

FORECASTING TOURISM DEMAND AND SUSTAINABLE MANAGEMENT IN YELLOWSTONE NATIONAL PARK

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Abstract: Modelling tourism demand over the long term is essential for the effective and sustainable management of established protected sites. In this study, the recreation visits at Yellowstone National Park were analyzed using a unique historical dataset covering the years 1904 to 2024. Using scenario forecasts through 2030, the results indicate a gradual increase over the last century from a very small beginning to multi-million annual visits. These cumulative trends include the influence of the car age and the expansion of the Mission 66 program, as well as significant disruptors such as the occurrence of World War II and the COVID-19 pandemic. These monthly visitations were modelled using the ARIMA approach. After testing the results using the criteria mentioned above, the final model applied was the SARIMA (2, 1, 1) (1, 1, 1,12), which indicates the dominance of annual seasonality and the visits return to normal rapidly, but lacks autocorrelation and volatility. These scenario-based forecasts indicate a mature demand pattern: the base projection elevation in annual visitations is from 4.19 million in 2026 to 4.36 million in 2030, with a planning range of 3.77 to 5.35 million. These findings illustrate the significance of summer congestion and the effectiveness of coupled time series and scenario modelling to deal with congestion in heavily utilized national parks.

Keywords: forecasting of tourism demand, SARIMA modelling, sustainable management of Yellowstone National Park, seasonality and scenario analysis

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INTRODUCTION

The management of tourism in national parks, especially those which are ecologically valuable, such as Yellowstone National Park, is rapidly emerging as a complex task owing to the increasing number of tourists, shifting seasonality, and other factors, in line with the incorporation of sustainability practices. Therefore, it has become crucial that national parks are essential for their natural preservation but also as a source for the sheer number of tourists who visit the parks in millions each year. Precise forecasting models for the management of these parks are therefore important for estimating visitor rates, for resource allocation, among other factors, in ensuring the sustainability of these parks, both natural and tourism (Chebli et al., 2024). Although there have been some studies on using time-series models in tourism forecasting, it appears that there are still very limited studies taken into account on incorporating the ever-changing concepts of green investment and its effects on tourism system management. Green investors, who aim to enhance Environmental, Social, and Governance variables, have been core agents that have helped in managing turbulence in the tourism industry by stressing sustainable future aspects. In a former research work, it has been shown that incorporating concepts of green investment into tourism businesses has helped improve visitor habits and boosted financial manageability. But not much consideration has been taken into account on incorporating investment features of green concepts with scientifically advanced forecasting models to enhance resource manageability and tourism system sustainability at national parks such as Yellowstone (Bergmann, 2024; Hellman & Ramsey, 2004; Liang et al., 2023).

In some works related to ecotourism, a scenario-based forecasting method was proved to be effective when the variables were both qualitative and quantitative (Shabrina et al., 2026). We also used simple scenario-based method to

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forecast expected visits in Yellowstone National Park from 2025 through 2030 applying the SARIMA models. The technique will involve the analysis of past data on the number of visits made to the park. This will also involve the use of seasonals in adjusting for the expected changes in visitor behaviors during the peak and off-peak periods.

Three scenarios will be used in an endeavor to establish the comprehensive visits expected in the park during the mentioned periods (Devi et al., 2024; Hu et al., 2025b; Shahriari et al., 2025).

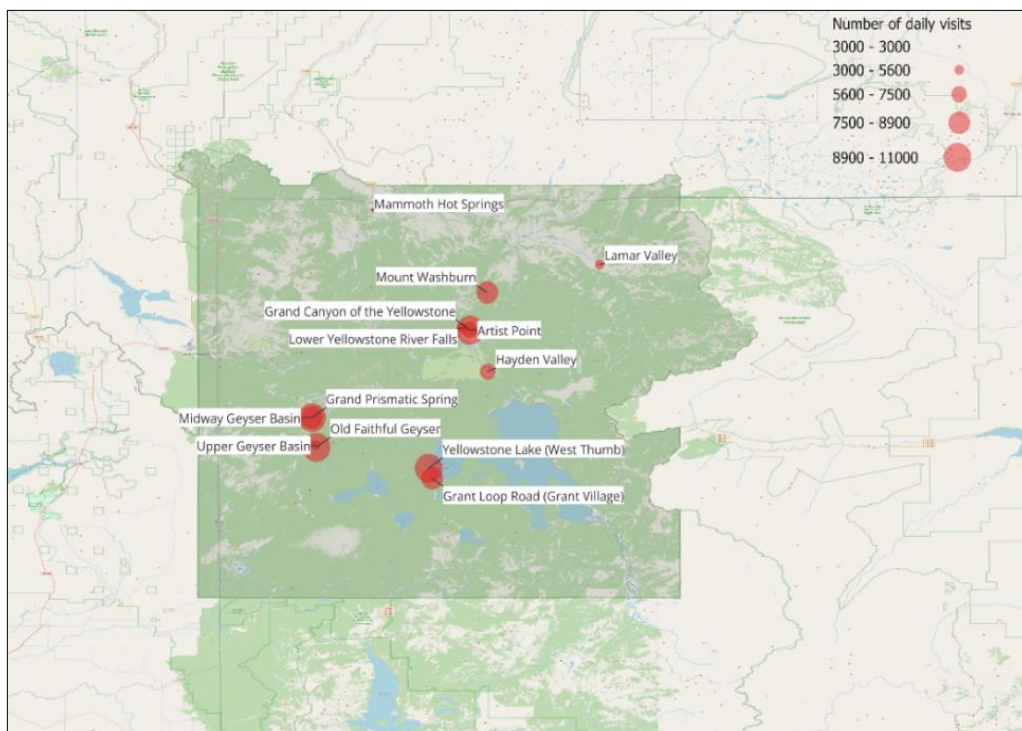


Figure 1. Visiting hot spots of Yellowstone National Park

This research seeks to demonstrate the integration of advanced forecasting models with sustainable tourism practices may greatly optimize the management of national parks. Specifically, the findings are intended to indicate not only continued visitor increases, but also the increasing gap between the best and worst-case estimates to indicate the imperative of adaptable management. In conclusion to the findings and implications of the research, two takeaways include the application of the research as guidance regarding a particular tourism future for Yellowstone National Park and the imperative of sound and environmentally conscious investment as the basis for a robust tourism management approach.

LITERATURE REVIEW

Tourism demand forecasting in Yellowstone National Park has been inextricably linked to the issue of maintaining balance between conservation and use and has necessitated approaches that combine rigor and flexibility. Traditional methods like ARIMA and SARIMA techniques in time series analysis offered empirical formulas for planning visitor stream patterns in very seasonal environments (Hu et al., 2025b; Song & Li, 2008). However, as noted by Li et al. (2025), these methods fail when faced with sudden shocks, leading researchers to employ sophisticated machine learning methods. Complementarily, the work of Kim et al. (2025), presents a compound pattern recognition system suited for short-term and minute-level predictions regarding operational problems like entrance congestion and holiday peaks.

But aside from improvements in methodology, there is a great importance placed upon the integration of forecasting models into a broader ecological or social system. For example, through a case study, Rinaldi et al. (2021) revealed that the Greater Yellowstone Ecosystem is affected by climate-related regime shifts, induced by shifts in temperature regimes, insects, and fire disturbances, which have altered the conditions of this forest's resilience, such that forecasts of visitors must continually be calibrated with ecological data such that visits forecasts do not exceed ecosystem thresholds. For their part, White et al. (2009) asserted the extent to which it is essential for Yellowstone's management agencies to base their actions on a better understanding of climate change impacts and other ongoing issues, such that Yellowstone appears to have moved toward greater evidentiary control of decision-making since the passage of the National Parks Omnibus Management Act of 1998, but engagement of science and management still faces challenges of political and social disagreement about their specific meanings and implications.

The social side of forecasting matters just as much. Morris & McBeth (2003) illustrate how Yellowstone and surrounding towns moved from old, extraction-based "Old West" economies to a newer mix focused on services and tourism, and how that change reshaped how people feel about the environment. Places that relied on extraction tended to see nature in utilitarian terms, while communities that leaned into tourism developed a deeper appreciation for nature. That shift boosts support for conservation, but it also sparks conflicts where the values of the "Old West" clash with

those of the “New West.” Cheng et al. (2022) argued that forecasting and management must involve local communities through participatory governance to build legitimacy and shared responsibility in conservation. Bergmann (2024) supplements the point by showing that participatory tourism tied to biodiversity protection strengthens both ecological health and local economic resilience, suggesting forecasts should be judged not only on accuracy, but also on their contribution to socio-ecological well-being. Recent discoveries reveal that the demand for visits is driven by more than ecological and economic changes; rather, discussions surrounding the topic online influence visitation patterns too.

Norman & Pickering (2023) reveal that the discussions of U.S. visits discussed online in the form of tweets follow the trends of respective visits, as ‘Yellowstone’ is a popular destination in online discussions too. Social media is therefore an additional source of information that can be used for forecasting visitation patterns; it paints the current picture of what the public is wondering and concerned about in terms of visitation patterns in the immediate future by providing current information regarding visitation patterns of the general public. This is backed by Geng et al.’s (2024) discovery that the post-COVID trend of less crowded destinations can be detected in mobile and internet data streams.

Human history and land use patterns also carry lessons concerning sustainable resource management (Ilies & Josan, 2009). For instance, Yonk et al. (2018) demonstrate that the natural equilibrium in the Northern Range of the Yellowstone region was maintained through the Indigenous controlled burns and hunting practices.

When these practices ceased, the consequence was the intended effect on the native habitats. Thus, the authors suggest the need to revisit the controlled burns and the elk and bison herds.

Equally, the complexity of mixed ecosystem service and disservice provision by migrating ungulates in the Greater Yellowstone Ecosystem is also investigated by Maher et al. (2023). The authors demonstrate the provision of both ecosystem services, in the form of recreation and cultural significance, as well as ecosystem disservices, in the form of crop damage and disease exposure, through the presence of elk, bison, and other species. The importance of forecasts in elucidating ecosystem service trade-offs is underscored by the imbalanced provision of ecosystem services among stakeholders.

Focusing on visitors in particular, Xu & Fox (2014) evidence how tourists’ attitude to sustainable development in national parks is dependent on where their values lie: within an anthropocentric or eco-centric perspective. Both perspectives hold support for conservation but for different reasons. In relation to Yellowstone National Park, this means that visitor demand forecasting has to take into account values-based segmentation because visitors to Yellowstone National Park may either be motivated by their own gain or by the intrinsic worth of nature.

Pulling these perspectives together, predicting tourism demand and guiding Yellowstone toward sustainable management requires an approach that is layered and thoughtful. Technically, new forecasting tools—from SARIMA models to deep learning and even social media insights—equip us to forecast visitation across horizons that are short and long. Ecologically, those predictions must account for regime shifts and ecosystem thresholds, setting expectations upon the realities of the landscape (Rinaldi et al., 2021; White et al., 2009). Socially, we need forecasts that listen to changing values within host communities (Morris & McBeth, 2003). Centrally, we need forecasts that honor participatory governance (Cheng et al., 2022) and afford biodiversity-linked economic futures (Bergmann, 2024).

Historically, we must be willing to acknowledge the deep, long-standing human footprint across this space (Yonk et al., 2018). Lastly, at the stakeholder level, we must weigh both the ecosystem services and potential disservices attributed to wildlife migrations (Maher et al., 2023) along with the varied visitor values (Xu & Fox, 2014).

Some studies show that development of rural recreational network is important in urban planning and for mitigating over-tourism (Fan et al., 2026). The common thread throughout this body of literature is clear: accurate forecasting matters, but it pays dividends only when situated within adaptive, science-based, and participatory processes.

Only through this integrated, interdisciplinary approach can Yellowstone balance its two goals: fostering tourism while protecting ecological and cultural integrity for future generations.

MATERIALS AND METHODS

Throughout the study we applied scenario-based forecasting which covered three scenarios: baseline, pessimistic and optimistic. For baseline scenario forecast we used SARIMA (Seasonal Autoregressive Integrated Moving Average) model. This model is used in a long time series data with seasonal changes. The dataset of recreational visits to Yellowstone National Park includes 120-year annual data, as well as 45-year monthly data, so we decided to use this method.

Seasonal ARIMA(p, d, q) \times (P, D, Q) on the monthly series y_t can be defined mathematically as follows (Box et al., 2015):

$$\Phi(B^S) \times \varphi(B) \times (1 - B)^d \times (1 - B^S)^D \times y_t = \Theta(B^S) \times \theta(B) \times \varepsilon_t$$

where

B – backshift operator, $By_t = y_{t-1}$;

$\varphi(B)$ and $\theta(B)$ are nonseasonal AR and MA polynomials (orders p, q);

$\Phi(B^S)$ and $\Theta(B^S)$ are seasonal AR and MA polynomials (orders P, Q);

d and D are degrees of seasonal and nonseasonal differencing;

ε_t – white noise,

The annual model is defined as the sum of monthly models (Box & Jenkins, 1970):

$$\hat{Y}_t = \sum_{i=1}^{12} \hat{y}_{t,i}$$

$y_{t,i}$ – monthly forecasting model.

We keep the baseline as most likely path and build optimistic as well as pessimistic paths through transparent multiplicative adjustments that encode assumptions about demand, infrastructure, closure etc.

Let t_0 be the compounding start year (we used $t_0 = 2024$). For year $t \geq t_0$ define (Box et al., 2015):

$$Y_t^{(s)} = \hat{Y}_t \cdot (1 + g^{(s)})^{(t-t_0)}$$

Where,

\hat{Y}_t – baseline annual;

$s \in \{\text{Optimal, Pessimistic}\}$ is the scenario;

$g^{(s)}$ – Annual growth or decline rate for the given scenario .

As the number of visitors coming to Yellowstone National Park is prone to strong seasonality, we can apply different growth or decline rates by month group (peak vs shoulder vs winter) and sum all this to annual:

$$\hat{y}_{t,m}^{(s)} = \hat{y}_{t,m} \cdot (1 + g_m^{(s)})^{(t-t_0)}, \quad Y_t^{(t)} = \sum_{m=1}^{12} \hat{y}_{t,m}^{(s_0)}$$

In our opinion peak months from June to September might get bigger optimistic uplifts and bigger pessimistic penalties than winter months.

RESULTS AND DISCUSSION

The dynamics of recreation visits to Yellowstone National Park documented from 1904 to 2024 are given below. The scatter plot shows annual recreation visits from the early 1900s through the early 2020s (Figure 2). The y-axis is visitor counts (up to approximately 6 million); the x-axis is year.

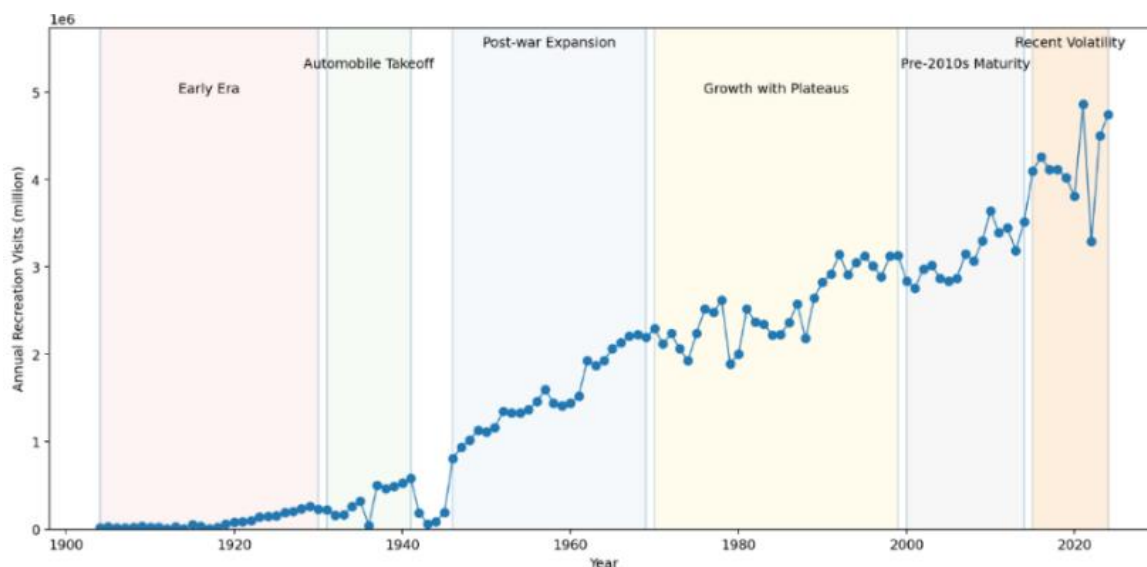


Figure 2. Recreation visits to Yellowstone National Park from 1904 to 2024¹

The early era (1904–1930) aligns with the park’s limited road access and the slow emergence of automobility. Yellowstone did not officially allow private automobiles until 1915, and early motoring remained difficult, so visitation stayed low and irregular². The automobile takeoff of the 1930s reflects expanding park road networks and America’s growing car culture; National Park Service (NPS) road histories document sustained road development in the 1920s–30s that helped lift visits³. The sharp interruption in the early-mid 1940s corresponds to World War II: wartime constraints depressed visitation across the National Park System (McDonnell, 2015).

The post-war expansion (1950s–1960s) is well-established in NPS history: surging postwar leisure travel, the 1956 Federal-Aid Highway Act, and the NPS Mission 66 build-out of visitor facilities produced a step-change in access and demand⁴. That boom fits broader scholarship on the interstate era and automobile tourism (Bennet, 2000) Through the 1970s–1990s, Yellowstone’s growth shows plateaus and oscillations, consistent with a mature system facing capacity and management limits noted by NPS during the Mission 66 aftermath and beyond⁵.

In the 2000s (pre-2010s maturity), national and park-level data show gradual drift with variability rather than a new structural surge⁶. Finally, recent volatility (2015–2024) is well documented: record or near-record highs in 2016 and 2021, a 2020 pandemic-related dip due to temporary closures, and a strong rebound thereafter. Yellowstone’s own releases report the 2020 closure window and subsequent peaks, and systemwide dashboards confirm the post-pandemic surge⁷.

¹ <https://irma.nps.gov/Stats/>

² <https://www.nps.gov/subjects/yellowstonetravelexhibit/private-automobiles.htm>

³ https://www.nps.gov/parkhistory/online_books/roads/shst.htm

⁴ <https://www.nps.gov/articles/npshistory-regrouping.htm>

⁵ <https://www.nps.gov/articles/000/mission-66.htm>

⁶ <https://www.nps.gov/subjects/socialscience/visitor-use-statistics-dashboard.htm>

⁷ <https://www.nps.gov/yell/learn/news/21001.htm>

Overall, a century-long upward trajectory from near-zero to multi-million annual visits, punctuated by historical shocks (war, pandemic) and management/capacity plateaus typical of a mature destination.

The results of the SARIMA analysis are given below (Table 1).

Table 1. Tested SARIMA models

order	seasonal_order	aic	bic	hqic	llf
(2, 1, 1)	(1, 1, 1, 12)	14170.5	14196.21	14180.56	-7079.25
(2, 1, 1)	(0, 1, 1, 12)	14170.92	14192.35	14179.31	-7080.46
(1, 1, 1)	(1, 1, 1, 12)	14174.01	14195.44	14182.39	-7082
(1, 1, 1)	(0, 1, 1, 12)	14174.82	14191.96	14181.53	-7083.41
(0, 1, 1)	(1, 1, 1, 12)	14195.54	14212.68	14202.25	-7093.77
(0, 1, 1)	(0, 1, 1, 12)	14197.01	14209.87	14202.04	-7095.51
(2, 1, 1)	(1, 1, 0, 12)	14219.99	14241.42	14228.38	-7105
(1, 1, 1)	(1, 1, 0, 12)	14250.81	14267.96	14257.52	-7121.41
(1, 1, 0)	(0, 1, 1, 12)	14259.34	14272.21	14264.38	-7126.67
(1, 1, 0)	(1, 1, 1, 12)	14259.44	14276.59	14266.15	-7125.72
(0, 1, 1)	(1, 1, 0, 12)	14299.08	14311.95	14304.11	-7146.54
(1, 1, 0)	(1, 1, 0, 12)	14328.56	14341.42	1433359	-7161.28

Table 1 below lists the shortlist of seasonal ARIMA models for the traffic data, with the seasonal parameter specified as 12. There are three models that stand out from the rest, being very close in ranking in terms of AIC values. The models that contain the smallest AIC are the (2,1,1)×(1,1,1) model (with an AIC of 14170.5), the (2,1,1)×(0,1,1,12) model (with the best HQIC of 14170.531), and the (1,1,1)×(0,1,1,12) model, which is among the best in terms of the BIC value of 14160.915. Essentially, these three models are very close in terms of AIC/BIC values of 0-4; therefore, they can be used very well in the modeling of traffic without making significant differences in the results, because they are more or less equal in performance or characteristics in providing very close values in terms of AIC/BIC ranking (Negre et al., 2024).

From the characteristics of the models in terms of differencing, the traffic can be assumed to be steady because of the trend (d = 1), and the seasonal pattern is regular in terms of the increasing and constant pattern from season to season in relation to the M.A.(1) or Q = 1 characteristic of the seasonal factors; therefore, the models should take into account the factors that should be removed from traffic data regarding the regular seasonal patterns noted in the traffic industry in the sense that there are considerable seasonal patterns regarding the regular M.A.(1) or Q = 1 in relation to the regular A.R.(1) or P = 1 characteristics of the models in the traffic industry that essentially follow the predictable patterns of summertime.

Table 2 summarizes parameters of the SARIMA (2, 1, 1) × (1, 1, 1, 12) model. Note that positively sloped autoregressions at lags 1 and 2 (ar.L1 ≈ 0.30, ar.L2 ≈ 0.14) indicate that there is persistence in performance in the short term, which means that one month of strong performance (or poor performance) will be followed by similar performance in the following one or two months. A close-to -1 value on the moving average at lag 1 (ma.L1 ≈ -0.98) reveals that there is an extremely high shock correction rate, indicating that unexpected peaks or troughs will be significantly corrected in the following month.

Table 2. Parameters of (2,1,1) × (1,1,1,12) SARIMA model

parameter	coef	std_err	z	p> z	ci_lower	ci_upper
ar.L1	0.296	0.038	7.756	0.000	0.221454	0.371221195
ar.L2	0.143	0.063	2.243	0.024893	0.018052	0.268020409
ma.L1	-0.98	0.02	-47.0083	0	-1.02419	-0.94220536
ar.S.L12	-0.13	0.07	-1.77443	0.075	-0.26872	0.01335017
ma.S.L12	-0.70	0.05	-12.4633	0	-0.81267	-0.59180459
sigma2	25317250308	0.00	2.78E+22	0	25317250308	25317250308

There are pronounced seasonal patterns in the data. The 12-month moving average is strongly negative-moving, ma.S.L12 ≈ -0.70, and highly significant, with the implication that any deviation in a month is generally offset in the same month a year later. This reflects the park’s regular yearly cycle. The 12-month seasonal autoregression is more modest, ar.S.L12 ≈ -0.13, and only borderline significant, implying a faint echo of the previous year’s level. The model uses regular and seasonal differencing, d = 1, D = 1, which implies that we take out trend and annual seasonality before estimating these dynamics. Taken together, these features establish a baseline that is seasonally stable and bounces back quickly from monthly shocks, with partial normalization from year to year. Table 3 presents goodness-of-fit for the estimated SARIMA (2, 1, 1) × (1, 1, 1, 12) model on 564 monthly observations. The log-likelihood -7079.25 gives insight into the model fit before penalties. AIC = 14170.5, BIC = 14196.21, and HQIC = 14180.56 are the post-penalty fit statistics; their lower magnitude indicates the better trade-off between the fit and complexity of the model.

Table 3. Information criteria for the selected SARIMA model (2, 1, 1) × (1, 1, 1, 12, monthly, s=12)

order	Seasonal order	nobs	AIC	BIC	HQIC	Log Likelihood
(2, 1, 1)	(1, 1, 1, 12)	564	14170.5	14196.21	14180.56	-7079.25

In Table 1, the spec with the lowest AIC that we chose to use for forecasting has the lowest values for BIC and HQIC. This means that the model is not over-parameterized for the sake of improved goodness-of-fit. From these metrics, it can be

concluded that the model is performing well in capturing Yellowstone’s visitation in comparison to competing alternatives. The Ljung-Box statistics examine the null hypothesis of no autocorrelation for the residuals of the SARIMA model of choice. The p-values at all considered lags, 6 (Q=6.63, p-value=0.356), 12 (Q=10.36, p-value=0.584), 18 (Q=17.08, p-value=0.517), and 24 (Q=26.68, p-value=0.320), are all greater than 0.05. This implies that it is not possible to reject the null hypothesis of no autocorrelation of residuals. In simpler terms, the residuals have the characteristic of being white noise when the non-seasonal and seasonal patterns for the system are factored away.

Table 4. Residual autocorrelation: Ljung-Box test for the selected SARIMA models

lags	Q	p-value
6	6.631228	0.3563
12	10.36485	0.583986
18	17.08222	0.517459
24	26.67525	0.319817

That indicates that the model is quite well-tuned, capturing the seasonal component properly, with no signs of significant AR or MA terms to include. In practical terms, that’s an indication that the baseline model used to create overlays for scenarios to become clearer is sufficient, with no bias in forecasts due to neglected serial correlation. The Ljung-Box test examines the behavior of the means but does not include variance. Therefore, other tests concerning ARCH have been carried out. For the overall model specification, the value of the ARCH-LM statistic (Table 5) is 37.91 with a p-value approximately 0.00016. This is well below the 0.05 threshold and so it means in the rejection of the hypothesis about the existence of constant variance in the residuals. This allows the interpretation that the variance in the residuals varies from one time period to the other on a 12-month cycle. This demonstrates how the residuals vary in variance in an ARCH manner. This can be taken as an indication that the model is appropriate in terms of autocorrelation since the Ljung-Box statistic is positive. Moreover, the variance in the residuals varies in an ARCH manner. This is an indication that the data is experiencing uncertainty levels in various months or years rather than consistently.

Table 5. Conditional heteroskedasticity: ARCH-LM test for the selected SARIMA model

ARCH LM (lag 12)	p-value
37.9097	0.000159

It is important because it ensures forecast intervals capture the right amount of uncertainty, as intervals which assume constant variance appear too narrow in volatile conditions but appear too wide in quieter conditions.

We formulated both positive and negative scenarios as straightforward overlays on a single, very well-established SARIMA model for Yellowstone. Our model reflects the month-to-month variations in the average case. We used regular differencing to account for the trend and seasonal differencing plus AR/MA terms for the seasonal variation so that the natural pattern of busy summer months and slow winters is evident without apparent remaining autocorrelation. From this strong starting point, we formulated our scenarios by using month-specific proportional changes that accumulate with the selected scenario year. The proportional method keeps the scale of variations in mind; that is, 5% change in July, when the park is busy, is more than the absolute change of the same percentage in February. We organize our months of interest into "peak", "off-season", and "winter" to integrate our own seasonality with what’s already incorporated in the base SARIMA. This arrangement allows us to account for asymmetric risk/prospect: smoke season poses a risk to the peak season but poses no problem to winter months. Note that our scenario layer remains independent of our statistical model. All adjustments to metrics can be done in a transparent manner to facilitate stress tests independently of our SARIMA mean structure.

This approach has strong foundations both in academic literature and in practice. Usually, the estimates of tourism demand are expressed by using time series or econometric models and then updated by using scenario estimates in cases of uncertainty in terms of access, closure, or changes in policies. Song & Li 2008 demonstrated that statistical models can be combined with expert estimates in the area of tourism forecasting (Song & Li, 2008). During the ‘era of COVID’, very many forecasts combined the statistical basis with the so-called ‘optimistic’, ‘central’, and ‘pessimistic’ scenario overlays in order to demonstrate different patterns of revival, seriously promoting the same message as scenarios can be placed upon models of forecasts. It is common practice for organizations like the OECD or the WTO to produce forecasts that are circumscribed by ‘optimistic’ and ‘pessimistic’ paths of the rate in different directions in order to incorporate the risks related to mobility or changes in policies ‘shocks.’ Forecasting textbooks describe the practice of using the SARIMA or ETS for the underlying model if official or extra-statistical information is judged significant (Slimane et al., 2024).

Table 6. Scenario-based forecast of annual visits to Yellowstone National Park

	Baseline	Optimistic	Pessimistic
2025	1198615	1237851	1171365
2026	4185541	4484697	3978632
2027	4204259	4658693	3901374
2028	4259728	4883154	3858233
2029	4310060	5110099	3812370
2030	4361109	5347048	3768609

Overall, the technique is quite realistic in terms of accounting for seasonal changes and follows the acceptable technique of adding expert estimates in appropriate cases, the underlying model accounts for average patterns, in reality while the percentage overlays provide a visible way of showing ‘what if scenarios.’ The data in Table 6 reflects a high degree of seasonality and a fully mature stage of growth. The forecasted values in Table 6 are derived from a SARIMA forecast chart, noting the presence of only a partial figure for the year 2025 compared to 2026 and subsequent years.

In 2030, the projection increases to 1.58 million visitors, which is approximately 42% higher than the pessimistic projection. This makes for a true stress test of capacity, staff, and infrastructure. In reality, managers can start to project their own base case daily needs and then employ this range to stress test parking and visitor flow, backcountry ranger presence and maintenance needs, backcountry development capacity, waste management systems, and wildlife protection measures (Bennett, 2000). In respect to overall policy and conservation needs, the optimistic projection places additional pressure on sensitive locations and a great need for developing prototypes for tools like restrictive visit periods, management of park buses and parking lots, equipment to increase trail carrying capacity, and improved visitor education programs. On the other hand, requirements for resilience planning, preparedness for unexpected funding shortfalls, and dynamic operating levels for flexibility are needed within the pessimistic projection. Due to dynamic change patterns posed by events such as wildfire smoke coverages, July to August short-term facility closures, and events concerning visitor or facility heating access disruptions, managers within parks should employ contingency planning with adjustments to their own annual forecasts and associated monthly adjustments.

These projections, taken together, suggest a fully developed system growing at a moderate rate. During the period from 2026 to 2030, the baseline results show a slight increase in the number of visitors from approximately 4.19 million to 4.36 million (plus 4.2%, indicating stabilization from the past fluctuations, retaining the summertime trend). However, the 2025 projection, with a value of 1.20 million, is not entirely accurate, as this estimate will only include the remaining months of the existing cycle, and more precise yearly analysis can only be done after adjusting the projection to include the entire year.

With very optimistic conditions: strong marketing, expanded capacity, easy access, and fewer area closures, visitation levels could grow to 5.35 million by 2030, which is more for 22.6% from the base projection, reflecting significant cumulative growth. Conversely, with very pessimistic conditions: continued summer haze from wildfires, sometimes-closed roads or geothermal areas, less-than-optimum macroeconomic factors, or more stringent safeguard policies, visitation levels could fall to 3.77 million by 2030, which is -15.7% from base.

On this trend, there is slow growth from its relatively level base, moderated by potential gains from better access/measurement, but hindered by continuing challenges from the environment/ regulations.

In figure 3 below, Yellowstone’s past visitation pattern is given in terms of the total visitation history over the months; the blue curve represents the visitation baseline projection by the SARIMA model up to 2030; and the light blue region is the scenario range showing the optimistic and pessimistic estimates surrounding the visitation target or aim in the later years of the projection period. From the data given in the total visitation history of the past years of Yellowstone’s superstation visitation pattern, the signal is very seasonal, reflecting peaks during the summer months of June to September and troughs during the close approach of winter freezes, though the peak heights in the past years have continuously increased except for the periods of changes or interruptions in the visitation pattern.

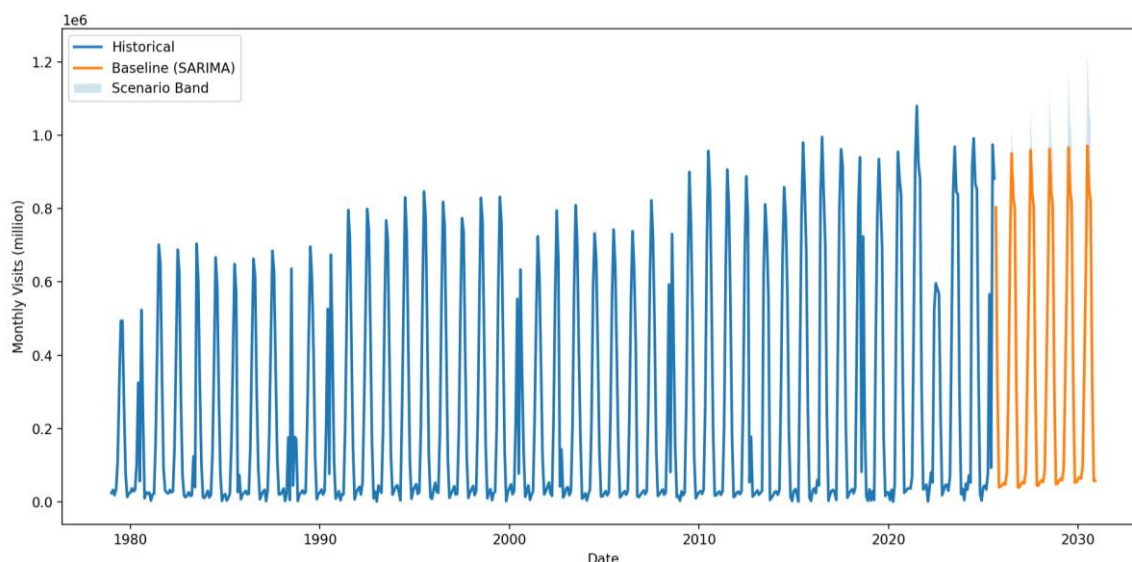


Figure 3. Scenario band around baseline forecast

Beginning now and looking into the forecast horizon, the base scenario maintains the usual cyclical pattern: summer peaks of 0.9 to 1.0 million visitor demand and winter troughs near 0. This represents a mature and stable demand profile. The range of possible demand shifts just a bit into the future, reflecting uncertainty rather than a data point indicating a trend: the high side looks at improved infrastructure and marketing, while the low side considers the risks posed by wildfire smoke or a macroeconomic downturn (Yonk et al., 2018). From an operational point of view, the map

verifies that the priorities in terms of summer seasonization should be in the areas of personnel, parking and traffic control, and guest services, while the winter demand is expected to remain very low.

From the planning point of view, the scenario spectrum can be used for stress testing (focusing on contingency plans and parking spillovers), while overall the map reveals a robust system that is well-seasonalized regarding peak activity in the summer season, light in the winter season, of moderate expected growth rate, and with well-defined but non-negligible uncertainty range till 2030. In the figure 3 above, the history of the number of visits to Yellowstone each month is traced out, and then three future scenarios are projected. These scenarios include the baseline forecast (orange), the best-case or optimal future (green), and the worse-case or pessimistic future (red).

In the past, the trend is clearly seasonal in the way that one needs to note the significant increase from June to September each year and the negligible number of visitors during the winter months. In the summer months, the number of visitors just keeps rising each year; this is interrupted sometimes by the shock effect, and then recovery.

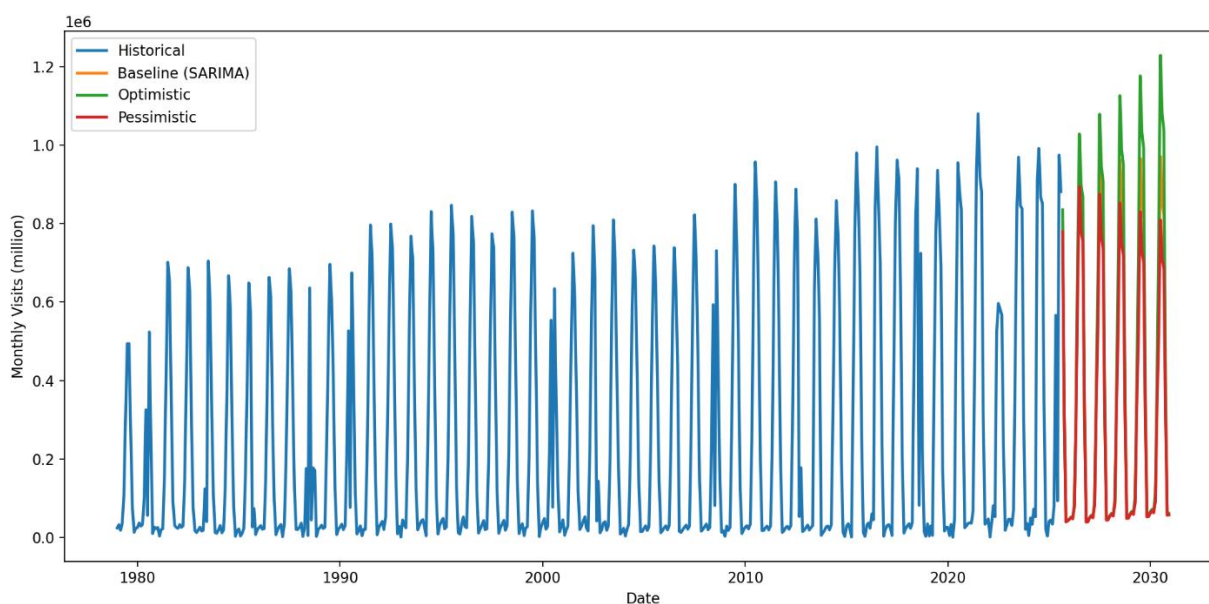


Figure 4. Yellowstone monthly visits: historical values and scenario forecasts

From the forecast start, the baseline preserves this seasonality and implies a mature, steady regime: summer highs stabilizing around the upper hundreds of thousands to approximately one million monthly visits, winters remaining minimal. The optimistic scenario arcs above the baseline, with progressively higher summer crests, consistent with smoother access, incremental capacity, marketing momentum, and fewer closures.

By contrast, the pessimistic path sits below the baseline, reflecting headwinds such as wildfire smoke, episodic road/geothermal closures, or macro softness that suppresses peak months most (Figure 4).

Practically, the figure signals that resource needs remain summer-concentrated under all scenarios, but the magnitude varies: optimistic conditions require more parking/traffic control, ranger and maintenance staffing, lodging and concessions throughput, and visitor-safety operations; pessimistic conditions reduce peak loads yet demand resilience planning for irregular disruptions. Overall, the system appears robust and season-locked, with moderate baseline growth and a widening yet manageable uncertainty envelope that should guide capacity buffers and contingency playbooks through 2030.

CONCLUSION

In this context, this study was concerned with projecting the number of visitors that can be anticipated at Yellowstone National Park, and then applying these projections to provide useful insights for managing these visitors sustainably. In applying an unusually prolonged series dating from 1904 through 2024, it can be seen from these results that Yellowstone's demand has an established, seasonal-based process that has been characterized by deeper, underlying forces such as automobility, continuing infrastructure expansion, and national trends towards leisure, which has been intermittently affected by external shocks such as war, pandemic, or natural resource constraints.

However, following these interruptions, demand tends to recover or revert at more elevated levels in each instance. On a monthly basis, for example, the appropriate SARIMA $(2,1,1) \times (1,1,1,12)$ is applied here for an accurate analysis of these demand factors. In applying these tests for diagnostics, it can be seen that these demand factors thwart these influences of shorter-term autocorrelation patterns or seasonal factors on an annual basis, for which these residuals are left free from identifiable patterns or trends. At the same time, however, these tests for conditional heteroskedasticity demonstrate an important consideration for managing these demand factors, for which, despite an identifiable, mean level that tends towards seasonal patterns that can be more definitively projected, there are identifiable levels of variance or uncertainty that group largely around these peak patterns or external shocks.

Baseline projections through 2030 are modest, with only slight increases in the number of visits from 4.2 million to a little over 4.36 million annually, indicating a stabilization effect following the pandemic peak but no new resurgence.

However, the scenario analysis presents a very broad spectrum of possible futures. Under the more positive outlook, annual visits might exceed 5.3 million by 2030, but the less positive outlook would approach 3.8 million. The difference of over 1.5 million by the end of the projection horizon determines the boundaries under which the park's infrastructural, human resource, and conservation mechanisms will have to perform.

From a managerial perspective, three considerations dominate. First, seasonality dominates every context: the true pressure comes predominantly in summer, so sustainable management should focus more on peak-period capacity, traffic management, staffing, and spreading visitors than on yearly totals. Second, uncertainty isn't flat and predictable; it's shock-driven. It is environmental hiccups, short closures, and access limits that often hit the peak months hardest, which means adaptive, month-by-month plans beat one-size-fits-all annual policies. Third, melding statistical forecasts with clear, scenario-based overlays gives a practical tool for decision-making. However, this work relies only on the time series data of past visits, therefore does not take into account strong factors such as the impact of community's behavior on the increase in the growing number of visitation (Sumarmi et al., 2026). Therefore, the results of the forecast have to be interpreted carefully and used only for shorter time span, for instance, by 2030.

This work illustrates the value of integrating long-term knowledge about the past with our present-day models and scenarios. Considering Yellowstone and other iconic destinations, it's not just about dealing with the increased flow of visitors in terms of good management is about staying the course through the variability and just getting through the shocks while maintaining the health of the system and the experience in the short season.

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