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FORECASTING FATAL TRAFFIC ACCIDENTS DURING EARLY COVID-19 AND INCREASED ENFORCEMENT ACTIVITIES: A CASE STUDY FROM HATAY PROVINCE, TÜRKIYE USING CLASSICAL TIME SERIES AND ENSEMBLE MACHINE LEARNING MODELS

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Abstract. This study investigates the temporal dynamics and predictive modelling of fatal traffic accidents in Hatay province, Türkiye, using both classical time series approaches (ARIMA, SARIMA, Holt–Winters) and machine learning techniques (Random Forest, Gradient Boosting). Monthly accident data from 2017–2021 were analysed through seasonal decomposition, stationarity testing, and comparative model evaluation. Results revealed a distinct seasonal pattern, with accident counts peaking during summer months and declining in winter, and a long-term trend showing a notable reduction in fatalities after 2017. Among the tested models, the Enhanced Gradient Boosting approach demonstrated the highest predictive accuracy (R^2 = 0.97, RMSE = 1.59), outperforming both classical time series and other ensemble methods. Forecast results for 2021 indicated seasonal peaks in June and

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August, corresponding to increased traffic density during the holiday period. The COVID-19 pandemic was associated with a marked short-term reduction in fatalities, though the effect appeared to diminish post-lockdown. These findings highlight the value of integrating advanced ensemble learning methods into traffic safety forecasting and underscore the importance of seasonally targeted interventions.

Keywords: ensemble machine learning, fatal traffic accidents, time series forecasting, traffic enforcement.

Introduction

Traffic accidents, which result in fatalities, injuries, and material losses, represent a major public health and safety concern at the societal level. Reducing accident rates, implementing effective control mechanisms, and establishing robust legal frameworks require comprehensive and systematic analyses. Over time, various statistical methods have been applied to interpret accident data and develop preventative strategies. Among these, time series analysis plays a particularly important role by revealing underlying trends and enabling forecasts that support future planning and risk mitigation.

In Türkiye, traffic enforcement data from 2017 to 2018 indicate notable increases in inspection activities: seat belt checks rose by 135.4%, mobile phone use checks by 52.7%, alcohol inspections by 27.5%, and pedestrian inspections by 43% (https://www.trafik.gov.tr/kurumlar/trafik.gov.tr/04-Istatistik/Genel/Denetim.pdf). These inspections were accompanied by various legal sanctions, particularly administrative fines. A nationwide study covering 1990–2023 highlighted that traffic fines, as a compulsory compliance mechanism, are a significant determinant in promoting safer driving behaviours (Ergin & Güler, 2025). Similarly, another study covering all provinces between 2008 and 2012 found that fines were more effective than inspections in reducing accidents, injuries, and fatalities. In particular, seat belt enforcement and speeding checks had a significant impact on lowering accident-related injuries and deaths. The correlation between enforcement measures and accident indicators was calculated to be around −0.30, suggesting that such measures could reduce accidents by approximately 10% nationwide (Sümer & Kaygısız, 2015). According to TÜİK (2024), the increase in traffic inspections and administrative fines became especially pronounced after 2017, with Hatay ranking among the top ten provinces in Türkiye in terms of traffic-related fatalities during the same period.

Time series methods, initially developed within econometrics, have since found broad applications across disciplines such as physics, engineering, and medicine (Popescu, 2020). In traffic safety research, these methods are essential for identifying temporal patterns in accident occurrences and supporting data-driven decision-making. Classical models such as ARIMA, SARIMA, structural break tests, and regression-based approaches have long formed the methodological basis of forecasting studies (Box et al., 2015; Yousefzadeh-Chabok et al., 2016; Hyndman & Athanasopoulos, 2021; Perron, 2006). In recent years, however, the integration of machine learning (ML) and deep learning (DL) algorithms has considerably enhanced the predictive power of time series forecasting (Ahmed et al., 2020; Li et al., 2022). ML-based models, including Random Forest and gradient boosting, have proven particularly effective in capturing nonlinearities, complex interactions, and multidimensional feature spaces commonly observed in accident data.

Additionally, the COVID-19 pandemic introduced abrupt global shifts in traffic behaviour and accident patterns. Recent studies have examined these changes in both pre-pandemic and post-pandemic contexts. For example, Shilling et al. (2021) found that lockdown measures significantly reduced accident frequencies, while Zhao et al. (2022) employed VAR and SARIMAX models to evaluate the impact of the pandemic on traffic incidents in China, identifying substantial changes in temporal trends.

Against this backdrop, the present study pursues two primary objectives: (i) to investigate the relationship between traffic enforcement measures, administrative fines, and the early COVID-19 period, and their combined impact on fatal traffic accidents across Türkiye, with particular attention to patterns observed in Hatay Province; and (ii) to model and forecast the monthly frequency of fatal traffic accidents using both classical time series models (ARIMA, SARIMA, Holt-Winters) and machine learning approaches (Random Forest, Gradient Boosting). By applying seasonal decomposition, stationarity testing, and comparative evaluation through performance metrics such as RMSE, MAE, and R^2, the study seeks to determine the most effective method for short- and medium-term accident forecasting. The findings are anticipated to contribute to data-driven traffic safety strategies – especially in regions with pronounced seasonal variability – and to facilitate the integration of machine learning techniques into transportation risk management frameworks.

1. Materials and methods

Dataset and data analysis. The dataset utilised in this study comprises monthly records of fatal traffic accidents in the province of Hatay, Türkiye, between 2017 and 2021. The analytical process applied to this dataset was conducted within a systematic framework, following the sequential steps outlined below.

a) Data Preprocessing: The dataset was examined for missing values and outliers. Temporal consistency and date formatting were validated. The series was aggregated at a monthly frequency, and basic line plots were used to visualise overall patterns. b) Descriptive Analysis: Seasonal decomposition – both additive and multiplicative – was applied to separate the series into trend, seasonal, and residual components, highlighting its temporal structure. c) Stationarity Testing: Augmented Dickey-Fuller (ADF) and KPSS tests were conducted to verify whether the series satisfied stationarity conditions required for time series modelling. d) Model Selection: Forecasting was performed using classical models (ARIMA, SARIMA, Holt-Winters) and machine learning models (Random Forest, Gradient Boosting). ARIMA: Captures non-stationary behaviour using AR, I, and MA components. SARIMA: Incorporates seasonal cycles and autoregressive structure; ideal for recurring patterns. Holt-Winters: Suitable for data with trend and seasonality; enables short- and long-term forecasting. Random Forest: A nonlinear ensemble model effective in complex, multivariate environments. Gradient Boosting: In recent years, machine learning approaches have been increasingly applied in time series forecasting, particularly for complex and multi-factor processes. Among these, Gradient Boosting has gained prominence due to its ability to model nonlinear relationships and multi-variable interactions with high accuracy, making it well-suited for forecasting tasks involving heterogeneous and context-dependent data (Friedman, 2001; Ke et al., 2017; Chen & Guestrin, 2016). e) Model Evaluation: Models were evaluated using RMSE, MAE, and R^2. The best-performing method was identified based on these metrics to ensure reliable forecasting. (Li et al., 2020; Sjösten, 2022; Basher & Sadorsky, 2022; Çifçi & Batur Sir, 2023).

To perform time series decomposition, the seasonal decompose function from the stats model's library was utilised, and both the Augmented Dickey-Fuller (ADF) and KPSS tests were likewise sourced from this package (Seabold & Perktold, 2010). For ARIMA and SARIMA modelling, the auto ARIMA function of the "pmdarima" library was employed (Hyndman & Khandakar, 2008). As the machine learning methods, the Random Forest Regressor class and Gradient Boosting from scikit-learn were adopted (Pedregosa et al., 2011).

2. Findings

To determine the seasonal structure of the series, additive and multiplicative models were compared, and the additive model, which yielded a lower error rate (RMSE = 6.75 compared to multiplicative RMSE = 7.35), was selected. Figure 1 presents the time series decomposition based on the additive model. In the first panel of the graph, the raw series is displayed, allowing for the observation of general changes and fluctuations over time. The second panel illustrates the trend component, which shows an increasing pattern from early 2017 to mid-2018, followed by a downward trajectory. The third panel reveals a strong seasonal pattern characterised by recurring peaks and troughs at similar times each year. Finally, the fourth panel displays the residual component, representing irregular fluctuations remaining after removing the trend and seasonality. While the residuals generally fluctuate randomly around zero, some periods exhibit notable deviations, suggesting that the model successfully captures the main trend and seasonal patterns, yet certain irregular effects remain unexplained.

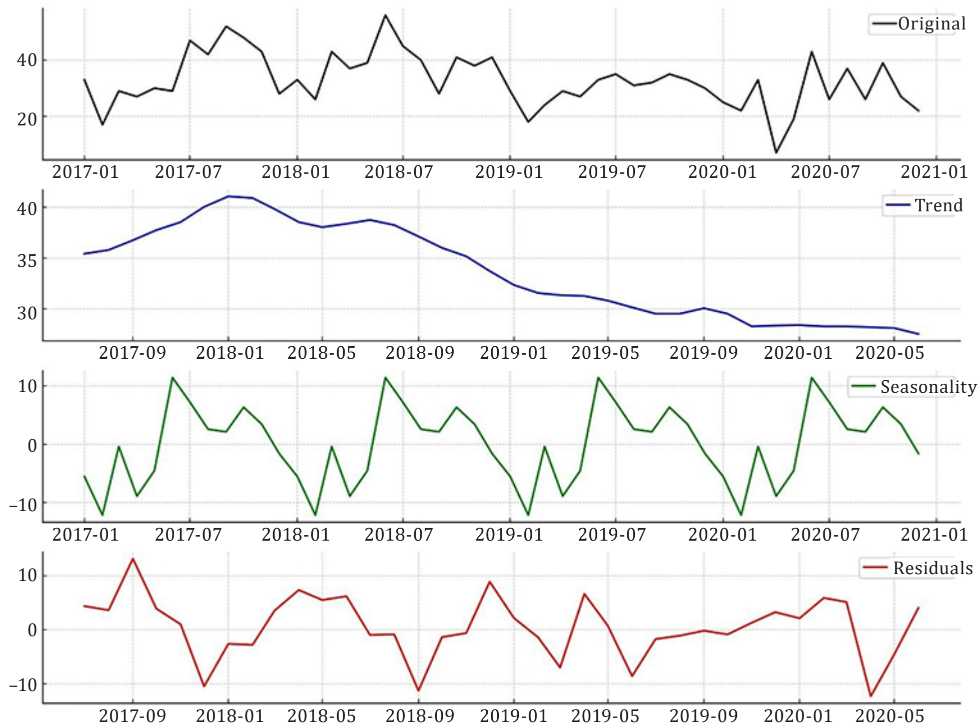

Figure 1. Time series decomposition: Trend, seasonality, and residual components

During the examined period, the trend component of monthly fatal traffic accidents exhibited a distinct pattern. Starting at approximately 35 cases in early 2017, the trend steadily increased and peaked at around 41 cases in the first half of 2018. Following this peak, a downward trend emerged, continuing throughout 2019, during which the trend level declined to nearly 30 cases by the second half of the year. As of 2020, the trend component stabilised in the range of 29 to 30 cases, indicating the continuation of this decreasing tendency. This overall trajectory suggests an upward trend until 2018, followed by a gradual decline. The post-2018 decrease may be attributed to various external factors such as enhanced traffic safety measures, changes in traffic volume, or new legislative interventions.

Seasonality analysis revealed significant periodic fluctuations within the year, offering valuable insights for preventive planning during high-risk periods. According to the seasonal effect plot presented in Figure 3, accident counts tend to rise by an average of 11.42 cases in June, while they drop by 12.15 cases in February. These findings indicate that fatal traffic accidents tend to increase during summer and decrease in winter. Factors such as weather conditions, variations in traffic intensity, and increased travel activity during the holiday season may contribute to this seasonal pattern. The results highlight the importance of designing traffic safety strategies that account for seasonal variability to improve the effectiveness of intervention measures.

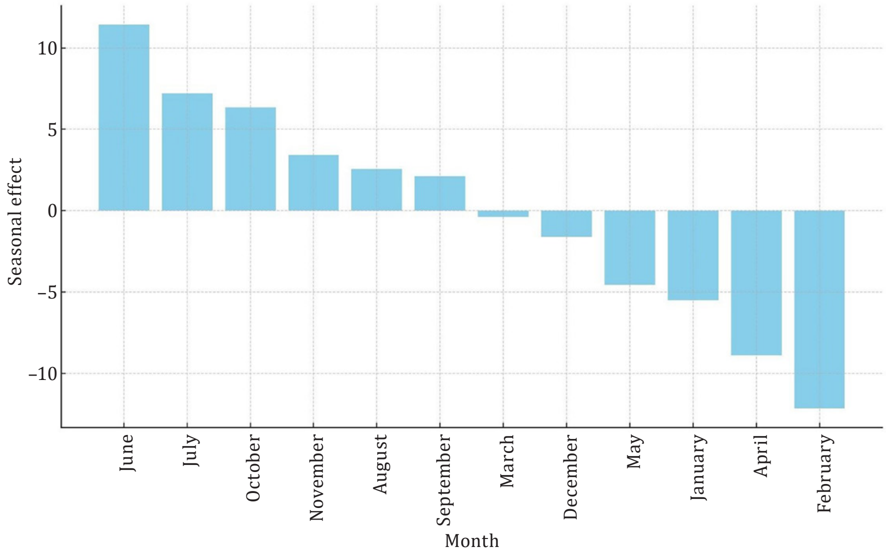

Figure 2. Distribution of seasonal effects in monthly accident counts

When evaluating the performance metrics of the four time series models employed in this study, the Gradient Boosting model emerged as the most effective, achieving the lowest error rates (RMSE = 1.59, MAE = 1.28) and the highest coefficient of determination (R^2 = 0.97). These results indicate that the model successfully explained 97% of the variance in the historical data. In comparison, the Random Forest (RMSE = 3.31, MAE = 2.56, R^2 = 0.88) and *Holt-Winters additive* model also performed reasonably well (RMSE = 6.39, MAE = 5.17, R^2 = 0.54), while SARIMA (R^2 = −0.30) and ARIMA (R^2 = −0.15) failed to adequately fit the data, as evidenced by their negative R^2 values. Based on these findings, it can be concluded that the Gradient Boosting model provides the most accurate and reliable forecasts for fatal traffic accidents in this context (Table 1, Figure 3).

Table 1. Comparative performance evaluation of time series forecasting models

Model	RMSE	MAE	R^2
Holt-Winters (Additive)	6.39	5.17	0.54
SARIMA	10.91	7.99	−0.30
ARIMA	10.12	7.34	−0.15
Random Forest	3.31	2.56	0.88
Gradient Boosting	1.59	1.28	0.97

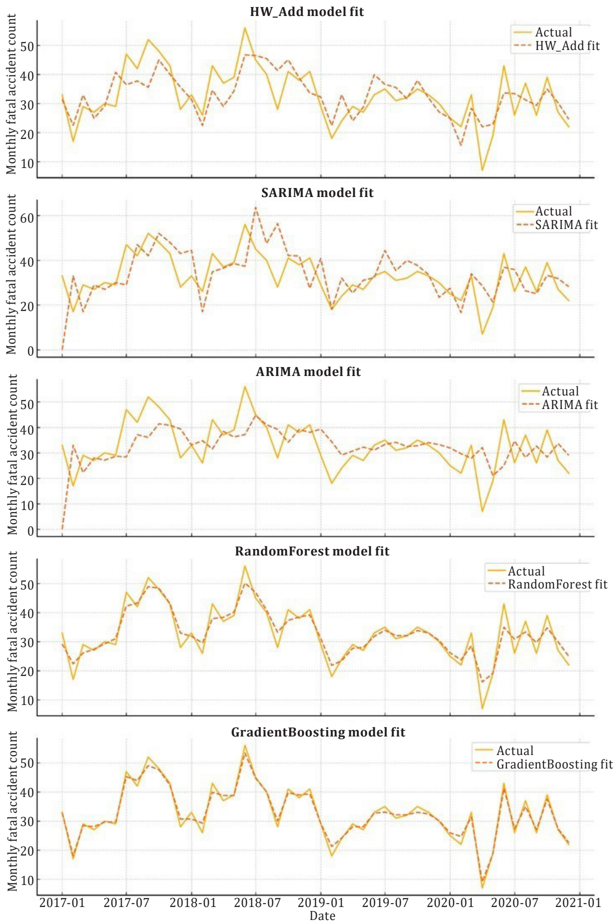

Figure 3. Comparative forecasting performance of different time series models (2020–2021)

The 12-month forecast of fatal traffic accidents for 2021, generated using the Enhanced Gradient Boosting model, is presented in Figure 4 and Table 2, along with corresponding 95% prediction interval. Based on the forecast estimates, accident counts during the first four months of the year are projected to range between 21.19 and 27.99, with the highest value observed in March (27.99; 95% PI: 22.69–34.69) and the lowest in February (21.19; 95% PI: 23.18–38.24). A statistically notable seasonal peak is anticipated in June, with the forecast reaching 36.36 (95% PI: 21.99–40.60), followed by elevated values in August (30.08; 95% PI: 22.39–41.26). This mid-year surge is consistent with seasonal patterns and is plausibly attributable to increased traffic density during the summer holiday period. In the final quarter, accident counts are expected to stabilise, ending the year at 22.46 in December (95% PI: 22.68–39.37), indicating no statistically significant upward or downward deviation from the preceding months.

Table 2. Monthly forecast of fatal traffic accidents for 2021 with 95% prediction interval (PI)

Date [January 2021 to December 2022]	Forecast	PI_Lower_95	PI_Upper_95
January	26.40	21.72	39.18
February	21.19	23.18	38.24
March	27.99	22.69	34.69
April	22.34	23.30	40.33
May	29.06	23.12	26.81
June	36.36	21.99	40.60
July	23.81	19.36	41.22
August	30.08	22.39	41.26
September	25.20	19.71	41.22
October	25.97	22.00	41.26
November	26.59	21.78	41.16
December	22.46	22.68	39.37

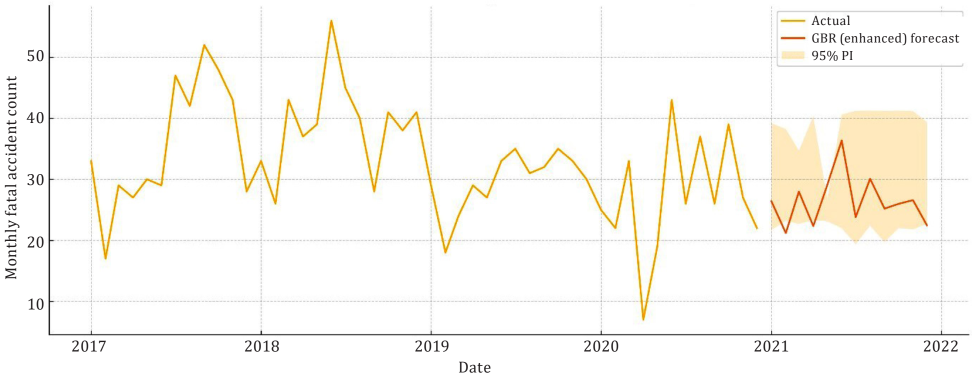

Figure 4. Twelve-month forecast of fatal traffic accidents using the gradient boosting model (with 95% PI)

3. Discussion

The findings of this study provide empirical evidence on the temporal patterns and predictive modelling of fatal traffic accidents in Hatay province, aligning with broader national trends. As illustrated in Figure 5, nationwide fatality rates have shown a substantial decline, particularly after 2017, a trajectory that parallels the reductions observed in Hatay (Figure 2). This parallelism suggests that nationwide enforcement strategies and administrative fine regimes have produced comparable safety outcomes at the provincial level. The sharp reduction in fatalities during 2020 can be largely attributed to the unprecedented mobility restrictions imposed during the COVID-19 pandemic, consistent with previous research highlighting the disruptive effects of the pandemic on traffic dynamics (Shilling et al., 2021; Zhao et al., 2022).

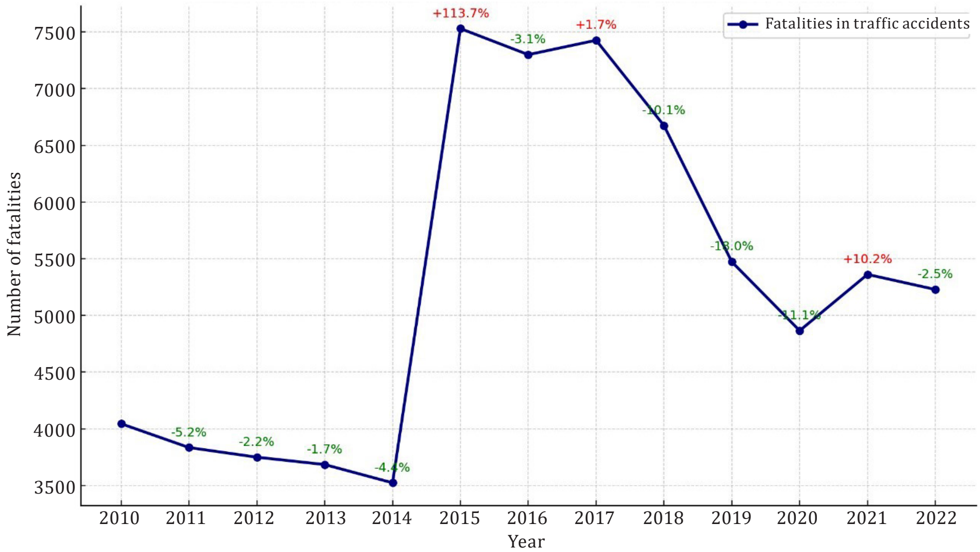

Figure 5. Annual trends in traffic accident fatalities in Türkiye (2010–2022) with annual % change based on TÜİK (2024) data

In Türkiye, COVID-19 mitigation measures – ranging from the closure of schools and public venues to weekend curfews and age-specific mobility restrictions – were initiated following the first reported case on 11 March 2020 and culminated in a full lockdown from 29 April to 17 May 2021 (Başeğmez & Aydın, 2022). As shown in Figure 6, Hatay experienced a marked decline in fatal accident counts following the onset of these measures, followed by a reversion toward pre-pandemic patterns. However, the absence of post-July 2021 data limits the ability to fully assess the long-term influence of the pandemic on fatality trends.

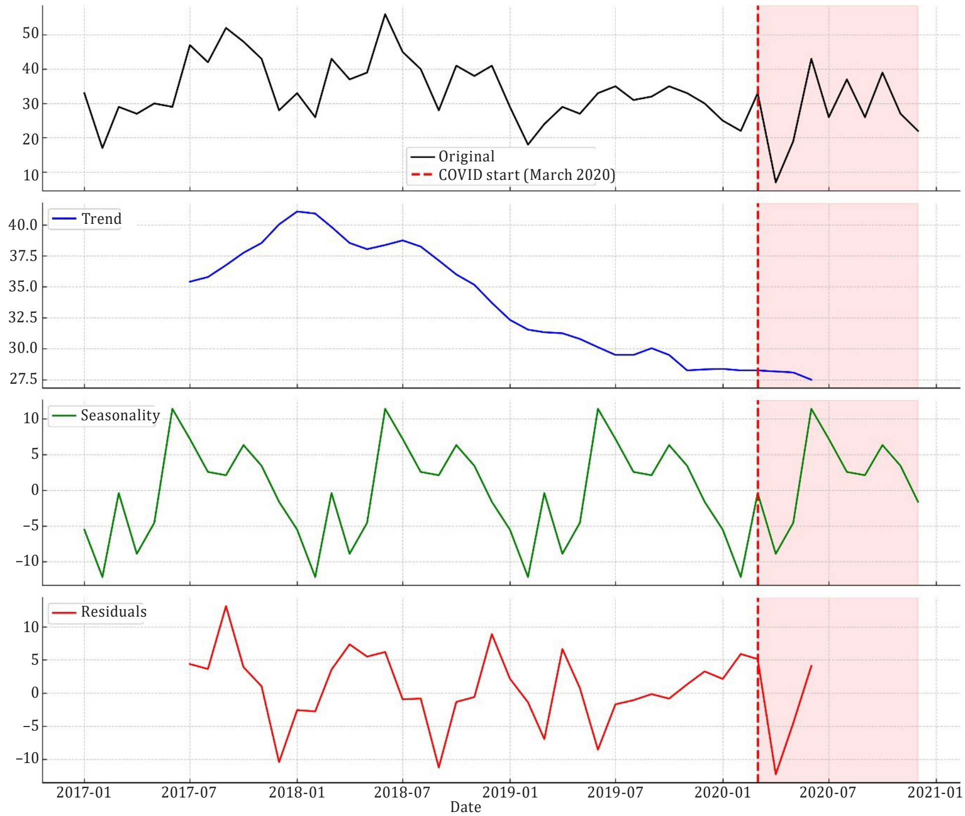

Figure 6. Time series decomposition of fatal traffic accidents in Hatay and the early impact of COVID-19

The comparative modelling results contribute to the growing literature on the differential performance of forecasting approaches under complex seasonal and trend conditions. In line with findings by Yousefzadeh-Chabok et al. (2016), SARIMA models in this study were able to reflect seasonal structures but underperformed in predictive accuracy, yielding a negative R^2 (–0.30). This outcome underscores the sensitivity of SARIMA/ARIMA performance to model order specification, particularly when datasets are short or affected by high noise levels (Figure 6) (Box et al., 2015). Similar limitations of purely linear models have been observed in other contexts, such as Ethiopia's Amhara and West Arsi regions, where unexplained volatility persisted despite acceptable model fit statistics (Getahun, 2021; Sheiso et al., 2024).

Conversely, the Enhanced Gradient Boosting model demonstrated superior performance, achieving the lowest RMSE (1.59) and MAE (1.28) values and explaining 97% of the variance in the historical data. This aligns with prior studies emphasising the robustness of ensemble learning methods – particularly tree-based algorithms – in capturing nonlinearities and complex seasonal dynamics (Friedman, 2001; Ke et al., 2017; Chen & Guestrin, 2016). The consistency of our findings with Yan and Shen (2022), who reported high predictive accuracy using Bayesian-optimised Random Forest models for accident severity, reinforces the applicability of ensemble-based approaches in traffic safety forecasting.

Forecast outputs from the Gradient Boosting model revealed a clear seasonal peak in June, with elevated counts persisting through August. While such patterns are likely attributable to increased summer traffic volumes and holiday travel, the relatively wide 95% prediction intervals observed across most months point to a degree of uncertainty in forward-looking estimates. This highlights the need for cautious interpretation of point forecasts, especially in policy and resource allocation contexts, and suggests potential value in supplementing univariate models with exogenous predictors such as traffic volume, meteorological variables, or enforcement activity (Popescu, 2020).

Lastly, the seasonal spikes identified here mirror patterns found in other geographical settings, such as Colombia (Rodríguez et al., 2015), where accident trends have been closely linked to behavioural and policy-related factors. Incorporating such contextual influences into hybrid or multivariate modelling frameworks, e.g., SARIMAX, VAR, or machine learning models with external regressors, represents a promising avenue for future research aimed at improving both the accuracy and interpretability of traffic accident forecasts.

Conclusion

The findings of this study underscore the potential of machine learning-based ensemble methods, particularly Gradient Boosting, in accurately forecasting fatal traffic accidents under conditions of strong seasonality and complex trend structures. While SARIMA and ARIMA models were able to capture seasonal patterns, their predictive performance was limited – especially when data length and noise levels presented modelling challenges. In contrast, Gradient Boosting achieved superior accuracy, suggesting that nonlinear, interaction-aware algorithms are better equipped to model real-world accident dynamics. The seasonal peaks identified during the summer months align with established associations between traffic density and accident risk, supporting the need for intensified enforcement and public awareness campaigns during these periods. The temporary decline in accident counts during the COVID-19 lockdown period further illustrates the influence of mobility patterns on road safety outcomes. Future research should extend the modelling framework to incorporate exogenous variables such as traffic volume, meteorological factors, and enforcement activity, as well as apply hybrid approaches that combine statistical and machine learning models. Such efforts can enhance both the accuracy and policy relevance of traffic accident forecasts, contributing to more effective and proactive road safety strategies.

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Conflict of Interest

The authors declare that they have no conflicts of interest concerning this publication.

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