtained for the Elastic Net model show that the root mean square error (RMSE) is 4.02 (billion USD), the mean absolute error (MAE) is 2.80 (billion USD) and the coefficient of determination (R^2) is 0.894. Within the same framework, the RMSE calculated for the CatBoost model was found to be 6.08 (billion USD), the MAE was 4.79 (billion USD) and the R^2 was 0.758 (Table 3). Therefore, in this dataset, under expanding training windows over time, Elastic Net performed better than CatBoost in terms of both error metrics and explanatory power; it showed a significant difference, particularly in terms of RMSE and MAE. This result demonstrates that a regularized linear structure in highly correlated annual tourism indicators can provide an advantage over more flexible gradient-boosting-based models in small-to-medium-sized datasets with a limited number of observations.

Notably, ARIMA (2,1,2) yields a negative out-of-sample R^2 (−0.966). Under the standard R^2 definition used in our evaluation, $R^2 < 0$ indicates that the model performs worse than an intercept-only (mean) benchmark on the corresponding test window. This behavior is expected under severe regime shifts: the abrupt collapse and rebound around the 2020 pandemic period introduces a structural break and extreme volatility that can substantially degrade linear univariate benchmarks such as ARIMA. In contrast, the multivariate machine-learning models leverage additional explanatory variables and capture non-linear patterns more effectively, resulting in improved out-of-sample accuracy (Table 3) (Zhang *et al.*, 2021).

The fact that the RMSE and MAE values of the Elastic Net model are lower than those of the CatBoost model, while its R^2 value is higher, indicates that this model exhibits relatively superior predictive performance on the dataset in question.

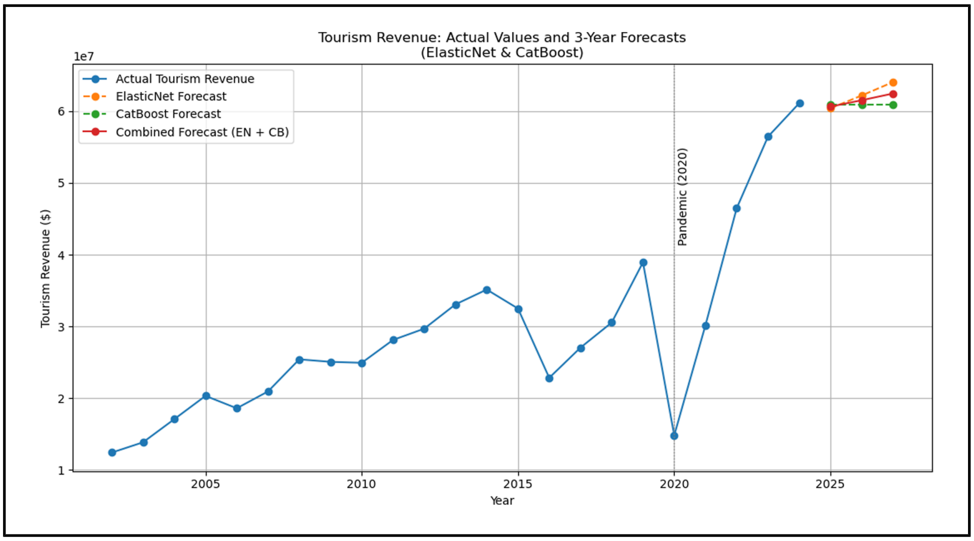
However, the graph in Figure 2 presents the short-term prediction dynamics and 3-year forward projections of the models together. For the 2025–2027 period, Elastic Net forecasts that tourism revenue will rise to approximately 60.4, 62.2, and 64.0 billion USD, respectively. CatBoost forecasts show a flatter profile, producing an almost flat path at around 60.9 for three years. Combined forecasts, created as a simple average of the two models, predict a more moderate increase between these two extremes, projecting tourism revenue to rise to approximately 60.6, 61.5, and 62.5 levels for 2025, 2026, and 2027, respectively. In this context, the ensemble

Table 3 Rolling-origin performance metrics for Elastic Net and CatBoost models

Model	*RMSE (billion USD)*	*MAE (billion USD)*	R2
Elastic Net	4.02	2.80	0.894
CatBoost	6.08	4.79	0.758
ARIMA (2,1,2)	17.34	12.19	−0.966

Note(s): RMSE = root mean squared error; MAE = mean absolute error; R^2 = out-of-sample coefficient of determination (negative values indicate worse performance than a mean benchmark). Lower RMSE/MAE and higher R^2 indicate better performance

Figure 2 Actual tourism revenue in the Türkiye case and 3-year model forecasts (Elastic Net and CatBoost)



approach balances Elastic Net's strong trend component with CatBoost's smoother forecast profile, providing a more cautious and stable reference scenario in terms of both past performance and forward-looking projections.

In addition to these multivariate machine learning models, a benchmark univariate ARIMA specification was also estimated for tourism revenues. Based on the full-sample AIC criterion, an ARIMA (2,1,2) model was selected and evaluated under the same rolling-origin (expanding window) framework. The resulting error measures indicate that the ARIMA model performs substantially worse than the Elastic Net and CatBoost models, with an RMSE of approximately 17.34 billion, an MAE of 12.19 billion, and a negative R^2 (−0.97) over the 2012–2024 evaluation period (a negative R^2 value indicates that the model performs worse than simply predicting the sample mean of the dependent variable). This suggests that, in the present setting, a purely univariate time-series approach fails to exploit the information contained in structural tourism indicators and does not provide a competitive benchmark relative to the multivariate machine learning models. Given the substantially inferior forecast performance of the ARIMA model, its predicted path is not displayed in Figure 2 in order to avoid clutter; instead, its error statistics are reported in Table 3.

The graph shows tourism revenues for the period 2002–2024 and combined forecasts for the period 2025–2027 obtained using Elastic Net, CatBoost, and the simple average of these two models. The vertical dashed line indicates the pandemic shock of 2020; thus, both the long-term trend before the crisis and the post-pandemic recovery process, as well as forward-looking projections, can be tracked on the same axis.

5.3 Model interpretability and key predictors

As an interpretability check, we begin with the standardized coefficients from the regularized linear model (Elastic Net) and subsequently corroborate the key drivers using SHAP (Shapley Additive Explanations)-based importance estimates from CatBoost.

Table 4 reports standardized Elastic Net coefficients (z-score predictors), allowing a direct comparison of the relative predictive contribution of each variable. The results show that Number of Visitors (VIS) is the strongest predictor (β = 0.216), followed by Museum Visitors (MV) (β = 0.072), while Blue Flag (BF) (β = 0.034) and Certified Facilities (CF) (β = 0.012) contribute

Table 4 Standardized Elastic Net coefficients			
Rank	*Predictor*	*Std. coef (elastic net)*	*Sign*
1	Number of Visitors (VIS)	0.216	+
2	Museum Visitors (MV)	0.072	+
3	Blue Flag (BF)	0.034	+
4	Certified Facilities (CF)	0.012	+

Note(s): Only non-zero standardized Elastic Net coefficients are reported; variables shrunk to zero by the penalty are omitted for brevity

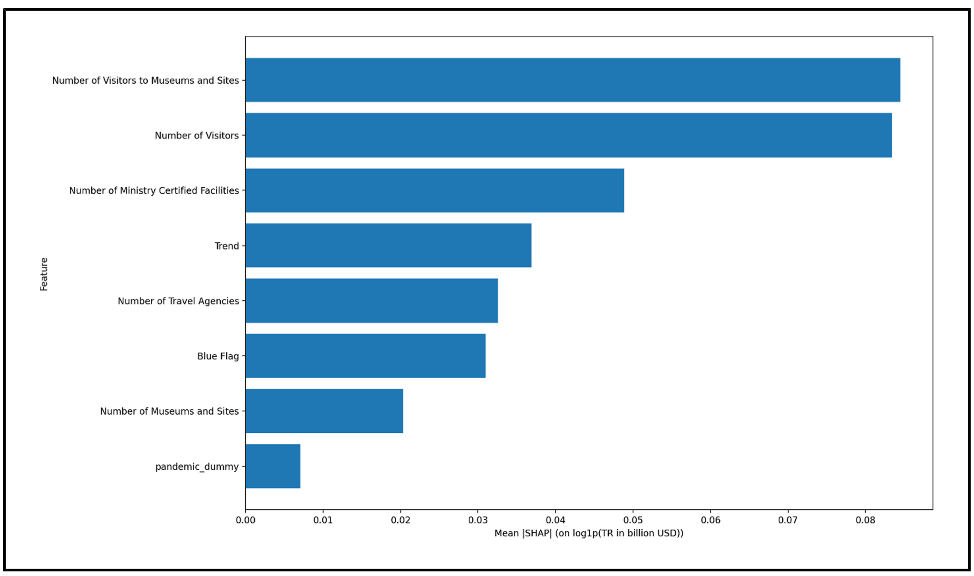
additional but smaller positive effects. The consistently positive signs indicate that higher values of these demand- and quality/supply-side indicators are associated with higher predicted tourism revenues within the forecasting framework; however, these coefficients reflect predictive associations rather than causal relationships. Figure 3 reports CatBoost global importance using mean absolute SHAP values.

Figure 3 presents CatBoost global feature importance based on mean absolute SHAP values. The results indicate that museum and site visitation (MV) and overall visitor volume (VIS) are the dominant drivers of the model's revenue forecasts, with substantially larger contributions than the remaining predictors. Supply-side and structural indicators particularly ministry-certified facilities (CF) and the Trend term provide additional explanatory power, while travel agencies (TA) and Blue Flag (BF) show moderate importance. In contrast, the pandemic dummy has relatively low global importance, suggesting that the broader demand and capacity indicators account for most of the predictive signal in the model.

6. Discussion

In this study, Türkiye's tourism revenues for the period 2002–2024 were analyzed using new generation forecasting methods; Elastic Net, CatBoost, and the combined forecasts of these models were compared. The findings reveal that tourism revenues exhibit a dynamic

Figure 3 CatBoost global feature importance. Note: Trend denotes a deterministic time index (t = 1, . . .,T); Pandemic dummy equals 1 in 2020 and 0 otherwise



characterized by strong structural trends and periodic shocks, and therefore both regularized linear models and gradient boosting-based approaches offer specific advantages. Evaluations conducted through rolling-origin cross-validation show that Elastic Net produces lower RMSE and MAE values compared to CatBoost, indicating that it can better manage the highly correlated structure of tourism data through regularization. Similarly, it has been reported in different contexts that Elastic Net improves prediction accuracy and estimates parameters more stably in datasets with multicollinearity issues and limited observations (Jung *et al.*, 2018; Tak and İnan, 2022; Elkhidir *et al.*, 2025). The fact that such models produce generalizable results, especially in annual series with relatively small sample sizes, can be considered an important methodological contribution in fields with limited observations, such as the tourism economy. Consistent with this, the benchmark univariate ARIMA(2,1,2) model estimated for tourism revenues produces much higher RMSE and MAE values and even a negative R^2, further underscoring the advantages of multivariate regularized and gradient boosting-based approaches in this context.

On the other hand, CatBoost's production of a smoother and less trend-sensitive prediction profile indicates that, while the model is flexible in capturing non-linear latent relationships, it may not perform as strongly as regularized linear structures on trend-heavy annual tourism data. Various applications have shown that gradient boosting and tree-based methods produce low-variance, conservative predictions in some cases; however, their clear superiority over linear models is sensitive to data structure and sample size (Perez *et al.*, 2022). However, studies also exist showing that CatBoost can outperform other tree-based algorithms in areas such as bicycle demand forecasting, restaurant pricing, tourism-related consumption decisions, and transportation preferences (Aydın *et al.*, 2023; Şahinbaş, 2022; Xu, 2025; Banyong *et al.*, 2025). This study shows that CatBoost exhibits more limited performance compared to Elastic Net in trend-dominant structures in Turkish data, but its potential may increase when combined with richer and higher-frequency tourism indicators.

Another important aspect of the findings is that the ensemble prediction approach offers a more balanced projection compared to individual models. When Elastic Net's strong upward trend and CatBoost's flattening prediction structure are combined using the ensemble method, they produce a more cautious, middle-of-the-road forecast for the coming years. An extensive literature demonstrating that prediction performance can be improved through model combination shows that simple or weighted combinations of predictions obtained from different methods can yield better results than individual models (Wang *et al.*, 2023; Petropoulos and Kourentzes, 2015). Specifically for tourism demand, combining econometric models based on different sets of explanatory variables has been shown to provide better forecasting performance than individual models (Wu and Blake, 2023). Similarly, this study demonstrates that an approach combining different aspects of Elastic Net and CatBoost models is an effective tool for reducing future uncertainty and producing more robust projections.

Graphical analyses and forward-looking projections indicate that Türkiye's tourism revenues showed a strong recovery trend in the post-pandemic period and that a steady upward trend will continue in the 2025–2027 period. However, the fact that the rates of increase are not as rapid as in the past is consistent with the post-pandemic period being defined in the international literature as a process of "gradual recovery" and "slow normalization." The latest tourism barometers published by the UNWTO emphasize that international tourism activity reached approximately 85–90% of pre-pandemic levels by the end of 2023, but that full recovery will take time (UNWTO, 2023). Similarly, studies examining the lasting effects of the pandemic on tourism demand reveal that recovery is occurring at different rates across regions and product types, with domestic tourism temporarily replacing international tourism in some destinations and uncertainty persisting (Gössling *et al.*, 2020; Plzáková and Smeral, 2022; Nie *et al.*, 2024). Numerous studies emphasize that the increase in tourism revenues is closely related to infrastructure investments, product diversity, sustainability practices, and global competitive conditions; therefore, achieving medium-term revenue targets depends not only on the trend continuing on its own but also on structural policies that increase sectoral resilience (Hall *et al*., 2015; Lew *et al*., 2021).

Overall, this study offers three important methodological contributions: (1) a systematic comparison of Türkiye's tourism revenues using modern statistical learning methods, (2) a realistic assessment of the changing performance of models over time using a rolling-origin framework, and (3) the production of a more balanced and policy-relevant reference projection using an ensemble approach. In this respect, the study offers both the literature and decision-makers a data-driven and flexible analytical perspective for understanding the complex dynamics of the tourism economy.

This study has some limitations. First, since the dataset used is annual in frequency, its capacity to capture high-frequency (monthly or daily) fluctuations and short-term demand shocks in detail is limited. Although we include a parsimonious COVID-19 indicator (2020 = 1) and a deterministic trend term, we do not model the shock using regime-switching structures, intervention analysis with multiple breakpoints, or robust loss functions; thus, forecast uncertainty may remain elevated around extreme shock periods. In such a small-sample setting, the risk of overfitting is non-negligible, particularly for flexible machine learning algorithms such as CatBoost, which can easily adapt to idiosyncratic patterns in the training data. Although the use of regularization, conservative hyperparameter settings, and rolling-origin cross-validation mitigates this problem to some extent, the possibility of residual overfitting remains a structural limitation of the analysis and should be borne in mind when interpreting the results. Second, the models are based solely on observed structural variables; external factors such as geopolitical risk, exchange rate volatility, social media sentiment, or global economic conditions are not included in the model. This choice stems from the desire to produce a "baseline" scenario based on infrastructure and demand indicators observed at an annual frequency, in line with the purpose of the study.

Therefore, the estimates obtained should be interpreted under the assumption that macroeconomic and geopolitical conditions remained within the observed range during the sample period; it should be noted that they may be vulnerable to external shocks such as sudden exchange rate shocks, sharp increases in geopolitical tensions, or viral campaigns and crisis content on social media. In future studies, integrating exchange rate level and volatility, global uncertainty and geopolitical risk indices, and behavioral indicators such as Google Trends or social media sentiment into the model would increase the resilience of the baseline path presented here to external shocks and broaden the scope of the forecasts' use in policy analysis. Finally, forward-looking forecasts are based on the assumption that past trends will continue, and there is a risk of deviation in forecasts in the event of unexpected shocks or policy changes. These limitations can be addressed in future studies by using broader variable sets, high-frequency data, and alternative machine learning/hybrid models.

7. Conclusion

In this study, Türkiye's tourism revenues for the period 2002–2024 were analyzed using modern statistical learning methods; Elastic Net, CatBoost, and simple ensemble predictions of these two models were compared. Rolling-origin (expanding window) cross-validation results showed that Elastic Net performed better than CatBoost in terms of both RMSE and MAE on the highly correlated multivariate tourism dataset; this demonstrates that a regularized linear structure still provides a robust and reliable framework for small-to-medium-scale annual series. CatBoost's production of a flatter and more conservative prediction profile, however, suggests that the model may be limited in trend-dominant annual series, but its potential to capture non-linear components could be evaluated in richer data structures. Consistent with this evidence, a benchmark ARIMA model estimated on the same series yields substantially higher forecast errors, confirming that the multivariate machine learning models provide a more informative and reliable basis for medium-term tourism revenue projections.

On the other hand, the ensemble approach, balancing Elastic Net's strong trend component with CatBoost's smoothing effect, is seen to offer a more moderate and cautious revenue path for the 2025–2027 period. The projections indicate that the steady upward trend in tourism revenues will continue in the post-pandemic period, while growth rates may be more measured compared to previous periods of rapid expansion. In this regard, the study proposes an approach that compares different model families and produces a combined reference scenario from their outputs, rather than focusing on a single "best" model; it contributes to the tourism economics literature at both the methodological and applied levels.

It should be emphasized that the 2025–2027 projections are reported in nominal (current-price) USD, consistent with the official reporting of tourism receipts. In an environment with elevated inflation and exchange-rate volatility, nominal USD receipts may diverge from real (inflation-adjusted) revenue dynamics and domestic purchasing-power outcomes; thus, the forecasts should be interpreted as nominal reference scenarios rather than constant-price projections.

The limitations of the study should be carefully considered when interpreting the results. The use of a dataset limited to an annual frequency and 23 observations constrains the capacity of complex deep learning models; moreover, the exclusion of external factors such as geopolitical risk, exchange rate volatility, social media indicators, and the global economic climate indicates that the projections represent a baseline ("trend") scenario based primarily on structural tourism indicators. Therefore, the projections obtained should be considered as a possible reference path that may emerge if current historical dynamics continue, rather than definitive forecasts.

In light of these findings, several recommendations can be developed for future studies. On the research front, working with monthly/quarterly high-frequency data; incorporating exchange rates, global demand indicators, online search behavior, and social media sentiment into the model; and expanding the current framework with LSTM, Transformer, and more advanced ensemble structures will increase both forecast accuracy and scenario diversity. Future research could (1) produce constant-price (real) tourism revenue forecasts by deflating receipts using an appropriate price index, and (2) explicitly incorporate macro variables such as USD/TRY movements, real effective exchange rates, and inflation indicators—potentially via scenario-based forecasting—to distinguish nominal from real revenue dynamics. On the policy front, rather than focusing solely on increasing visitor numbers, strategies that increase per capita spending through product diversification, quality infrastructure investments, strengthening cultural and sustainable tourism segments, and risk management mechanisms that increase resilience to shocks should come to the fore. Such a systematic and data-driven approach will be a key enabler in achieving Türkiye's medium- and long-term tourism revenue targets.

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