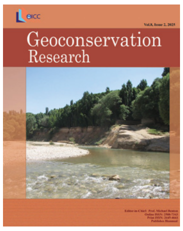

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Neural Network Modeling for Forecasting Tourism Demand in Stopića Cave: Balancing Visitor Management and Geoconservation

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Abstract

We predict the number of tourist visits to Stopića Cave using three different approaches: the Auto-Regressive Integrated Moving Average (ARIMA) model, Support Vector Regression (SVR), and the hybrid NeuralProphet method. ARIMA and SVR are classical statistical and machine learning techniques, respectively, while NeuralProphet combines elements of both - incorporating seasonality, trend decomposition, and neural network structures. Forecasting performance across all methods is evaluated on the available dataset, with NeuralProphet outperforming the other models. This hybrid approach enables more effective modeling of non-linear patterns and temporal variability, resulting in greater predictive accuracy. Additionally, Google Trends data is integrated as an external variable to improve model precision. In practical terms, the results can provide essential information for decision-making and sustainable tourism management, offering valuable insights into visitor dynamics at Stopića Cave and a data-driven foundation for addressing issues such as carrying capacity in Serbia's most visited cave. Accurately forecasting tourism demand is essential for managing visitor pressure at natural attractions, particularly sites experiencing pronounced seasonal fluctuations such as Stopića Cave. Reliable predictions support planning, resource allocation, and sustainable management efforts.

Keywords: NeuralProphet, Tourism demand forecasting, Geoconservation, Cave management, ESCAM framework, Stopića Cave (Serbia)

Introduction

Modeling tourist demand includes a complex but necessary set of activities and analyses that can determine market norms and directly shape tourist offers (Buhalis 2005; Frechtling 2012). Understanding tourist demand enables efficient allocation of resources, sustainability of revenue management, infrastructure planning, and risk management (Buhalis 2000; Ritchie & Crouch 2003; Dwyer *et al.* 2009; Vanhove 2022). Bearing in mind that this type of modeling indicates market trends, consumer behavior and preferences, management structures that manage tourist destinations can use this information to identify niche markets and new trends. Therefore, forecasting tourism demand can have significant impacts on maintaining optimal competitive markets within the tourism industry (Crouch *et al.* 1999; Frechtling 2012). Based on the prediction of demand dynamics, it is also possible to adapt competitive pricing strategies, within which prices at destinations can be increased and decreased depending on the expected tourist demand (Song & Turner 2006; Martins *et al.* 2017; Li & Srinivasan 2019; Abrate *et al.* 2019). In addition, Song & Witt (2012)argue that understanding tourist demand can influence the development of new products and services, which are compatible with the evolving needs and preferences of tourists. Tourist demand can also dictate the efficient use of marketing resources to maximize reach and impact (Buhalis 2000; Holloway 2004; Sigala *et al.* 2012; Hudson 2023), which is crucial for branding and competitiveness. Furthermore, operational efficiency is yet another factor on which tourist demand can have a significant impact. Mandal (2018) states that sustainable operational efficiency within the tourism industry largely depends on data-driven decision-making; thus, exploring tourist demand is also a step towards enhanced productivity optimization. This includes managing inventory, schedules, and the number of employees (Lenny Koh *et al.* 2007; Lovelock 2013; Shabanpour *et al.* 2018).

The applicability of tourism demand modeling is especially evident when it comes to special forms of tourism affirmation (Burger *et al.* 2001; Trauer 2006; Xie *et al.* 2021). In the case of nature-based tourism (Dimitrov 2013; Aliani *et al.* 2018; Rice *et al.* 2019; Abu *et al.* 2021), forecasting tourist demand can be of great importance for adjusting carrying capacity measures in certain destinations. Extensive research (O’Reilly 1986; Butler 1999; McCool & Lime 2001; Liu 2003; Fennell & Ebert 2004; Lobo *et al.* 2013; Zelenka & Kacetl 2014; Lobo 2015; Guo & Chung 2017; Carrión-Mero *et al.* 2021; Cheablam *et al.* 2021; Sunkar *et al.* 2022) indicates that carrying capacity is one of the most important indicators of sustainable and responsible tourism, especially when it comes to highly vulnerable destinations, both from natural processes and from anthropogenic influence. Therefore, predicting the increase in tourist demand can be of great importance for management structures, because it can indicate the need to implement certain measures to prevent overexploitation and over-tourism.

In the last few decades, there has been a development of tourism of specialized interest, which focuses on geological attractiveness. Geotourism includes the affirmation of geologically significant landscapes and places that can have a certain market value obtained through the interpretation of knowledge (Gordon 2018). Education and conservation of geodiversity are the primary elements of geotourism and as such have the most important role in the identification and valorization of geoheritage (Bentivenga *et al.* 2019). Therefore, geotourism through the transfer of knowledge provides value to geologically significant areas, both for the needs of tourism development (Dowling & Newsome 2006; Chen *et al.* 2015a; Dowling & Newsome 2018; Ólafsdóttir 2019) and for the effective implementation of geoconservation efforts (Brilha 2002; Gray 2005; Burek *et al.* 2008; Henriques *et al.* 2011; Crofts *et al.* 2020; Williams *et al.* 2020).

In the case of karst landscapes, which represent one of the most vulnerable areas in which tourist activities are carried out (Ruban 2018; Telbisz & Mari 2020; Zhang *et al.* 2023), geoconservation is a basic indicator of ethically responsible use of karst resources (Taheri & Groves 2021). Within the karst areas, the sites that are mostly used for mass tourism are caves (tourist caves; i.e., show caves). A detailed study on global cave tourism that explored the number of tourist visits (Chiarini *et al.* 2022) indicates a very high number of visits to show caves. China boasts the highest annual visitation rate, with 19 million tourists to its cave destinations. In the United States, 9.9 million annual visitors have been recorded and within Europe, France stands out by having 5.2 million tourists annually to its caves, followed by Spain with 2.9 million visitors. Germany and Italy contribute significantly to the global cave tourism landscape, each hosting 2.4 million and 2.3 million tourists annually. Evidently, caves are a major focus of tourists around the world. Due to geoconservation standards and protection, it is necessary to pay special attention to modeling and monitoring the global tourist demand for cave tourism. Moreover, significant challenges within cave tourism are reflected primarily in the negative consequences that arise from the very arrangement of the cave for tourist use. This includes the installation of artificial lighting, construction, and introduction of substances harmful to the underground ecosystem (Chiarini *et al.* 2022). In addition, the harmfulness of tourism for caves is reflected in the increase in subterranean temperature, CO2 levels, and changes in air humidity (Pulido-Bosch *et al.* 1997; Baker *et al.* 1998; Šebela *et al.* 2015; Novas *et al.* 2017; Constantin *et al.* 2021). However, caves represent important destinations for multidisciplinary education, interpretation of human history, and environmental dynamics. For this reason, it is necessary to maximize the sustainable economic affirmation of caves, so that cave tourism is compatible with geoconservation standards. The advantage of management structures is that there are significant possibilities for monitoring and control within the caves themselves. In particular, visitors cannot walk outside the marked paths and cannot visit places in the cave that are not adequately lit and arranged for visiting without specialized equipment. Thus, monitoring is in most cases at a high level, and this provides the possibility of effective quality control and the protection of the subterranean ecosystem.

The aim of this paper is to model tourist demand for the Stopića cave in West Serbia. In previous years, this cave had an exceptional increase in the number of tourist visits, and it became the most visited, surpassing the Resava cave, which for decades was the most visited in Serbia. This unique case represents an important local economic indicator that occurred as a result of the proximity of Zlatibor, which is a highly visited mountain center. The analysis includes a comprehensive time series dataset comprising the monthly visitation figures spanning from the year 2010 through 2023, thereby encompassing a total of 168 months of observational data. This temporal scope allows an exploration of visitor trends, facilitating forecasting methodologies to be employed effectively. Through modeling of these visitation patterns, we aim to gain insights that are essential for enhancing strategic planning and management practices in the context of Stopića cave's visitor economy and geoconservation.

Research Area

The region of West Serbia is characterized by extensive karst landscapes with numerous caves and related karst features (Djurović 2021). However, compared to Eastern Serbia, this region has fewer caves open for tourist visits. Stopića Cave is a protected natural monument, situated on the northeastern slopes of the Zlatibor Mountain in Western Serbia (Durlević *et al.* 2023). It is located below the Zlatibor–Sirogojno road (Fig. 1), approximately 250 km from Belgrade, 30 km from Užice, 19 km from the Zlatibor tourist center, and only 3.5 km from the Sirogojno ethno-village. The cave represents the subterranean continuation of the Trnava stream, which enters through the upper opening of the cave. After flowing for about 117 m underground, the cave river merges with the waters of the Prištevica, a left tributary of the Veliki Rzav. The entrance of Stopića Cave is posi-

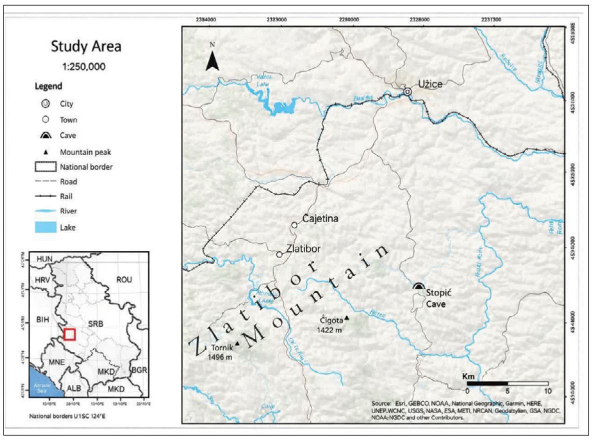

Figure 1. Location of the case study (Vuković & Antić 2019).

tioned at an elevation of 776.96 m and is notable for its dimensions (18 m high and 35 m wide). The cave covers an area of 7,911.5 m² and has a total volume of approximately 120,000 m³. The zone adapted for tourist visits has a total length of 1,691 m (Lazarević 2012).

Stopića Cave consists of five distinct sections: the Bright Hall, the Dark Hall, the Great Hall with rimstone pools, the Canal with Pools, and the River Canal. The tourist-adapted portion contains several notable features, including a large entrance chamber, a waterfall, and a series of rimstone pools. The rimstone pools are formed through the deposition of limestone and they appear as depressions bordered by sinuous, reddish stone rims. Water accumulates within these basins and flows from one pool to another, creating a cascading effect that significantly enhances the cave's aesthetic and geological value (Lazarević 2012).

Methods

Discussion of Forecasting Methods

Methods for forecasting time series can be divided into three categories: classical statistical methods, methods based on maximum likelihood (ML), and hybrid methods that fuse both model and data-driven methodological approaches.

Classical statistical forecasting methods used perform best before ML methods started to outperform them, as demonstrated in several early time-series forecasting competitions, e.g., in M3 (Makridakis & Hibon 2000). These methods attempt to identify patterns, trends, seasonality, and irregularities in the data observed over different time periods. They are particularly useful for understanding the underlying structure and pattern of the data and therefore offer interpretable forecasts for stakeholders. For forecasting tourism demand, the most widely used statistical forecasting method is ARIMA and its versions which include seasonality and/or exogenous variables (see Song *et al.* [2019] and references therein). Exponential Smoothing (ES) is also used in many studies that forecast tourism demand (Athanasopoulos *et al.* 2009; Fildes *et al.* 2011).

In recent years, ML techniques have become popular for forecasting tourism demand, such as NN (Claveria *et al.* 2015; Chen *et al.* 2012), SVR (Chen *et al.* 2007; Chen *et al.* 2015b) and others. The most important advantage of data-driven methods is that they do not require stationarity or a specific distribution of time series. Moreover, these models can explain non-linear relationships between input and output variables without a priori knowledge about them. However, the interpretability of these models is uncertain. Also, in some applications, the amount of available data can still be too small for ML techniques to train well, so practitioners should carefully choose model complexity to avoid overfitting.

Hybrid methods bridge the gap between classical statistical and scalable deep learning (DL) models by uniting them. Those methods were the best performers in the M4 forecasting competition (Makridakis *et al.* 2020). In recent years, they have also been used in many forecasting applications. For the purposes of tourism demand forecasting, in (Nor *et al.* 2018) ARIMA and NN have been combined to forecast Malaysia's tourism demand. Similarly, Abellana *et al.* (2021) combined Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and SVR for modeling Philippine tourism demand. In this study, we model tourism demand in Stopića cave by using the NeuralProphet (Triebe *et al.* 2021) hybrid method. As baseline methods, we use ARIMA as the most popular statistical/classical method and SVR, a frequently utilized ML method for tourism demand forecasting.

Although the findings from the latest M5 time-series forecasting competition (Makridakis *et al.* 2022) demonstrated that modern pure ML methods based on decision trees, such as the Light Gradient Boosting Machine (LightGBM) method (Ke *et al.* 2017) now outperform hybrid methods, they are not appropriate for our study because of the limited size of the time series and the risk of overfitting.

Apart from forecasting tourism demand exclusively based on its previous values, it is worth mentioning that many studies investigate how exogenous variables can help in predicting targeted time series. The most popular explanatory variables of this kind are internet big data such as Google Trends (Sun *et al.* 2019; Li *et al.* 2020; Gunter & Önder 2016; Park *et al.* 2017; Volchek *et al.* 2019; Clark *et al.* 2019) and social media and online reviews such as TripAdvisor (Hu *et al.* 2022). We also consider Google Trends for modeling our time series.

In addition to forecasting tourism demand, this study incorporates the E-SCAM (Antić *et al.* 2025) framework to translate predicted visitor pressure into meaningful conservation and management implications for the cave. The Extended Show Cave Assessment Model (E-SCAM) used in this study is an updated version of SCAM (Antić *et al.* 2022) and includes three groups of indicators: Speleological Value (SV), Infrastructure Value (IV), and Tourist Value (TV). Each indicator consists of several sub-indicators scored on a 1–5 scale. SV includes 12 sub-indicators grouped into scientific-educational value, landscape and aesthetic value, and protection, while IV includes five sub-indicators and TV 21. In the original model, the final indicator ratings are calculated by multiplying the authors' scores by expert-derived importance factors, incorporating feedback from specialists in speleology, cave climate, show-cave infrastructure, and tourism.

For the purposes of this study, only the speleological and infrastructure components were used, as they are directly relevant to assessing geoconservation sensitivity under varying levels of visitor pressure. The neural-network visitation forecasts were not used to alter E-SCAM weights but served as the basis for assigning each month to a relative pressure category (High-Peak, Moderate, Low-Moderate). These pressure categories were then interpreted through the corresponding E-SCAM indicators to identify likely conservation needs and management responses.

Auto-regressive Integrated Moving Average

The Auto-Regressive Integrated Moving Average (ARIMA) model is one of the most frequently used models in time series analysis (Box *et al.* 2015). The model is constructed to predict future trends of non-stationary data and represents an extension of the Auto-Regressive Moving Average (ARMA) model. It can be efficiently applied to eliminate trends and the non-stationarity of the mean using differencing between consecutive observations.

The ARIMA model is generally denoted by ARIMA(p,d,q) ,where represents the order (number of lags) of the auto-regressive model, is the degree of differencing and q denotes the order of the moving-average model. For a given time series ARIMA (p,d,q) model is given by a formula

$$\left(1-\sum_{i=1}^{p}\psi_i L^i\right)(1-L)^d y_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\epsilon_t, \qquad (1)$$

Where t is a positive integer, L is the lag operator defined as $L^i y_t = y_{t-i}$, ψ_i are the coefficients of the auto-regressive part of the model, θ_i are the coefficients of the moving average part and ϵ_t are error terms. The error terms ϵ_t are assumed to be independent with normal $\mathcal{N}(0,\sigma)$ distributions. There are several methods for determining values of parameters p,d and q such as Augmented-Dickey Fuller (ADF) test, the Autocorrelation Function (ACF), and the Partial Autocorrelation Function (PACF).

As the number of tourist visits generally depends on the period of the year, it is useful to include the seasonal component in the model. But the seasonal data require seasonal differencing to become stationary. For this purpose, the SARIMA model is used. SARIMA model is denoted by ARIMA $(p,d,q)(P,D,Q,M)$, where M represents the seasonal period, i.e., number of observations per year, and P,D and Q are auto-regressive, differencing and moving average terms for the seasonal part of the model, respectively.

The Seasonal Auto-Regressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model represents another generalization of the ARIMA model that includes both seasonality and exogenous variables. In this paper, the Google Trends data are used as one of the most popular tools in forecasting. The model has excellent performance which will be verified through results on tested data.

Support Vector Regression

The Support Vector Machine (SVM) is an ML model initially developed for classification and later adjusted for regression (SVR). Here we briefly introduce SVR (Cortes *et al.* 1995), one of the most powerful techniques for solving both linear and nonlinear regression problems.

The linear regression model in general is given by

$$y = \langle \alpha, x \rangle + \beta, \tag{2}$$

where $y \in \mathbb{R}$ is the dependent variable, $x \in \mathbb{R}^m$ is the independent variable, $\alpha \in \mathbb{R}^m$ and $\beta \in \mathbb{R}$, are unknown coefficients and $\langle \alpha, x \rangle$ denotes the inner product between α and x. Classical linear regression models are based on estimating unknown coefficients for the given training set D= $\{(x_i, y_i)\}$, $i \in \{1,2,\dots,n\}$ by minimizing the sum of squared prediction errors (differences between the actual and the predicted values of the dependent variable). The SVR model gives us the flexibility to define how much error is "acceptable" in finding prediction values. Instead of a simple regression line (or hyperplane in high-dimensional spaces), the goal here is to find a tube (Fig. 1) on the distance (margin) ϵ from the line (ϵ -insensitive tube). In that way, the model only cares about data outside the tube. In other words, the coefficients α and β , which describe the relationships between y and x , are found such that the prediction errors are minimized while the margin between the regression line and the closest data points is maximized at the same time.

More concretely, the coefficients α and β are in SVR estimated by minimizing the regularized cost function under constraints:

$$\text{minimize } \frac{1}{2}||\alpha||^2 + \gamma \sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

$$\begin{aligned} y_i - \langle \alpha, x_i \rangle - \beta &\le \epsilon + \xi_i \\ \langle \alpha, x_i \rangle + \beta - y_i &\le \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0,\ i &\in \{1,2,\dots,n\}, \end{aligned} \tag{3}$$

where γ is the balancing parameter between the regularization term of the cost function and the training error calculated as the sum of ξ_i and ξ_i^*, which are slack variables that represent positive and negative deviations outside $[-\epsilon, \epsilon]$ region (see Fig. 1).

To solve equation (3), the dual quadratic problem is formed:

maximize

$$\sum_{i=1}^{n} y_i(\lambda_i - \lambda_i^*) - \epsilon \sum_{i=1}^{n}(\lambda_i + \lambda_i^*) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\lambda_i - \lambda_i^*)(\lambda_j - \lambda_j^*)\langle x_i, x_j\rangle$$

$$\sum_{i=1}^{n}(\lambda_i - \lambda_i^*) = 0 \quad (4)$$
$$0 \le \lambda_i, \lambda_i^* \le \gamma,\ i \in \{1,2,\dots,n\},$$

where λ_i and λ_i^* are Lagrange multipliers that satisfy $\lambda_i\lambda_i^* = 0$. Finally, the decision function (2) has

$$y = \sum_{i=1}^{n}(\lambda_i - \lambda_i^*)\,K(x, x_i) + \beta, \quad (5)$$

where $K(x,x_i) = \langle x, x_i\rangle$ in the linear case. In the non-linear case, k represents the kernel function that transforms the data in a higher dimensional space to be suitable for linear separation, e.g., polynomial kernel $(K(x,x_i) = \langle x, x_i\rangle^d)$ and Gaussian $(K(x,x_i) = e^{-\frac{||x-x_i||^2}{2\sigma^2}})$.

When SVR is applied for time series forecasting, the independent variable contains time series lags, and the dependent variable is the next observation in the time series.

NeuralProphet

In this study, we deploy NeuralProphet (Triebe *et al.* 2021) as a hybrid time series forecasting method. It is an extension of Facebook's Prophet (Taylor & Letham 2018), it provides information for interpreting outputs (predictions) from internal parts of the model and therefore, it is an Explainable Artificial Intelligence (XAI) method. Interpretability of NeuralProphet is achieved because the model is based on an additive decomposition of time series. It combines the classic time series components with scalable NN blocks and in that way, it can fit non-linear relationships. Two such NN modules are the auto-regression and covariate components and these enable it to demonstrate better predictive accuracy in comparison to Facebook's Prophet.

More formally, NeuralProphet decomposes the time series into multiple additive components where each produces h future predictions at the same time. For a single time step forecast $(h = 1)$, the model is given as:

$$\hat{y}_t = T(t) + SE(t) + AR(t) + LR(t) + FR(t) + EH(t) \quad (6)$$

where T(t) is the trend at time t,SE(t) models the seasonal effects at time t,AR(t) includes the auto-regression effects at time t based on past observations of the time series of interest,LR(t) captures the regression effects at time t for lagged observations of exogenous variables (covariates),FR(t) accounts for the regression effect of future-known exogenous variables at time t and EH(t) represents the effect of certain events and holidays at time t. Each of the described components can be excluded if it is not relevant to the targeted time series.

The *trend* is modeled in a classic way, as a piecewise linear function with the growth rate which can change at a predefined number of points, so-called changepoints (model hyperparameter).

The *seasonal component* is modelled by Fourier terms (Harvey *et al.* 1993), with terms for seasonality with periodicity l:

$$SE_l(t) = \sum_{j=1}^{m}\left(a_j \cos\left(\frac{2\pi jt}{l}\right) + b_j \sin\left(\frac{2\pi jt}{l}\right)\right). \quad (7)$$

The number of Fourier terms is by default set to be $m = 6$ with $l = 365.25$ for yearly seasonality, $m = 3$ with $l = 7$ for weekly seasonality, and $m = 6$ with $l = 1$ for daily seasonality. Mode details can be found in Triebe *et al.* (2021).

Auto-regression (AR) predicts the future values of the target variable by using a linear combination of its past values. The auto-regressive model AR (p) is defined as:

$$y_t = s + \sum_{i=1}^{p}\psi_i\, y_{t-i} + \epsilon_t, \quad (8)$$

where p is the number of linearly combined past time steps and the intercept is denoted with. Coefficients ψ_i control the direction and power/significance of included past values on the future value and ϵ_t is the noise term. The classical AR model produces only one prediction $(h = 1)$. Therefore, for a prediction horizon with the number of steps $h > 1$,classical AR models have to be estimated. The AR module in NeuralProphet is based on a modification of AR-Net (Triebe *et al.* 2019), which allows a single model to make forecast steps for $h > 1$. Three types of auto-regression, linear, deep and sparse, can be considered within the AR module. The linear AR is single NN with only one layer, which has p inputs, h outputs, and it does not have biases nor activation functions, so it is essentially the same as a classic statistical AR. Deep AR consists of a fully connected NN with an arbitrary number of hidden layers and non-linear activation functions, such as the rectified linear unit (ReLU), after each layer, apart from the final one. The first layer inputs are p last observations, the outputs of the final layer are future values, whereas the number of hidden layers and the number of neurons in them are controlled by the user. Finally, sparse AR allows the AR order p to be chosen as higher at the beginning, and then, with the use of a regularization, only a few past observations can be forced to have weights that are not equal to . It is merely a way of selecting the most significant time series lags.

The *lagged regressor* component is almost the same as the AR component - the only difference is that the inputs are the past values of exogenous variable instead of the targeted time series. An individual lagged regressor component has to be made for each covariate if there are multiple ones.

The *future regressors* component is the same as the lagged regressor, except that we need to know the future values of exogenous variable and not only its past values.

Two types of *events and holidays* can be considered: user-defined events, where the user feeds the model with information about uncommon events or country-specific holidays, where the user only provides the name of a country and the model automatically takes into account its national holidays. In both scenarios, events and holidays are binary variables with values when the event occurs and otherwise.

In case NN modules are deployed within NeuralProphet, the Huber loss function during training is optimized by PyTorch optimizers, where the user can define all relevant training hyperparameters such as learning rate, number of epochs, batch size, etc.

Results

Data Description and Experiment Design

Forecast modeling of tourism demand for Stopića cave included the use of time series with the number of visitors for each month during 2010–2023 (168 months in total). The number of visitors changed during the entire period (Fig. 2), and this time series has a strong seasonal component, meaning there are yearly peaks during the summer period (July and August) when many people go on summer vacations, whereas during winter the number of visits is much lower. This pattern is visible during the entire period, and it repeats each year. Apart from the seasonal component, a growing trend is also seen, especially in the second half of the considered time frame. Another interesting event is that the highest number of visits happened during the summer of 2020, during the COVID-19 pandemic, when Serbia was in partial lockdown. Many countries had travel restrictions, so vacations were spent mainly in the country of origin. This happened to domestic tourists in Serbia, who could not travel abroad and so they spent holidays in Serbia, which caused the highest number of visits in the history of Stopića cave at that time.

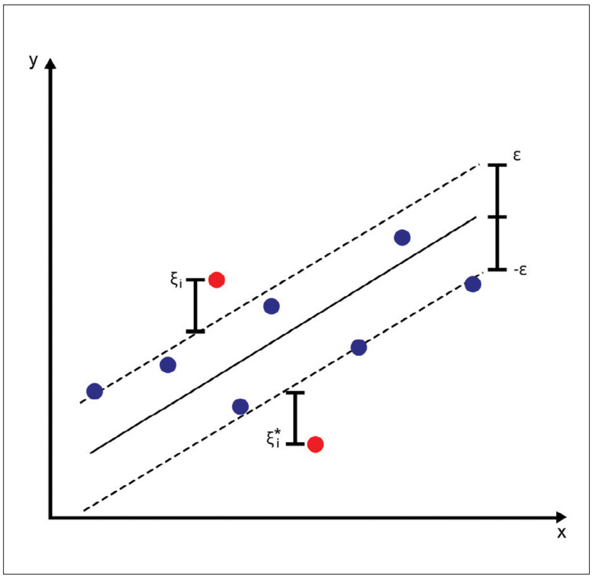

Figure 2. SVR model.

Apart from an official number of visitors, we downloaded the Google Trends index for the keyword “Stopića pećina” (pećina meaning cave in Serbian) for the considered period; we used this Serbian term because most of the tourists who visit the cave are domestic tourists (more than 95 %). The provided time series also has a monthly frequency, and it measures the search volume of the chosen keyword, which indicates search interest. It has values from $[0,100]$ where 100 corresponds to the highest popularity of the keyword. To visualize both time series together, we scaled the number of visits y_t to also be from $[0,100]$ as $100 * (y_t - \min_t(y_t))/(\max_t(y_t) -$. The two-time series are strongly correlated (Fig. 3; correlation coefficient is 0.84), having similar seasonality, trend, and peaks. It seems that many visitors to the cave searched for the name of the cave on the web, either just before their planned visit or at the same time. For our models, we try to include this series as an exogenous variable.

Evaluation

To evaluate the methods, we split the time series with the number of visitors into two parts - the first 156 months (period 2010–2022, 92.86% of the entire time series) were used for training the ML methods and the remaining 12 months (year 2023, 7.14% of the entire time series) were used for testing. For the testing phase, we predict/forecast the number of visitors and compare predicted values with actual ones.

For comparison of forecast number of visitors with the real ones, we choose RMSE defined as:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{9}$$

where T is the size of the data used in evaluation (T=12 in our case), and y_t and $\hat{y}_t$ are the actual and predicted numbers of visitors at time t. The smaller the measure, the closer are the real and predicted values. When comparing predictions of different models, the model with the smallest RMSE is considered the best.

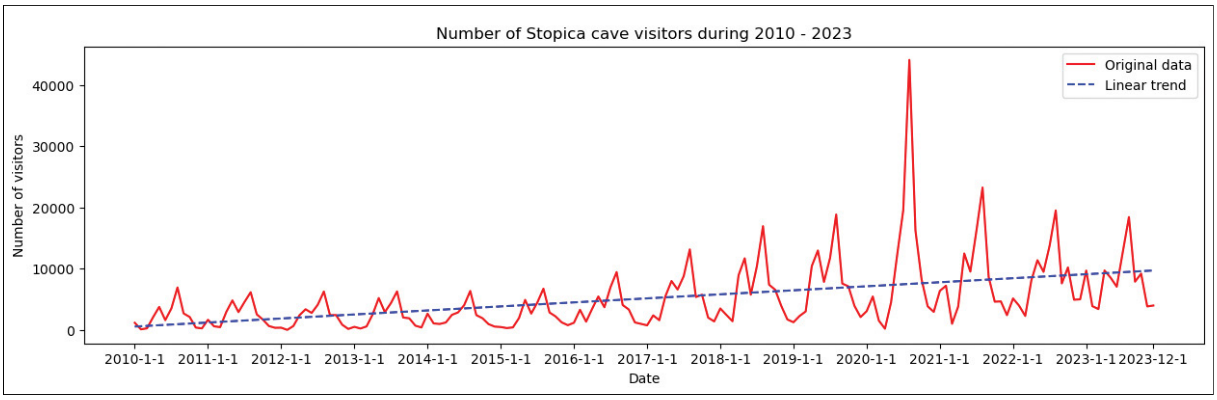

Figure 3. Number of Stopića cave visitors during 2010-2023, monthly frequency, together with its linear trend.

In addition, we also report Pearson's correlation coefficient defined as

$$r = \frac{\sum_{t=1}^{T}(y_t - mean(y_t))\,(\hat{y}_t - mean(\hat{y}_t))}{\sqrt{\sum_{t=1}^{T}(y_t - mean(y_t))^2}\,\sqrt{\sum_{t=1}^{T}(\hat{y}_t - mean(\hat{y}_t))^2}}$$

where sample means are obtained as $mean(y_t) = \frac{1}{T}\sum_{t=1}^{T} y_t$ and $mean(\hat{y}_t) = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t$. The correlation coefficient varies between -1 and 1. In our case study, we expect to have a positive correlation between predicted and measured data, and the closer the measure is to 1, the higher the correlation between real and predicted values. When comparing predictions of different models, the model with the highest r will be considered the best.

Comparing the Models

The first model we consider is ARIMA. Inspecting ACF and PACF, we conclude that the number of lags (order of auto-regressive model) that should be included in the model equals $p = 3$, whereas the degree of differencing should be d=1 and order of moving-average q=0 . To predict the entire 12 months, we fit 12 ARIMA models since a single model can only predict the number of visitors for one month ahead. The plot of the actual vs. predicted number of visitors for 12 months during 2023 (Fig. 4) gives $\mathrm{RMSE} = 4652.32$ and $r = 0.28$. Further, we include in the same model also a seasonal component for which we use a single lag p=1 , degree of differencing D=1, order of moving-average Q=0, and M=12 since we have monthly data. Including the seasonal component into ARIMA (Fig. 5) gives more accurate predictions as the RMSE significantly decreased to 3250.70 while the correlation coefficient increased to r = 0.79. Finally, we included Google Trends as an external regressor, and this led to a further decrease of RMSE=2908.27 while the correlation coefficient stayed almost the same, as r = 0.77. This gave the best fit among all considered ARIMA variants (Fig. 6).

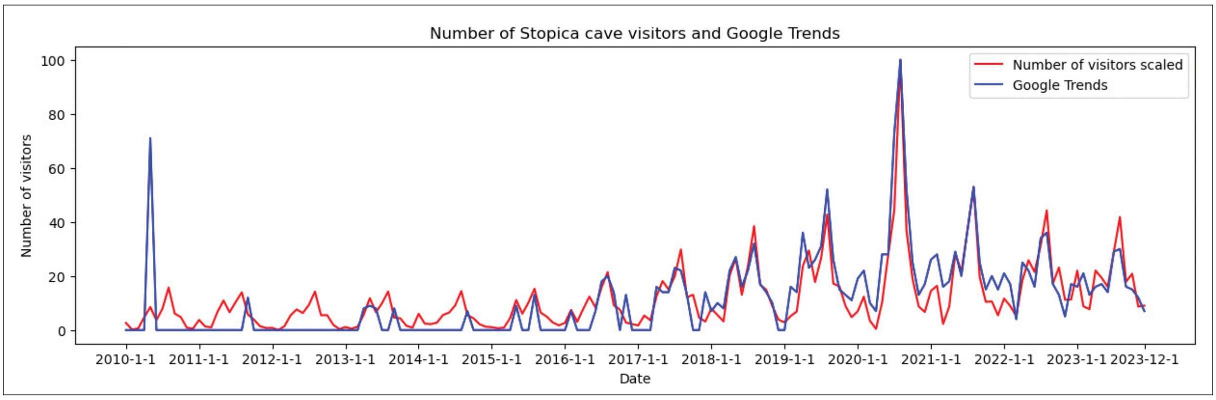

Figure 4. Number of Stopića cave visitors during 2010-2023 (scaled to [0,100]) and Google Trends index.

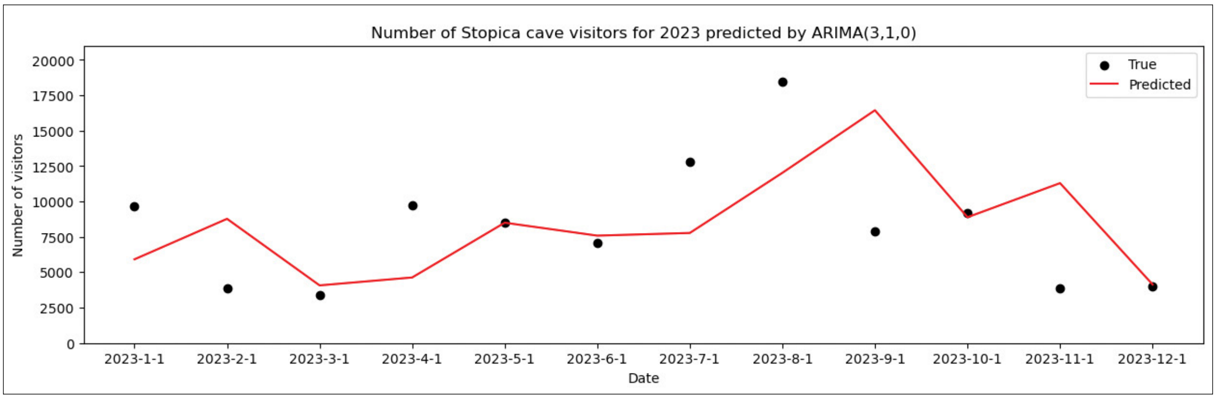

Figure 5. Prediction of number of visitors for 12 months for 2023 obtained with ARIMA model, "RMSE" = 4652.32, r= 0.28.

Next, we train SVR on monthly data from 2010–2022. To make a fair comparison between different models, here we also consider three past values of the time series to predict future ones. SVR with Radial Basis Function (RBF) kernel, regularization parameter $C = 10$ and $\epsilon = 0.05$ tube is fitted, leading to predictions (Fig. 7) with RMSE =4430.33, which is a little bit better than the RMSE obtained with pure ARIMA, but it is worse than the estimated SARIMA and SARIMAX models. Correlation coefficient r = 0.29 indicates the same conclusion, that SVR performs a little bit better than ARIMA, but significantly worse than estimated SARIMA and SARIMAX models.

Finally, we experimented with the NeuralProphet model. We included in the model yearly seasonality, a growing trend with the default number of trend changepoints, three lags of time series, and two lags of Google Trends as an external lagged regressor. For modeling non-linearity, NN with 2 hidden layers containing and nodes, respectively, is included in the model. Here we intentionally choose NN of small size to prevent overfitting since the data we have has a relatively small number of observations from the ML perspective. The model is optimized with PyTorch AdamW optimizer with a learning rate of 0.003. The actual and predicted number of visitors for 2023 (Fig. 8), and by comparing NeuralProphet RMSE with RMSE of previous models, the best fit is obtained by the estimated hybrid NeuralProphet model with the chosen parameters explained above. For this model, the computed RMSE=1976.90 and it is approximately 30% lower than the smallest ARIMA models (SARIMAX) or more than 50% lower than the RMSE obtained by SVR. The correlation coefficient for this model, r =0.93, suggests strong correlation of predicted and measured data, and is significantly higher than the correlation coefficient

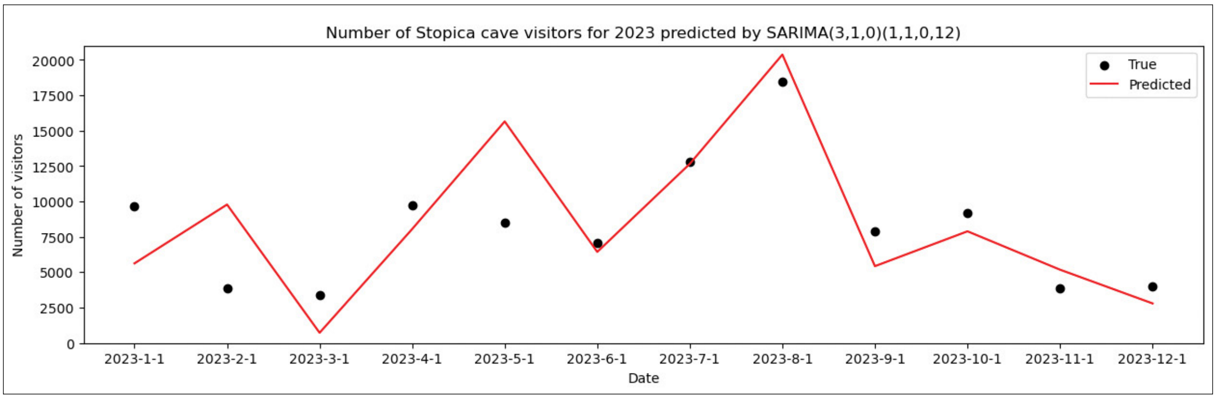

Figure 6. Prediction of number of visitors for 12 months for 2023 obtained with SARIMA model, "RMSE" = 3254.70,r = 0.79.

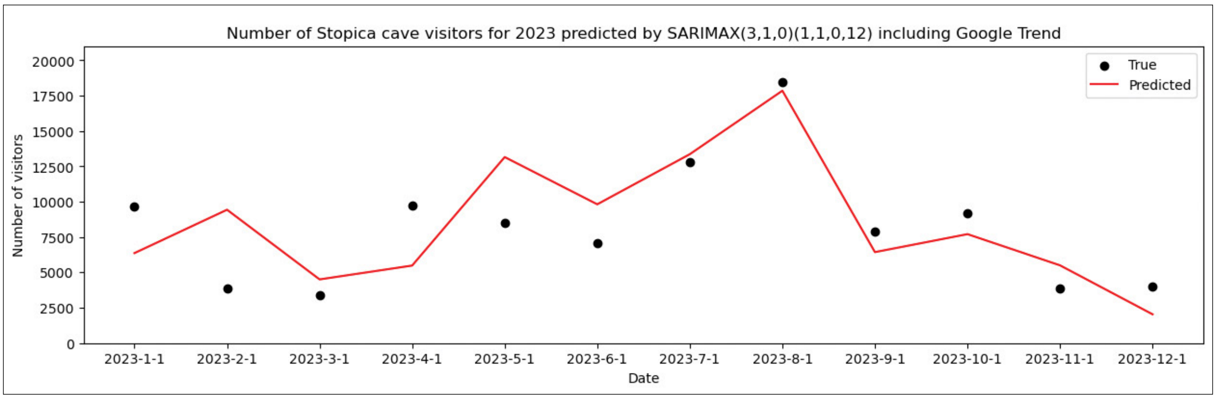

Figure 7. Prediction of number of visitors for 12 months for 2023 obtained with SARIMAX - ARIMA which includes a seasonal component and Google Trends as an exogenous variable leading to the most accurate predictions, "RMSE" = 2908.27,r = 0.77.

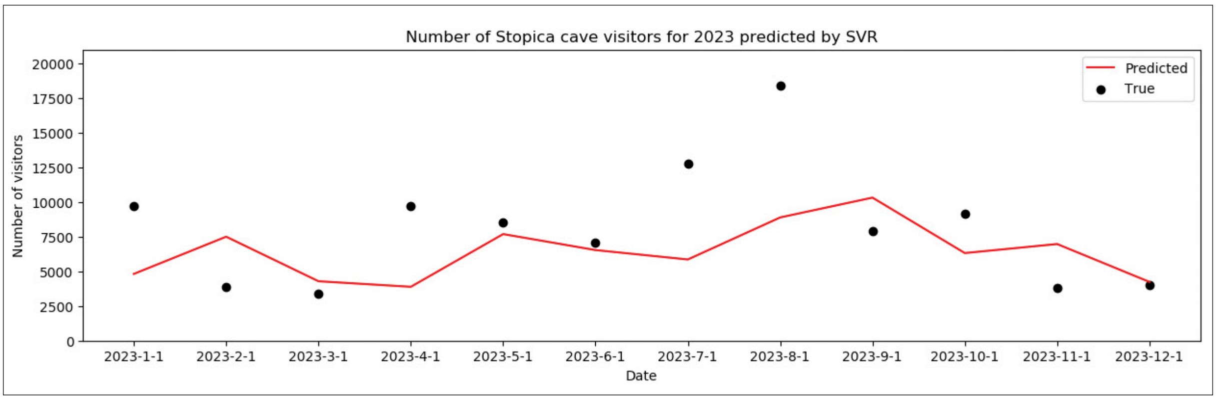

Figure 8. Prediction of number of visitors for 12 months for 2023 obtained with SVR model, "RMSE" = 4430.33 ,r = 0.29.

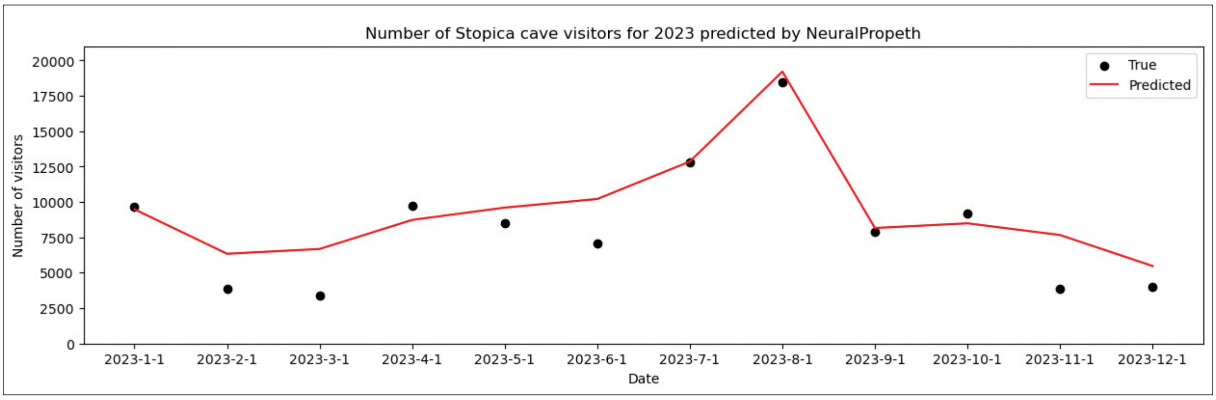

Figure 9. Prediction of number of visitors for 12 months for 2023 obtained with the NeuralProphet model, "RMSE" = 1976.90,r = 0.93.

obtained with all ARIMA models as well as SVR.

The estimated trend and seasonal components as well as parameters for and lags of the targeted time series and Google Trends, respectively (Fig. 9) emphasize that the possibility to extract estimated model parameters (Fig. 10) is of great importance for stakeholders and policymakers. This is an additional advantage of the NeuralProphet model since many ML based models are like a "black-box" for experts to understand.

Discussion

Insights into Stopića Cave Tourism Demand

Cave tourism includes unique opportunities and challenges that require specialized strategies for effective management. The analysis of touristic demand of Stopića cave indicates the dynamism of the demand for the most visited cave in Serbia and gives touristic implications that may be of importance to tourist organizations and decision-makers. Like many other destinations, Stopića cave has visitation patterns that are influenced by seasonality, external events, and visitor preferences. The peak periods of visits during the summer represent the importance of adapting to seasonal growth, which includes optimizing the visitor experience. The increase in visits during the summer months of 2020 is the result of the COVID-19 pandemic, which was associated with travel restrictions and a need to adapt to domestic tourism. The most significant influence on visits to Stopića cave is the proximity of the mountain/tourist center Zlatibor. During the pandemic, many visitors stayed at this tourist center, which offers tourist activities throughout the season. A visit to the Stopića cave is one of the optional trips from the Zlatibor tourist center, which are often carried out as individual trips or as part of organized group excursions offered by tourist agencies. This increase in the number of visits di-

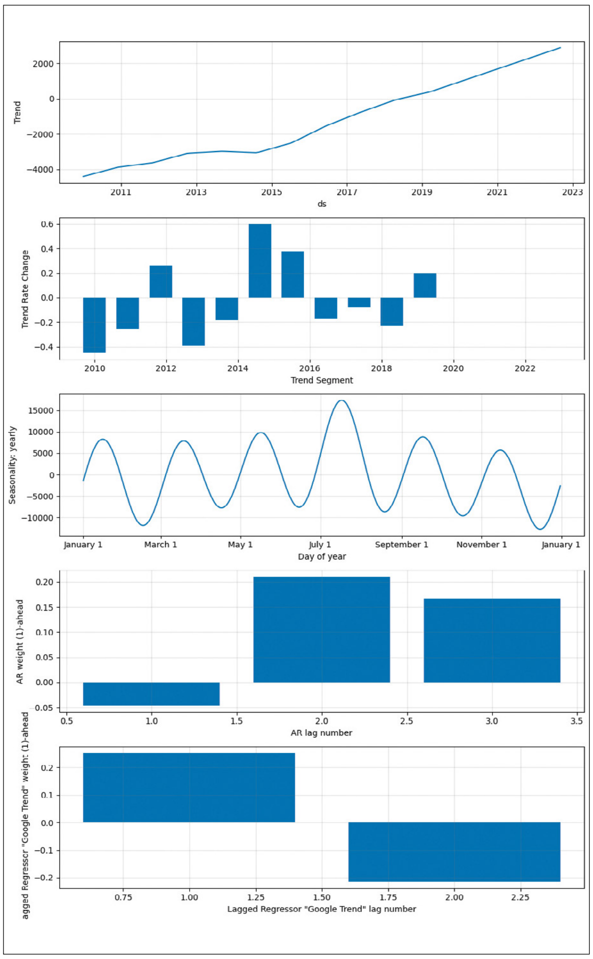

Figure 10. Estimated parameters of NeuralProphet model.

rectly affects the sustainability of Stopića cave as a tourist-accessible cave.

The sustainability of cave tourism requires a delicate balance between visitor access and conservation. By quantifying tourism demand patterns, seasonal variations, and visitation trends, we gain valuable insights that can inform steps toward carrying capacity estimates and the development of effective management strategies. In order to translate these insights into specific actions to promote sustainable cave tourism management, it is necessary to conduct environmental monitoring and risk assessments. Nevertheless, the data shows future peak visitation levels, thus periods of potential overcrowding. This information is crucial for managing visitor access, optimizing tour routes, and implementing crowd control measures to prevent ecological degradation in sensitive areas. Recognizing these high-impact periods, tourism authorities can implement proactive management measures, such as visitor quotas, timed entry tickets, or temporary closures, to prevent environmental degradation and preserve the integrity of the subterranean ecosystem.

Furthermore, patterns in online search activity indicate a strong connection with the actual number of visitors, which further shows evident public curiosity and potential visitation intent. Exploring online search behavior can guide targeted marketing strategies and promotional efforts aimed at attracting visitors to the cave. Therefore, by gaining insights into online search, cave management can anticipate visitor trends and thus generate sustainable adaptive management strategies. This is also a conclusion from other similar studies to forecast tourism demand of various touristic sites (Sun *et al.* 2019; Li *et al.* 2020).

Cave Management and Geoconservation

An insight into the tourist demand for the cave enables the planning of adequate measures of environmental monitoring in order to determine the dynamics of anthropogenic influence. With an increase in demand, it is necessary to establish continuous monitoring of climatic parameters from the increased presence of visitors, such as changes in temperature, air humidity, and CO_2 emissions. Improved security is also necessary not only for the visitors themselves and the required infrastructure, but also for the cave itself. Precautionary measures are required to maximize the protection of fragile aspects of the cave, such as speleothems and groundwater quality.

As we have seen, tourism at Stopića Cave is seasonal, with visitor pressure varying throughout the year. Understanding these patterns is crucial for anticipating periods of potential ecological stress and implementing conservation strategies. Based on the observed trends and forecast visitation patterns, we categorized the months into relative pressure scenarios reflecting potential impact on the cave environment (Table 1).

This analysis (Table 1) integrates data from the neural network method with the geosite assessment framework E-SCAM (Extended Show Cave Assessment Model), and focuses on the geoconservation aspects of show cave management through the use of E-SCAM indicators (Antić *et al.* 2025). In line with the aim of this paper, Tourist Values are excluded. Outcomes expected from predicted tourism pressure are matched with relevant E-SCAM indicators, including speleological dimensions (aesthetic qualities, scientific importance, and protection) and infrastructure elements (such as pathways, handrails, and lighting). At the subindicator level, practical measures are proposed for different months and pressure levels, allowing for detailed and situation-specific recommendations.

The pressure categories ("High-Peak," "Moder-

Table 1. Seasonal Pressure and Geoconservation Implications

Month	Relative Pressure	Expected Geoconservation Outcome	Indicators from E-SCAM (Speleological & Infrastructure)
November-March	Low-Moderate	Minimal impact; maintain baseline sustainability	• Speleological Aesthetic—general maintenance to prevent deterioration; Scientific—low-intensity monitoring; Overall protection—long-term conservation measures implemented. • Infrastructure Pathways—inspection and upkeep; Handrails—minimal intervention; • Lights—baseline illumination to preserve cave environment.
April-June	Moderate	Prevent local overcrowding and formation wear	• Speleological Aesthetic—minimized visual and tactile damage from visitors; Scientific—maintains integrity of formations for research; Overall protection—regular monitoring to prevent degradation. • Infrastructure Pathways—managed to guide visitor flow and reduce formation contact; Handrails—ensure safe movement while protecting delicate structures; Lights—controlled illumination to reduce human impact.

July	High-Peak (1)	Reduce ecological degradation and maintain cave integrity	• Speleological Aesthetic—strict limits on visitor proximity to fragile formations; Scientific—safeguards ongoing studies from disturbance; Overall protection—heightened oversight during peak season. • Infrastructure: Pathways—rerouting or temporary closures in sensitive zones; Handrails—reinforced or added in high-traffic areas; Lights—timed lighting to prevent excessive wear and humidity changes.
August	High-Peak (2)	Protect fragile areas during peak-season pressure	• Speleological Aesthetic—barriers or restricted zones to protect fragile formations; Scientific—restrict access to sensitive research sites; Overall protection—emergency intervention plans for high-impact areas. • Infrastructure Pathways—ensure non-slip, durable surfaces; Handrails—inspect and maintain for high use; Lights—energy-efficient lighting to minimize environmental stress.
September-October	Moderate	Maintain sustainable tourism levels	• Speleological Aesthetic—regular cleaning and visitor management to maintain visual integrity; Scientific—monitoring continues at moderate intensity; Overall protection—routine checks. • Infrastructure Pathways—maintain condition; Handrails—minor repairs as needed; Lights—adjusted for visitor volume.

ate," and "Low-Moderate") are defined from the observed clustering in monthly visitation data and the corresponding model predictions. July and August consistently form the highest-demand cluster, with visitor numbers significantly above all other months, which justified their classification as High-Peak. April-June and September-October occupy an intermediate range in both the empirical data and forecasted values, forming the Moderate category. The remaining months show lower visitation and are grouped as Low-Moderate.

This categorization allows for a conservation-centered interpretation of visitor demand. The high-pressure periods represent the greatest risk for ecological degradation. In contrast, the low-pressure months offer opportunities to maintain baseline conservation efforts while supporting ongoing tourism. By framing the seasonal variation in terms of relative pressure and expected conservation outcomes, the study provides a preliminary assessment of the cave's resilience to visitor impacts, enabling tourism authorities and conservation managers to anticipate periods of potential overuse, prioritize monitoring efforts, and plan for adaptive management strategies that align with sustainable tourism.

The seasonal pattern of tourism at Stopića Cave isa shaped by a combination of broader tourism trends and local conditions. The cave is open throughout the entire year, with only its opening hours changing seasonally (24 October–5 April: 09:30–16:30; 6 April–15 July: 09:30–18:00; 16 July–10 September: 09:30–19:00; 11 September–23 October: 09:30–18:00). While increased travel during the summer holiday period contributes to higher mobility in general, the rise in cave visitation during this time is better explained by destination-specific factors. Show caves are more appealing in summer due to generally favorable weather. This aligns with the summer peak on Zlatibor Mountain, which contrasts with the winter peak associated mainly with ski tourism. For these reasons, the seasonal increase in visitors to Stopića Cave reflects the environmental suitability and the complementary summer offer of the wider destination, rather than vacation timing alone.

Conclusion

Three different methods are explored for modeling tourist arrivals in Stopića cave in Serbia every month - classical ARIMA with and without a seasonal component and Google Trends as exogenous variable, the pure ML method SVR and the hybrid NeuralProphet method which combines classical and ML concepts. The best fit for the chosen test period of one year is obtained with NeuralProphet, which is modeled by a shallow NN, and Google Trends as an exogenous variable. The estimated NeuralProphet model, apart from giving the best predictions for the considered time series, also outputs the significance of the influence of lags for both auto-regressive and exogenous variable parts, helping policymakers to better understand the model.

Our choice of a hybrid time-series and machine-learning approach incorporating exogenous variables (e.g., Google Trends) proved more practical and more accurate than traditional statistical methods. This is because the proposed framework effectively captures seasonal fluctuations, non-linear growth patterns, and the influence of external factors. Such flexibility and predictive precision are essential for the effective management and sustainable development of a sensitive natural tourism site such as a cave, where both overestimation and underestimation of visitor numbers may lead to ecological degradation or suboptimal resource utilization. In contrast, multi-criteria analyses often require the evaluation of numerous criteria (e.g., attractiveness, accessibility, environmental conditions), a process that can be time-consuming, subjective, and less suitable for dynamic forecasting of visitor demand.

Our results have important implications for the touristic affirmation of caves. The implementation of advanced forecasting modeling enables management structures to make strategic moves such as sustainable management of resources and conservation efforts. Trends in tourism demand and the impact of seasonality and external events show an increase in tourist visitation to Stopića cave, stressing the need to establish adequate protection measures that can ensure long-term subterranean environmental sustainability. This involves monitoring microclimate indicators such as temperature fluctuations, air humidity, and CO_2 emissions, which will contribute to understanding the anthropogenic impact on Stopića cave, as well as its vulnerability. Establishing monitoring programs and tracking visitor trends are crucial for tourism authorities so they can assess the effectiveness of carrying capacity measures and adapt management strategies to ensure the long-term sustainability of Stopića cave as a tourist destination.

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“Authors contribution

B. Bajić and S. Milićević explored different mathematical models for time series analysis and did experiments. They wrote also methods, evaluation and results sections. A. Antić wrote introduction and discussion and participated also in evaluation of experiments and interpretation of obtained results. S. Marković and N. Tomić supervised work, participated in work conceptualization and gave useful feedback on experiments and text.”

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