IATSS Research 48 (2024) 230–244

Contents lists available at ScienceDirect

IATSS Research

journal homepage: www.sciencedirect.com/journal/iatss-research

Research Article

Impact of COVID-19 on road crashes in Thailand

Apichai Tongpradubpetch, Kunnawee Kanitpong *

Department of Civil and Infrastructure Engineering, School of Engineering and Technology, Asian Institute of Technology, 58, Khlong Luang, Pathumthani 12120, Thailand

ARTICLE INFO

Keywords:
COVID-19
Road crash
Time series
SARIMA
Interrupted time series

ABSTRACT

The main goal of this study is to investigate the impact of COVID-19 on road crashes in Thailand using time series and interrupted time series analysis. To achieve the goal, road crash data from the Department of Highway (DOH), which includes total crashes, single vehicle crashes, fatalities, fatal crashes, speeding crashes, and drunk driving crashes, was obtained to conduct Seasonal Autoregressive Integrated Moving Average (SARIMA) time series models and Interrupted Time Series (ITS) models. SARIMA models were applied to forecast the number of crashes in the absence of COVID-19 then compare them to the observed values to identify the difference. The impact of a policy change aimed at addressing the spread of COVID-19 was assessed using ITS models on a time series accident dataset. The goal was to ascertain if the intervention had a meaningful and causative impact on the outcome. The result showed that the first wave of COVID-19 caused a significant reduction in all road crash indicators instead of skyrocketing to a peak. After releasing the lockdown measures from the first wave of spreading, an increase was found in all of the crash indicators as well. However, the third wave of COVID-19, which lasted longest for nearly 7 months, also caused a decrease in the number of crashes, but not as much as the first wave of the outbreak. Moreover, the result from the interrupted time series also revealed that curfews and the closure of entertainment places are associated with a significant decrease in the number of speeding crashes and drunk driving crashes from 10 p.m. to 4 a.m., respectively. It can be observed that the COVID-19 countermeasures, such as curfews and bans on the sales of alcoholic beverages, led to a drop in the number of speeding and drunk driving crashes.

1. Introduction

Since December 2019, COVID-19, also known as Coronavirus, has been spreading through numerous countries around the world at a high infection rate. On March 11, 2020, the World Health Organization (WHO) officially declared COVID-19 a pandemic. By November 2, 2021, COVID-19 had infected more than 200 million people worldwide, with a total of 246,951,274 confirmed cases and 5,004,855 casualties reported in 188 out of 193 countries [1]. Meanwhile, road crashes remain one of the most critical issues causing fatalities each year. Road crashes rank as the 8th leading cause of death [2] and are a major public concern that many governments are actively addressing. Moreover, road crashes result in substantial economic losses due to the cost of treatment, the loss of labor and productivity from those who are killed or disabled due to their injuries, property damage expenses, and travel delays. Thailand, in particular, is one of the countries most affected by road crashes. In 2015, Thailand had the second-highest number of road fatalities per 100,000 people in the world and the highest in Asia [3]. Additionally, when considering only fatality rates among motorcyclists, Thailand ranked first in the world. Therefore, it is crucial and urgent to formulate policies and take steps to reduce the number of road crashes in the country.

On January 31, 2020, the Thai Ministry of Public Health announced the first confirmed COVID-19 case in the country. Subsequently, the virus rapidly spread over a wide area, infecting a large number of people. Thai authorities declared an emergency decree to prevent and reduce the risk of the virus spreading among the populace. These policy implementations forced people to avoid non-essential travel and outdoor activities, encouraging them to work and stay at home. The policy also temporarily closed schools and other places with a perceived risk of virus transmission. People had to limit their movements to essential activities, resulting in a decrease in traffic volume. Similarly in the neighboring country like Malaysia, the government also declared a movement control order around the same time to mitigate the spread of COVID-19.

Due to the reduced traffic volume, the number of road crashes was expected to be lower than usual [4], as indicated in previous studies that

* Corresponding author.
E-mail addresses: st121470@ait.ac.th (A. Tongpradubpetch), kanitpon@ait.ac.th (K. Kanitpong).

https://doi.org/10.1016/j.iatssr.2024.04.001
Received 10 August 2023; Received in revised form 20 February 2024; Accepted 13 April 2024
Available online 14 May 2024
0386-1112/

reported changes in the number of crashes in proportion to traffic volume [5]. However, the pattern and certain categories within this proportion may change, especially in an unprecedented event like the COVID-19 pandemic. Some risky behaviors, such as speeding, may increase because low traffic volume is likely to lead to impairments in drivers' ability to accurately perceive and control their own speed, making them more inclined to take risks [6]. Due to travel restrictions, the reduction in miles driven and driving days per week was 35% and 37%, respectively, in the United States in April 2020 [7]. This reduction should, in turn, decrease the risk of vehicle-related injuries, following the model: 'Traffic Injury = Exposure x Risk x Injury Probability' [8]. However, previous studies exploring the impact of COVID-19 on road crash patterns found that, although there were fewer road crashes overall, risky driving behaviors, such as speeding [9] and drunk driving [10], increased. Therefore, it is important to investigate what truly transpired and what changed in road crash patterns in each country. Although similar measures were implemented to improve road safety, drivers' behaviors and their level of compliance with traffic rules differed significantly during the COVID-19 period. It can be concluded that road safety depends entirely on the compliance of road users with traffic laws [11]. As a result, a detailed analysis and understanding of the road crash pattern in Thailand during the COVID-19 pandemic period is essential.

As mentioned earlier, the main purpose of this study is to investigate the impact of COVID-19 on road crashes in Thailand. Specifically, the study aims to achieve the following objectives:

1. To compare road crash data between before COVID-19 and during the COVID-19 pandemic period and find out how each of the road crash indicators, such as the number of total crashes, fatalities, fatal crashes had changed during the COVID-19 pandemic.
2. To identify the impact of policies that were announced by Thailand's governmental agencies and significant factors affecting road crashes during the COVID-19 pandemic.

To be more specific, this study focuses on the impact of the COVID-19 pandemic on road crash data on national highways managed by the Department of Highway. The study uses crash data from the Highway Accident Information Management System (HAIMS), provided by the Department of Highway. The collection of monthly crash data started in January 2009 and ended in December 2021. Data from January 2009 to December 2019 were used to forecast data for two years later (2020 and 2021), assuming that COVID-19 would not have occurred. Information regarding the timeline of announcements and declarations made by Thai authorities to control the COVID-19 pandemic situation from early 2020 to the end of 2021 was also gathered to facilitate a more in-depth investigation of periods when the number of road injuries and fatalities changed. In this study, only announcements and declarations that could affect traffic volume and people's mobility, such as curfews, travel restrictions across provinces, prohibitions on the sale and consumption of alcohol on the premises, and the closure of entertainment venues, were considered.

2. Literature review

2.1. COVID-19 pandemic's effect on road crash

To control the spread of the COVID-19 pandemic, governments in many nations announced lockdown restrictions, forcing people to stay home as much as possible and reduce non-essential activities that required movement. Due to the lockdown restrictions, the number of road collisions has dramatically decreased in many cities around the world. Gupta et al. [11] revealed that road fatalities significantly decreased but in different trip patterns. A significant reduction in road fatalities was observed because work-related trips frequently involved time-sensitive situations during rush hours (the morning and afternoon peaks), greatly increasing the risk of road fatalities. Additionally, it was found that fewer trips for shopping and leisure activities were associated with a decline in traffic fatalities. Sutherland et al. [12] found that vehicle collisions have declined with a steady trend during the COVID-19 pandemic. Saladié et al. [13] also detected a similar reduction in vehicle collisions or traffic crashes due to the COVID-19 pandemic. To compare the impact of the COVID-19 pandemic on road collisions with the same period in previous years, Doucette et al. [14] indicated that the average number of daily crashes was lower in the post-stay-at-home period than the pre-stay-at-home period. Further, crash rates in 2020 were significantly lower than the average of the previous 3 years for almost all types of crashes except fatal ones. Single vehicle fatal crash rates were higher than the combined averages of 2017, 2018, and 2019 during the post-restriction announcement. The study showed that single vehicle collisions and fatal crashes increased during the lockdown, while multi-vehicle crashes decreased. It was hypothesized that the increase in single vehicle crashes due to increased driving speed was associated with decreased traffic volume and reduced law enforcement. Similarly, Doucette et al. [15] found that the fatal crash rate for 2020 during the stay-at-home order period was 23% higher than in earlier years (2017–2019).

Some studies revealed that the older generation is also the most vulnerable to mortality associated with the COVID-19 pandemic. After the stay-at-home order was announced, Rapoport et al. [16] reported a two-thirds drop in the proportion of driving injuries and fatalities among adults 80 years of age and older within the first month when physical-distancing measures were implemented after the COVID-19 pandemic was put in place. In the first 50 days of the COVID-19 pandemic, Barnes et al. [17] also documented a comparable decline in the proportion of motor vehicle collisions related to adults 65 years of age and older. Furthermore, some earlier research has shown that older adults drive less at night, possibly because of declining vision. Therefore, it is not surprising that they would reduce their driving and mobility in the face of a new significant health concern.

Inada et al. [18] used time series analysis to examine how COVID-19 affected fatal motor vehicle collisions caused by speeding. The study discovered that from 2015 to 2020, the total number of police-reported traffic violations steadily decreased, but the number of speed-related violations increased between 2019 and 2020, such as speeding, impeding pedestrians, failing to stop at stop signs, and failing to stop at railroad crossings. Qureshi et al. [19] also used ARIMA time series models to perform in-depth analysis on the effect of mandated societal lockdown to reduce the transmission of COVID-19 in road crashes. The study indicated that there has been a significant decline in road traffic crashes that result in just minor or no injuries, but not in those that cause serious or fatal injuries. Barnes et al. [17] found a large and significant decrease in overall crashes, hit-and-runs, crashes involving injury, crashes involving ambulances, and minor crashes, but found no significant change involving pedestrians or fatal crashes. In addition, this study also revealed the impact of the COVID-19 lockdown on traffic crashes in different time aspects. The study showed that the COVID-19 lockdown decreased crashes both during rush hour and non-rush hour, but the decrease was larger during rush hour. Further, the travel restriction decreased mobility for both daytime and nighttime crashes; however, the effect was larger during the daytime. Catchpole and Naznin [20] revealed that the fatal crash counts were down by 10% during the COVID-19 period, and fatalities were down by 8% for the same period. Specifically, fatalities decreased for drivers, motorcycle riders, passengers, and pedestrians during the pandemic period but increased for pedal cyclists. During the lockdown period, the number of road collisions, injuries, and fatalities also decreased, but these declines were proportionate to the traffic volume (Sekadakis et al. [21].

2.2. COVID-19 pandemic's effect on traffic volume

Generally, several previous studies have shown that travel

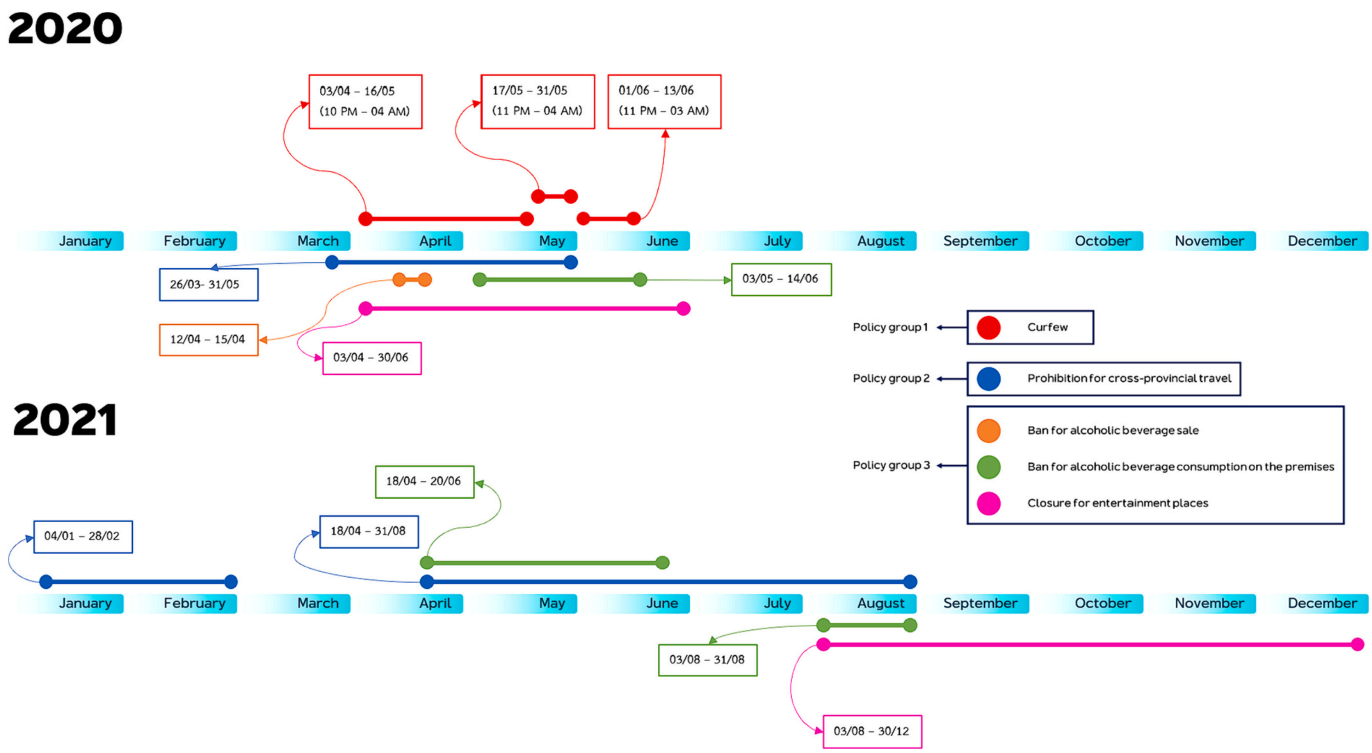


Fig. 1. Timeline of COVID-19 response measures in Thailand in 2020–2021.

restrictions resulted in a significant decrease in traffic volumes [14]. In their study, Gupta et al. [11] not only explored the effects of COVID-19 on road fatalities but also looked at the impact of the COVID-19 pandemic on mobility patterns.

Regarding the decrease in driving exposure in the younger generation, Stavrinos et al. [7] studied changes in adolescent driving behaviors before and during restrictions related to COVID-19. Teens reported driving less during the COVID-19 restrictions. Moreover, in another interesting approach aiming to quantify the effect of the COVID-19 pandemic on driving behavior and road safety during the lockdown, there was a significant reduction in the volume of people driving and walking due to the spreading of Coronavirus [22].

2.3. COVID-19 pandemic's effect on risk-taking behavior

Risk-taking behavior is considered the most important factor contributing to road crashes. Due to the decrease in traffic volume and travel, many drivers tend to drive faster, more recklessly, and engage in more risk-taking behaviors. Vanlaar et al. [10] revealed that some drivers admitted they were likely to exceed speed limits, be distracted, drink and drive, and use drugs while driving during the pandemic compared to before the pandemic. Patwary and Khatta [23] found that the difference in the number of fatal crashes between 2020 and 2019 was associated with increased violations, including speeding, reckless driving, and alcohol and drug use.

Focusing on the rise in vehicle speeding, Lee et al. [9] found that drivers appeared to be using empty roads as an excuse to drive faster, making streets and highways potentially more dangerous. This finding suggests that traffic may be a major controlling factor in vehicle speeds. Dong et al. [24] concluded that the aggressiveness and inattentiveness of drivers increased significantly after the outbreak of COVID-19. Shahlaee et al. [25] indicated that many drivers have developed a habit of speeding after receiving stay-at-home orders. Moreover, Dong et al. [26] found that more people staying at home increased the probability of a motorcycle crash because faster traffic might result in more injuries and fatalities involving drivers of motor vehicles.

3. Research methodology and data collection

In this study, the analysis was divided into two parts according to the objectives. The first part of the study is to compare road crash data from before and during COVID-19 pandemic and to determine how road crash indicators such as total crashes, fatalities, and fatal crashes changed during the COVID-19 pandemic (2020–2021). The road crash data in 2020 and 2021 was forecasted using the historical data from 2009 to 2019 by applying time series analysis. The forecasted data represents the situation when COVID-19 does not exist and is then compared to the road crash data during the COVID-19 pandemic. The second part of the study is to evaluate the impact of policies that were announced by the Thai government on road crashes during the COVID-19 pandemic. The interrupted time series analysis was used in this second part of the study.

3.1. Time series analysis

Time series analysis is a statistical technique used to forecast the values of relevant variables that have been observed sequentially over time. Forecasting time series data estimates how the series of observations will continue in the future [27]. Time series analysis is well-suited for studying how a specific event, such as the COVID-19 pandemic, affects data collected over time. It can capture and model temporal trends in road accident data, helping to identify patterns and changes.

In this study, the Autoregressive Integrated Moving Average (ARIMA) models were used for time series forecasting. The ARIMA models are widely used in transportation research and are thought to be the most common time series models. Their popularity can be attributed to their well-defined theoretical background and straightforward calculations [28]. Thus, the ARIMA models were the most appropriate to use to investigate how COVID-19 has affected road crashes [29].

3.2. Interrupted time series analysis

Interrupted time series (ITS) design is a quasi-experimental research design for assessing the effects of interventions. In ITS studies, the same

Table 1
Descriptive statistics for the road crash indicators (monthly data) 2009–2019.

Variable	Mean	Std. error	Maximum	Minimum	Sample size
Total crashes	1146.96	393.14	2550	593	132
Single vehicle crashes	614.41	200.80	1350	354	132
Fatalities	165.15	79.97	392	42	132
Fatal crashes	126.62	69.94	334	35	132
Speeding crashes	875.79	245.07	1715	487	132
Drunk driving crashes	20.99	29.72	117	1	132

subjects and set of tools are used to collect data at multiple time points (similar to time series studies) before and after intervention (the interruption in time series) [30]. ITS is considered one of the best designs for determining causality when randomized controlled trials (RCTs) are neither feasible nor desirable. The difference between time series and interrupted time series (ITS) analysis is that ITS will be used when a time series is obtained and when researchers want to determine whether changes occurred in the series correspond with events that occurred at one or more time points. Time series analysis, on the other hand, examines the data from the past to identify patterns and components before running the best suitable model to forecast possible data in the future.

3.3. Data collection

Road crash data was obtained from the national highways crash database called HAIMS (Highway Accident Information Management System), provided by the Department of Highway (DOH). The database consists of daily road crashes, fatalities, fatal crashes, drivers' and occupants' demographic information, roadway and weather conditions, types of vehicles, use of safety equipment, and time of crash. To accomplish the first objective, monthly crash data was collected from January 2009 to December 2021, and at which the data from January 2009 to December 2019 was used to forecast the crash data for the next two years (2020 and 2021). Road crash data was reported in six different road crash indicators, including total crashes, single vehicle crashes, fatalities, fatal crashes, speeding crashes, and drunk driving crashes.

To achieve the second objective, monthly road crash data was collected from January 2015 until December 2021 in six different road crash indicators akin to the first objective. Fig. 1 illustrates the policies and countermeasures announced by the Thai government in the Emergency Decree to prevent and control the spread of COVID-19 from January 2020 to December 2021. They included banning the sale and consumption of alcoholic beverages on the premises, closing entertainment venues, limiting cross-provincial travel, and enforcing nighttime curfews. This section of the study identifies how these regulations affected road crashes during the COVID-19 pandemic.

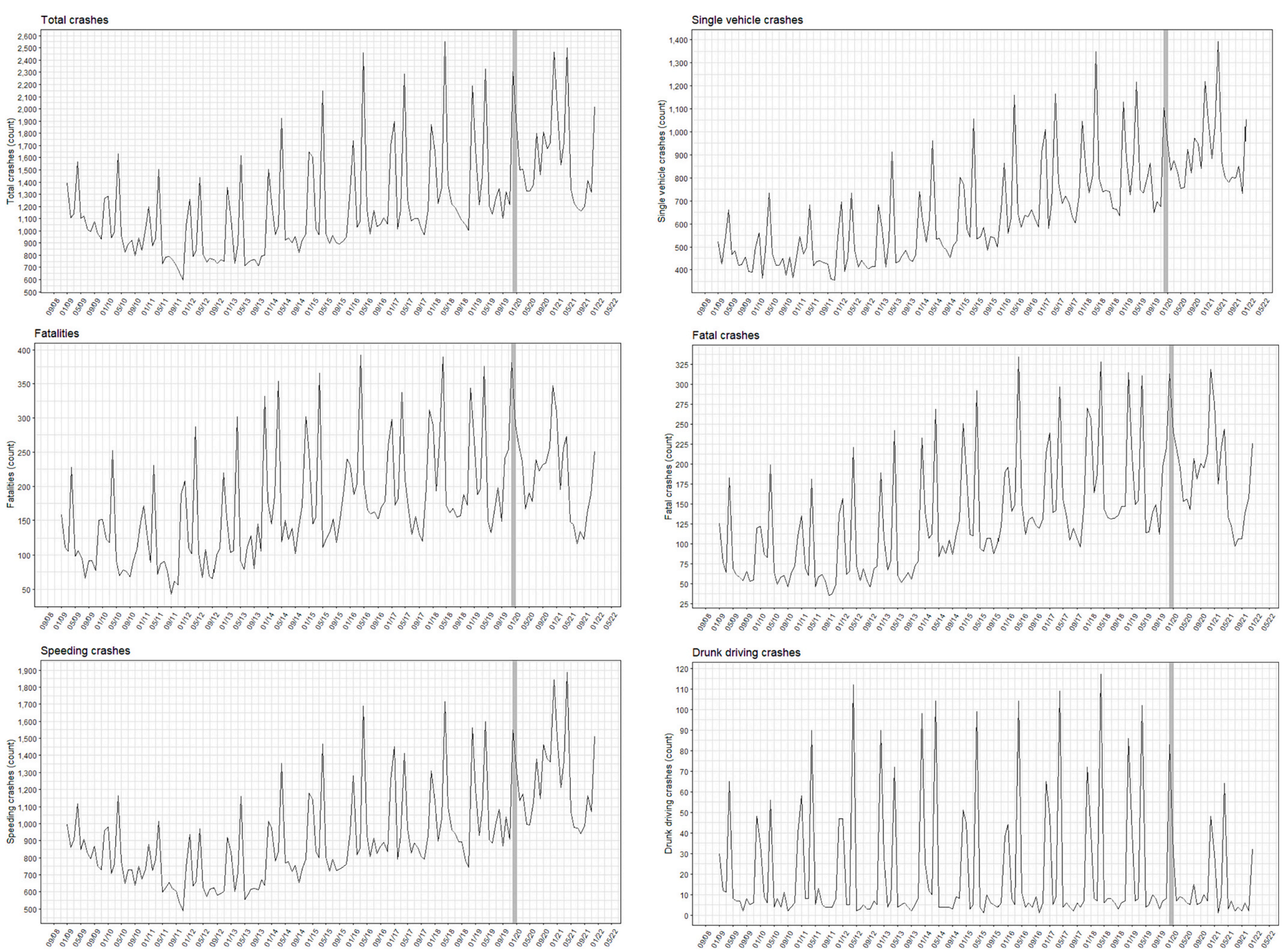


Fig. 2. Time plot of total, single vehicle, fatalities, fatal, speeding, and drunk driving crashes.

Table 2
SARIMA model parameters.

Variable	Model
Total crashes	ARIMA(0,1,1)(1,1,0) [12]
Single vehicle crashes	ARIMA(0,1,1)(0,1,1) [12]
Fatalities	ARIMA(1,0,1)(1,1,1) [12]
Fatal crashes	ARIMA(1,0,0)(2,1,1) [12]
Speeding crashes	ARIMA(0,1,1)(1,1,0) [12]
Drunk driving crashes	ARIMA(0,0,0)(2,1,1) [12]

4. Results and analysis

There are two components to analyze in the study based on the objectives. The first part of the study is to compare road crash data from before and during the pandemic and find out how each road crash indicator (e.g., the number of total crashes, fatality rates, and fatal crashes) had changed during the pandemic period using the time series modeling analysis. The second part of the study is to identify the impact of policies announced by Thailand's government agencies on road crashes during the COVID-19 pandemic, using the interrupted time series modeling. The monthly road crash data gathered across a variety of time periods were used in both portions of the study.

Table 1 provides the statistical summary of monthly road crash data over an 11-year period (2009–2019), representing the timeframe preceding the onset of COVID-19 (132 months) and categorized based on various indicators. As indicated in Table 1, the monthly occurrence of single vehicle crashes constitutes more than half of the overall collisions (53.57%). Typically, these incidents involve actions such as veering off the road and overturning or colliding with roadside structures, both of which carry severe consequences. Additionally, the data reveals that a significant majority of crashes (76.36%) are attributed to instances of excessive speeding, aligning with findings from the ThaiRoads Foundation (2022), which identified excessive speeding as the predominant cause of accidents in Thailand.

Fig. 2 presents time plots of monthly crash data over a 13-year timeframe. The data clearly demonstrate the characteristic of seasonality, which consistently has two peaks in the number of road crashes per year. The first peak is during the New Year's holiday season, from late December to early January. Another peak period is the Songkran holiday (Thai New Year's holiday) in mid-April. All road crash indicators were displayed in the same trend before and after the COVID-19 pandemic, which began in early 2020. In April 2020, which was the start of the COVID-19 spreading in Thailand and was anticipated to have the largest number of crashes in the year, the number of crashes was significantly lower than usual. Moreover, all road crash indicators were much lower after April 2021 than they were prior to the COVID-19 pandemic.

4.1. Comparison of road crash data before COVID-19 and during COVID-19 pandemic using time series modeling

To test how well the data can be used for predicting future values, the data was divided into two parts. The first part involves training the data, which makes up 75% of the data collected between 2009 and 2019 (January 2009 to March 2017). Another part is testing the data, which includes the remaining 25% of the data (April 2017 to December 2019). After we separated the data into 2 parts (Jan 2009 to Mar 2017 as the training data and Apr 2017 to Dec 2019 as the test data), a one-step forecast which use SARIMA model will be implemented on the training data to predict the number of accident cases in April 2017. Subsequently, the training data, now incorporating the actual number of accident cases in April 2017, will be used to predict the number of accident cases in May 2017, and this process will continue sequentially. To obtain the best SARIMA models, the auto.arima function in forecast packages in R was used. Table 2 provides a summary of the model parameters of each road crash indicator, which can be observed that all models implement first-seasonal differencing because they all exhibit apparent seasonality. Table 3 illustrates the model specification for each model and the information criteria.

Table 3
Summary of the optimal SARIMA models.

Variable	Model parameters	Estimate	Std. error	AIC	BIC	AICc
Total crashes	ma1	−0.799	0.06	1500.8	1509.1	1501.0
	sar1	−0.246	0.09			
Single vehicle crashes	ma1	−0.885	0.04	1344.0	1352.3	1344.2
	sma1	−0.427	0.10			
Fatalities	ar1	0.764	0.17	1165.5	1182.2	1166.2
	ma1	−0.579	0.21			
	sar1	0.265	0.14			
	sma1	−0.867	0.16			
	drift	1.074	0.15			
Fatal crashes	ar1	0.445	0.09	1087.1	1103.9	1087.9
	sar1	0.443	0.13			
	sar2	−0.300	0.12			
	sma1	−0.793	0.14			
	drift	0.977	0.12			
Speeding crashes	ma1	−0.809	0.05	1446.8	1455.1	1447.0
	sar1	−0.462	0.09			
Drunk driving crashes	sar1	0.278	0.11	871.7	885.7	872.2
	sar2	−0.410	0.09			
	sma1	−0.671	0.12			
	drift	0.046	0.03			

Table 4
Performance metric on test set.

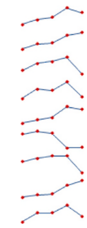
Variable	MAE	RMSE	MAPE	sMAPE
Total crashes	128.79	156.69	8.96	8.94
Single vehicle crashes	60.74	76.50	7.48	7.31
Fatalities	27.26	32.43	13.64	13.34
Fatal crashes	22.30	26.86	13.67	13.36
Speeding crashes	104.98	135.99	9.79	9.67
Drunk driving crashes	3.35	5.98	28.14	24.45

A one-step forecast will be applied to the training data in order to forecast the number of crashes from April 2017 to December 2019 to test how well the data can be used for prediction. Table 4 presents the performance metric test set of the estimated SARIMA models. Mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (sMAPE) are used in this study to evaluate the accuracy of the forecasting. Hyndman & Koehler [31] suggested that the sMAPE should not be used for a number of reasons. The forecasting performance of a model is considered highly accurate if the MAPE value is less than 10% and good for less than 20% [32]. However, the MAPE and sMAPE of drunk driving crashes are more than 20% because the number of drunk driving crashes is quite low.

Table 5 shows data trends during 2017–2019, called the pre-pandemic period, and during 2020–2021, called the outbreak period. These trends provide a general indication of what happened during the COVID-19 pandemic before conducting time series analysis. From Table 5, total crashes, fatalities, fatal crashes, speeding crashes, vehicle kilometers traveled (VKT), and fatality rate per VKT show a similar pattern, progressively rising until 2020 and then decreasing in 2021. The number of total crashes and speeding crashes has slightly dropped. However, the data on fatalities, fatal crashes, VKT, and fatality rate per VKT drastically dropped in the second year of the COVID-19 pandemic.

In contrast, single vehicle crashes and the crash rate per VKT have

Table 5
Annual road crash data between before and during COVID-19 pandemic.

Indicator	2017	2018	2019	2020	2021	Trend
Total crashes	15,936	17,045	17,554	19,806	18,654	
Single vehicle crashes	9326	9840	9952	10,714	11,037	
Fatalities	2409	2651	2700	2856	2299	
Fatal crashes	1953	2221	2183	2423	2003	
Speeding crashes	11,963	12,664	13,071	15,304	14,663	
Drunk driving crashes	276	302	285	156	162	
VKT	269.866	276.917	282.142	282.317	246.723	
Total crashes/VKT	59.051	61.553	62.217	70.155	75.067	
Fatalities/VKT	8.927	9.573	9.570	10.116	9.318	

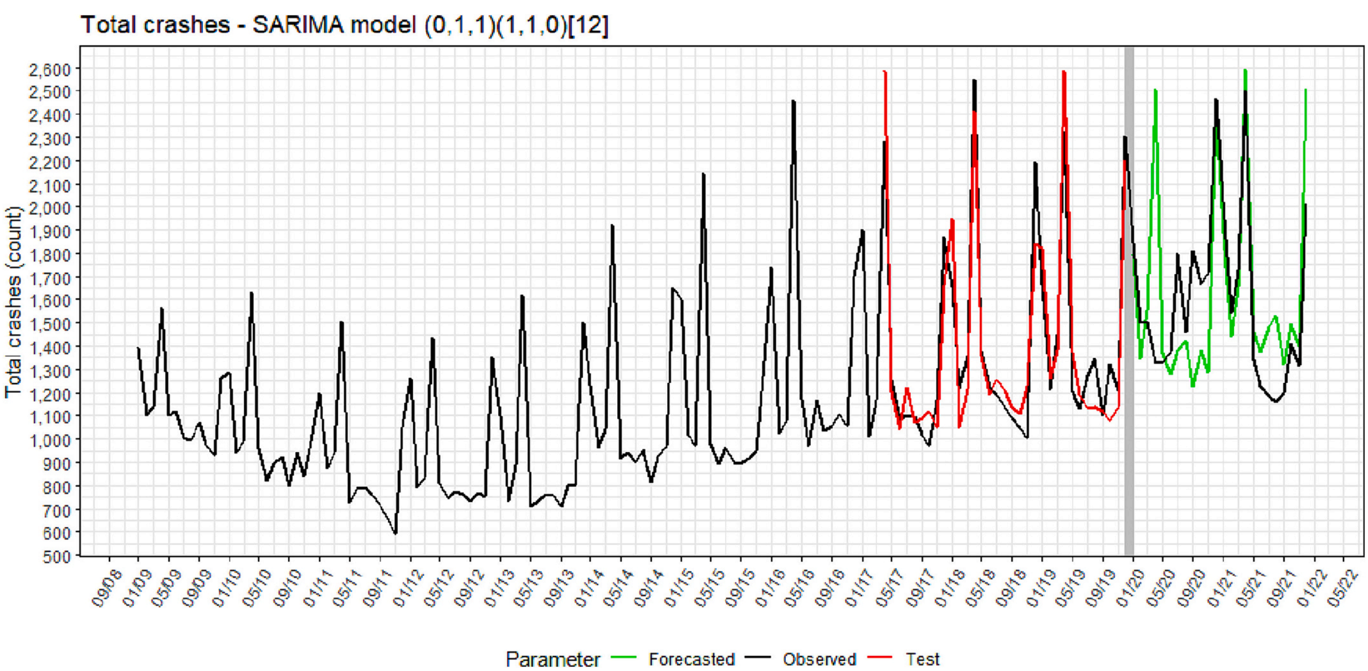


Fig. 3. SARIMA forecasts of total crashes (2009–2021).

both increased during COVID-19. The reason that the number of single vehicle crashes increased may have been because there were significantly fewer cars on the roads during the pandemic. For that reason, people tend to use higher speeds or pay less attention to the road while driving, leading to single vehicle crashes. Similarly, the crash rate per VKT also increased in 2021, which could be due to lower VKT during COVID-19. It means that there was a higher risk of crashes during the COVID-19 period. However, the number of crashes that involved drunk driving significantly decreased during COVID-19.

4.1.1. Total crashes

After conducting the time series analysis, Fig. 3 presents the plot of monthly total crash forecasts based on the SARIMA (0,1,1)(1,1,0) [12] model. Fig. 4 also displays a depiction of all crashes with an emphasis on the years 2020 and 2021, when the COVID-19 pandemic was spreading through the nation. The first difference was in April 2020, which was the first COVID outbreak in Thailand. Since most people had not been vaccinated to reduce the severity of the disease, the government had to reduce the likelihood that the infection would spread widely. The comparison between observed and forecasted values reveals that, during April 2020, about 47.14% fewer total crashes were observed compared to the SARIMA forecasts. In that period, several counter measures had been applied, including curfews (people were prohibited from leaving their places at night), prohibition of cross-provincial travel (people should not travel across provinces unless there was a need or permission from governmental agencies), ban on alcoholic beverage consumption on the premises, closure of entertainment venues, and ban on alcoholic beverage sale (during the Songkran’s holiday for the whole country, but for some provinces, it might be banned for a longer time period).

After the number of COVID-19 new cases began to decrease in May 2020 and the pandemic situation began to stabilize, people started to return to their normal lives. It was during this period that the number of total crashes climbed beyond what the model had predicted between July 2020 and November 2020. In this period, the number of total crashes increased by about 26.19%. The reason for this change may be due to the relaxed lockdown measure, which enabled people to travel

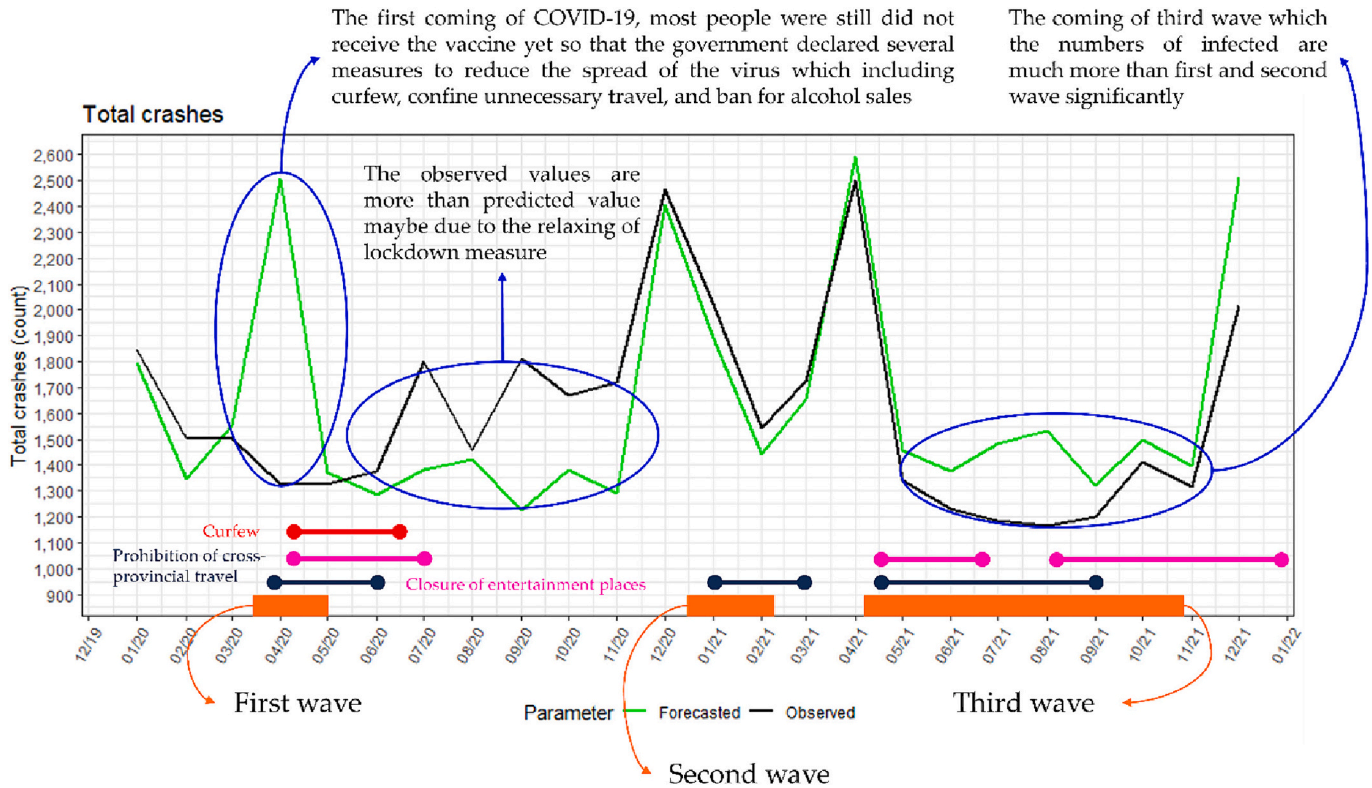


Fig. 4. COVID-19 impact investigation on total crashes.

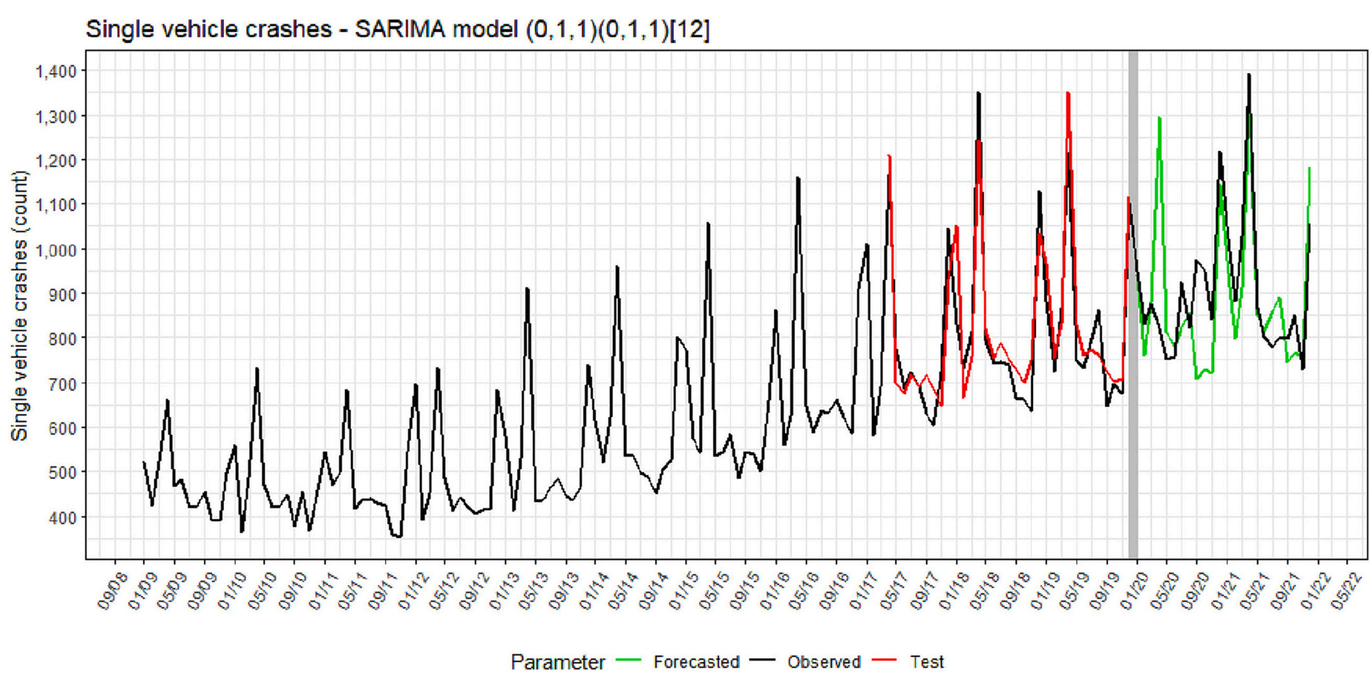


Fig. 5. SARIMA forecasts of single vehicle crashes (2009–2021).

more freely after the first spread of COVID-19. Then, the number of total crashes was close to the forecasted number in December 2020, which is once again during the yearly peak. Although there was a second wave of outbreaks from late December 2020 to February 2021, there was not much difference between the forecasted and actual total crashes because the second wave of spreading was minor, affecting only a few provinces, such as Samut Sakhon and nearby provinces.

Another significant change is in the third wave from May 2021 to the end of the year 2021, which is considered the most severe with a high number of infections. The number of patients is more than 10 times that of the second wave, causing this wave to last for a considerable amount of time. Due to the longer duration and the greater severity of the outbreak, the predicted number of crashes is higher than observed figures. During this wave, the number of total crashes has decreased by up

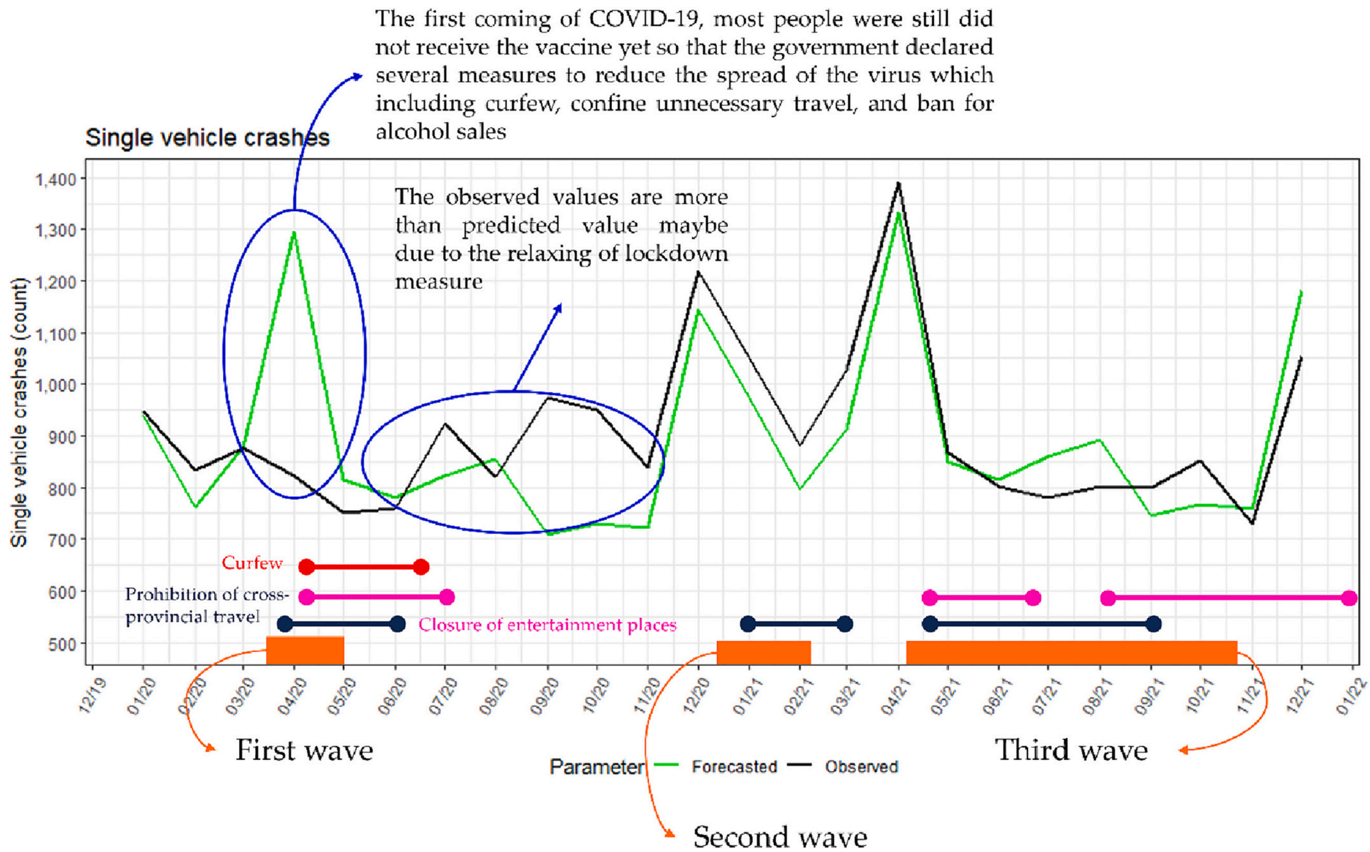


Fig. 6. COVID-19 impact investigation on single vehicle crashes.

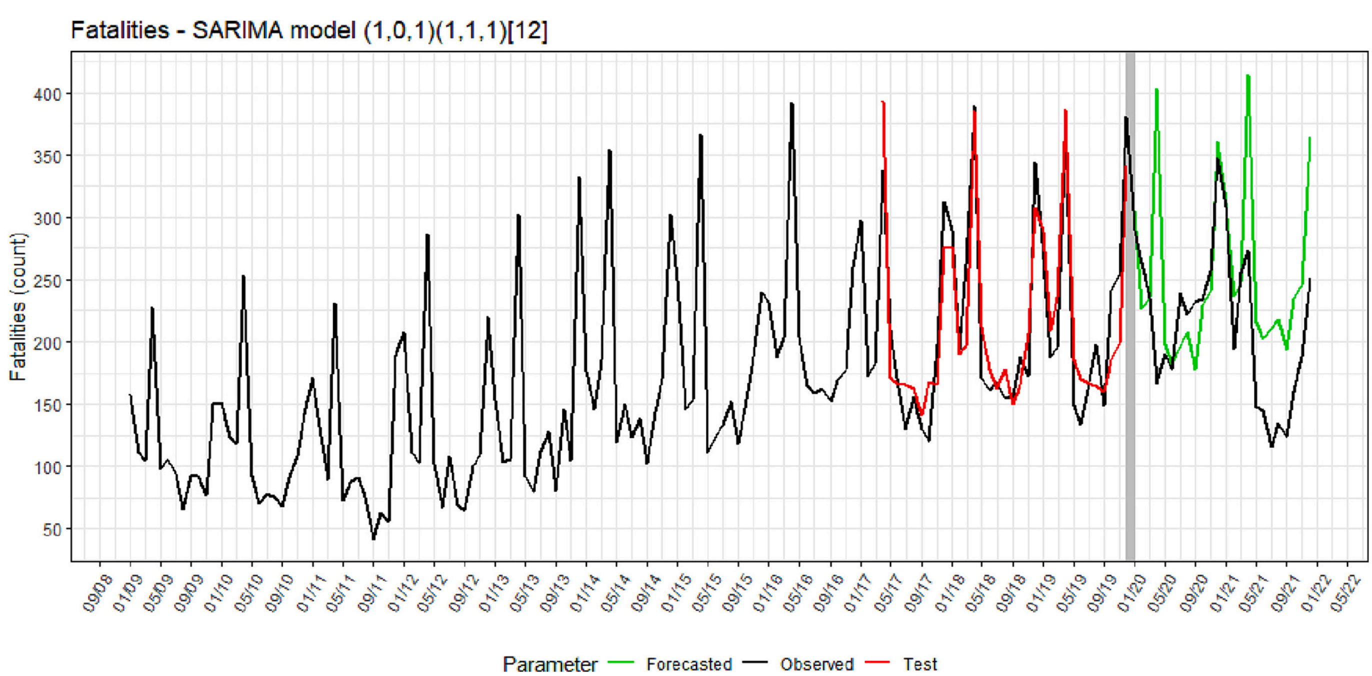


Fig. 7. SARIMA forecasts of fatalities (2009–2021).

to 14%.

4.1.2. Single vehicle crashes

Fig. 5 illustrates the graphical representation of single vehicle crash predictions derived from the SARIMA(0,1,1)(0,1,1) [12] model. The data exhibits a similar trend to the total crashes data. In Fig. 6, the plot contrasts the projected and actual counts of single vehicle crashes during the COVID-19 period. During the initial pandemic wave, as depicted in Fig. 6, there was a 36.49% reduction in actual single vehicle crashes compared to the forecasted figures. Following the easing of lockdown

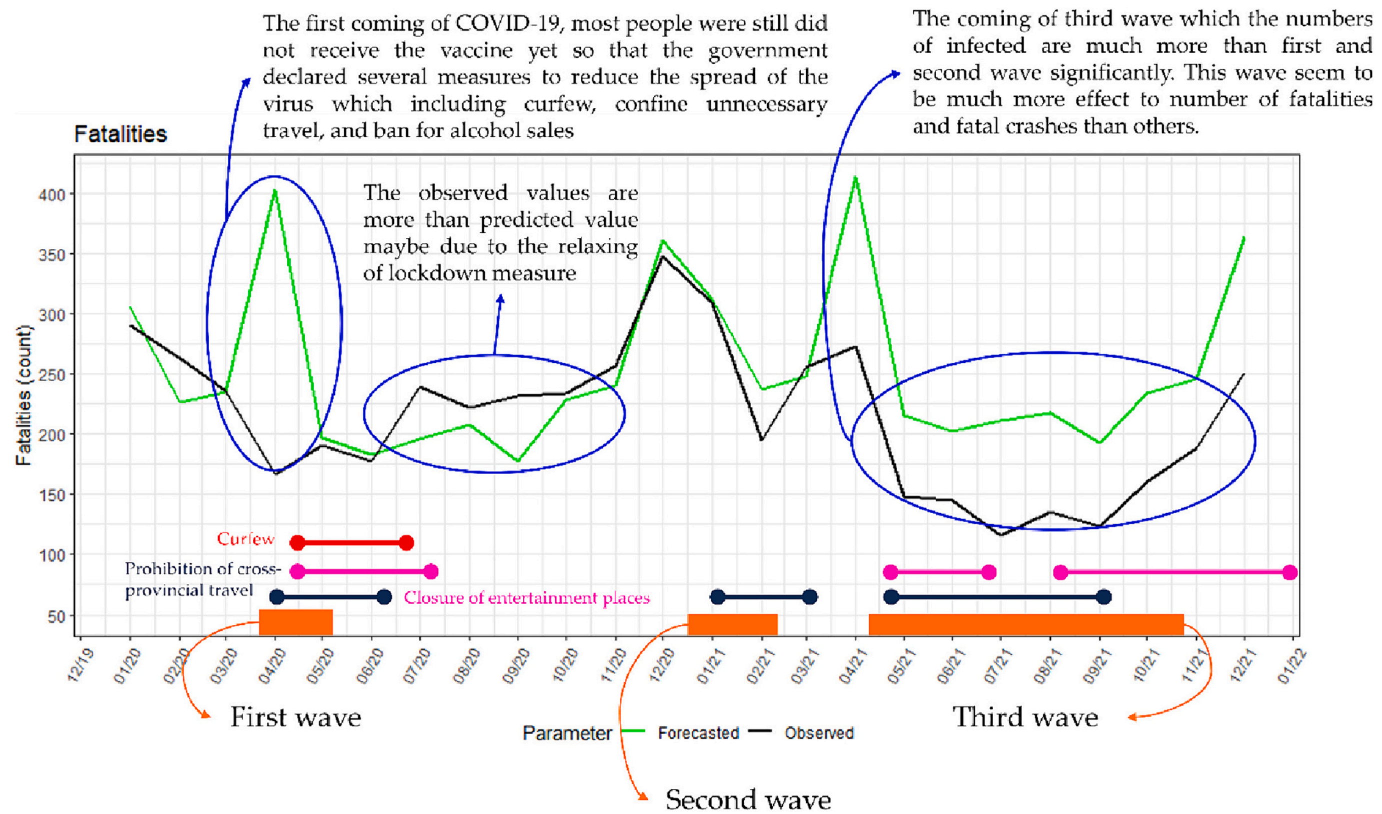


Fig. 8. COVID-19 impact investigation on fatalities.

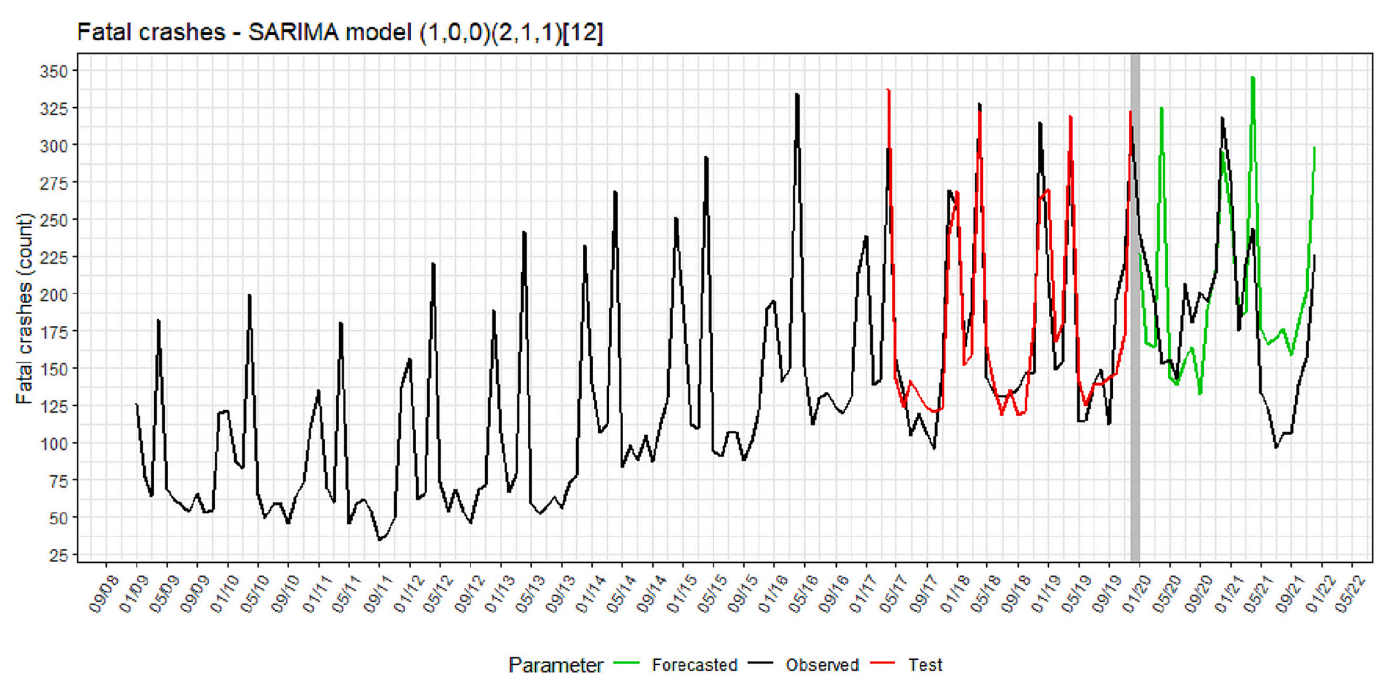


Fig. 9. SARIMA forecasts of fatal crashes (2009–2021).

measures, there was a notable 17.33% increase in single vehicle crashes, particularly prominent in September and October 2020. However, from May 2021 to December 2021, only a modest 2.67% decrease in single vehicle collisions was observed.

4.1.3. Fatalities

In Fig. 7, fatalities resulting from road crashes are depicted using the SARIMA(1,0,1)(1,1,1) [12] model. Similar to the two preceding indicators, a substantial 58.56% decrease in fatalities was identified during the initial wave of the pandemic, as illustrated in Fig. 8. Likewise, there was a subsequent 12.65% rise in fatalities following the relaxation

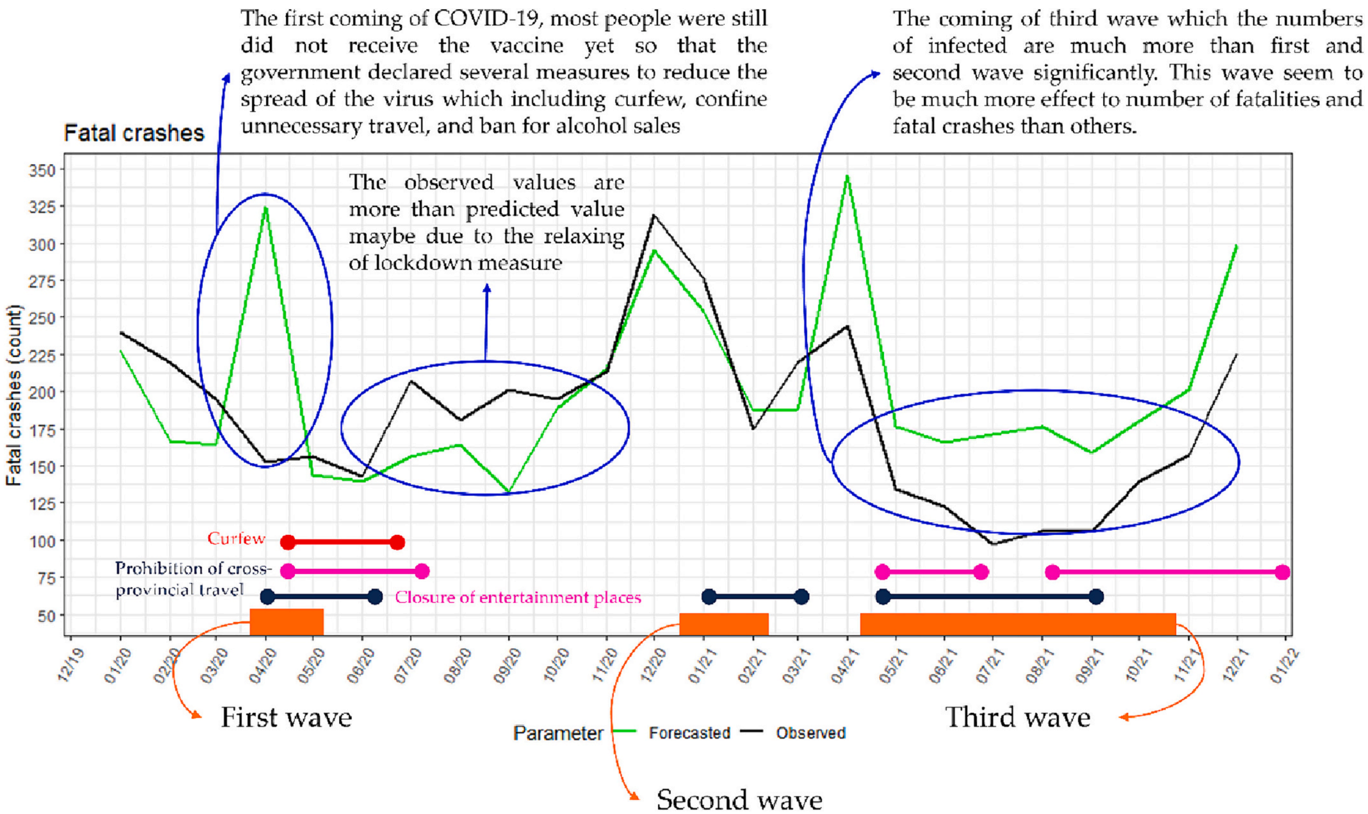


Fig. 10. COVID-19 impact investigation on fatal crashes.

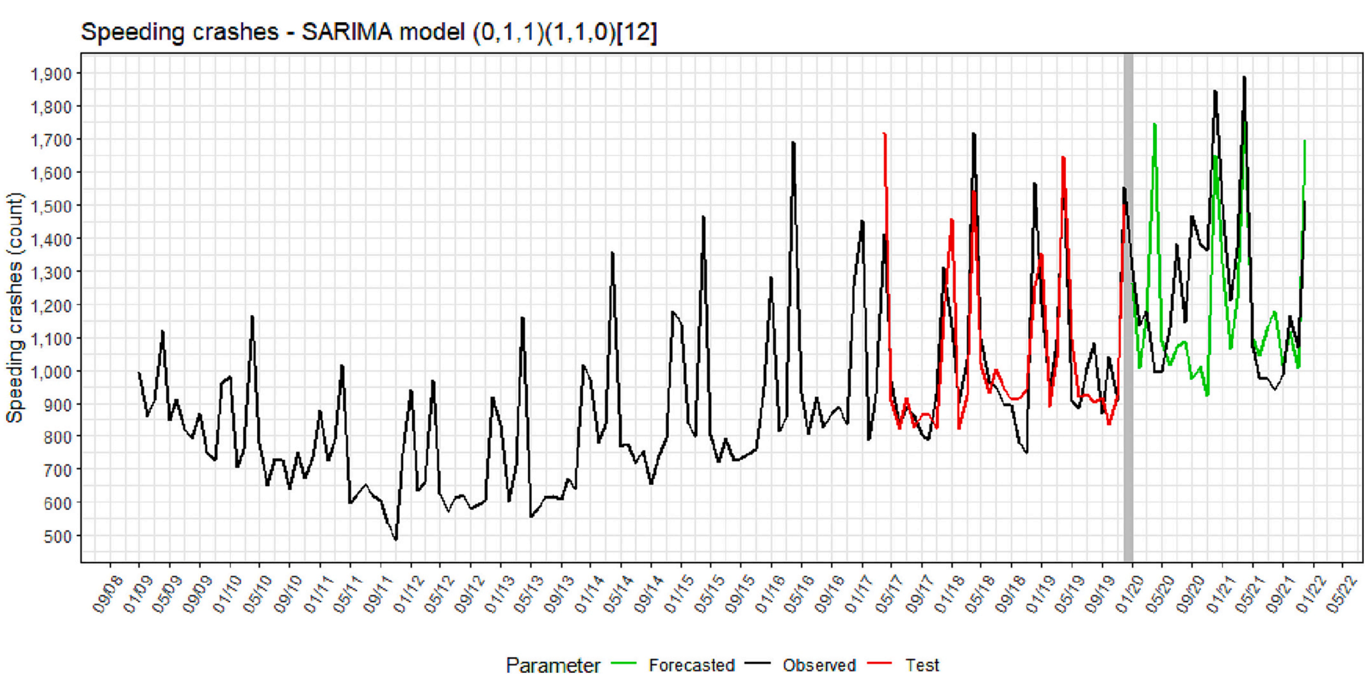


Fig. 11. SARIMA forecasts of speeding crashes (2009–2021).

of lockdown measures. While there was a decline in the number of fatalities in the third wave, consistent with the trends observed in the previous indicators, the decrease commenced in April 2021 instead of May 2021. The reduction in fatalities was approximately 32.77%. It appears that the third wave had a more pronounced impact on fatalities compared to both total crashes and single vehicle crashes.

4.1.4. Fatal crashes

Fig. 9 displays the graphical representation of fatal crash predictions using the SARIMA(1,0,1)(2,1,1) [12] model. In April 2020, there was a notable decrease in fatal crashes compared to what would have been expected in the absence of COVID-19. Fig. 10 depicts the alignment between predicted and observed values in 2020 and 2021,

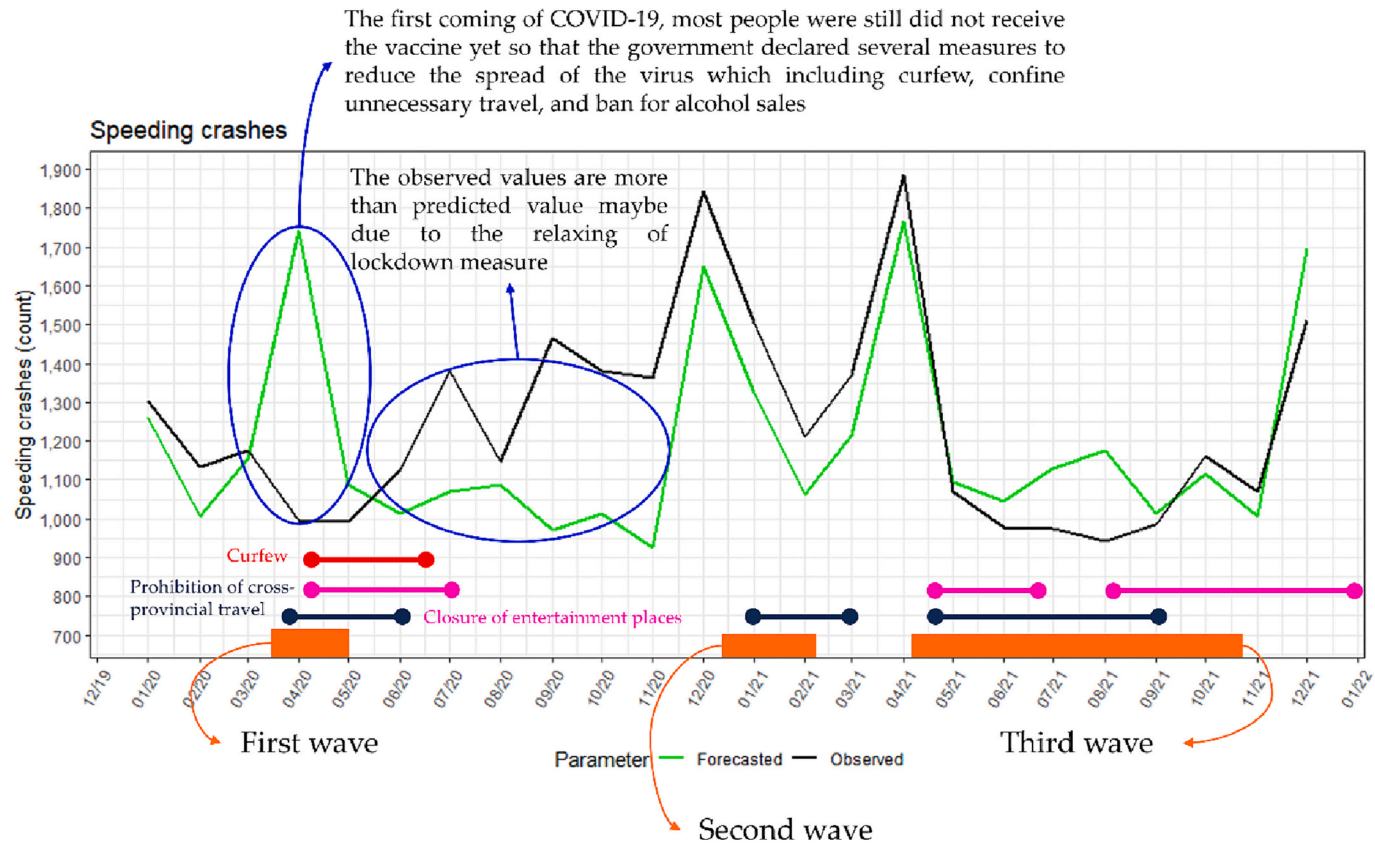


Fig. 12. COVID-19 impact investigation on speeding crashes.

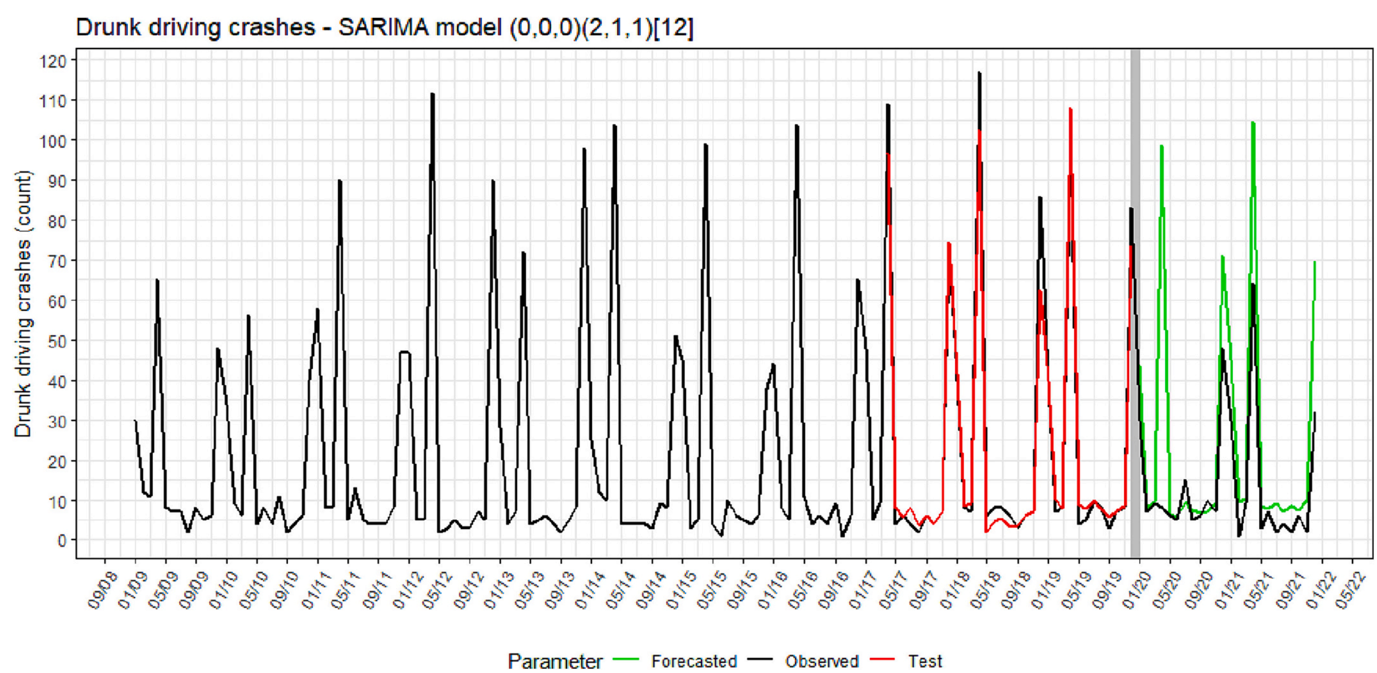


Fig. 13. SARIMA forecasts of drunk driving crashes (2009–2021).

demonstrating a consistent trend with fatalities.

4.1.5. Speeding crashes

Fig. 11 illustrates the graph of projected speeding crashes based on the SARIMA(0,1,1)(1,1,0) [12] model. Similarly, a substantial decline was noted during the initial lockdown. Fig. 12 presents the SARIMA model predictions for speeding crashes in 2020 and 2021, highlighting the disparities between observed and forecasted values. In April 2020, there was a 42.91% reduction in speeding crashes, followed by a subsequent 32.99% increase between July 2020 and November 2020.

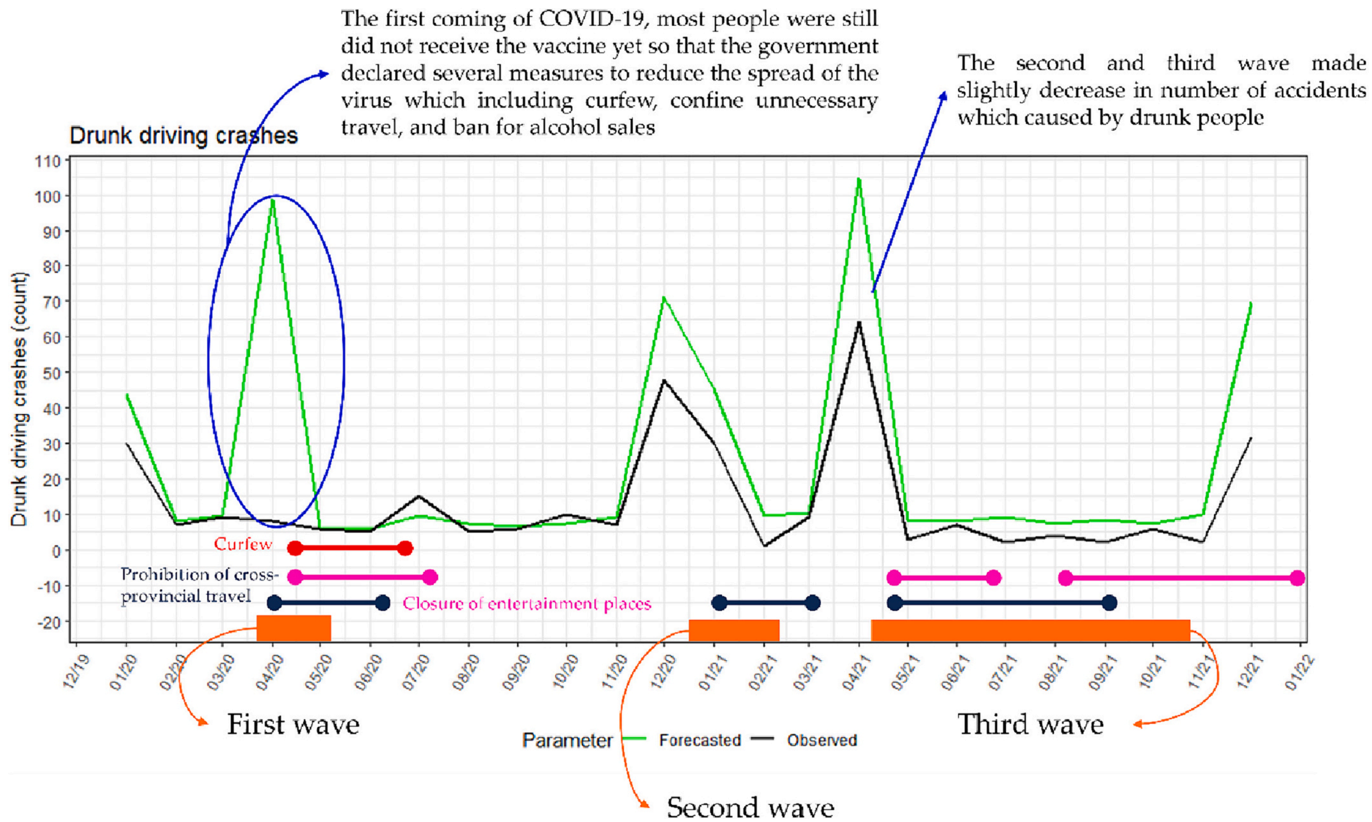


Fig. 14. COVID-19 impact investigation on drunk driving crashes.

Table 6
SARIMA models parameters for objective 2.

Variable	Model
Total crashes	ARIMA(0,0,0)(1,1,0) [12]
Single vehicle crashes	ARIMA(0,1,1)(0,1,0) [12]
Fatalities	ARIMA(1,0,0)(0,1,1) [12]
Fatal crashes	ARIMA(1,0,0)(0,1,1) [12]
Speeding crashes	ARIMA(0,0,0)(1,1,0) [12]
Speeding crashes (10 pm – 04 am)	ARIMA(0,0,0)(0,1,1) [12]
Drunk driving crashes (10 pm – 04 am)	ARIMA(0,0,1)(0,1,1) [12]

Finally, a 6.33% reduction was identified during the prolonged period of the COVID-19 waves.

4.1.6. *Drunk driving crashes*

Fig. 13 depicts the graph representing the forecast for drunk driving crashes using the seasonal ARIMA(0,0,0)(2,1,1) [12] model. Notably, the data reveals a decrease in the number of drunk driving crashes during the lockdown period. In Fig. 14, a comparison is made between the projected and observed values of drunk driving crashes over a two-year span. A substantial 91.90% reduction was identified during the initial wave, while slight decreases were observed during the second and third waves.

4.2. *Evaluation of the impact of COVID-19 policies announced by government on road crashes during COVID-19 pandemic using the interrupted time series modeling*

Table 6 and Table 7 present the summary of the model parameters for all road crash indicators and the model specification for each model and information criterion, respectively.

Table 8 presents the performance metric test set of the estimated SARIMA models and the R-squared of interrupted time series models.

Table 7
Summary of the optimal SARIMA models for objective 2.

Variable	Model parameters	Estimate	Std. error	AIC	BIC	AICc
Total crashes	sar1	−0.334	0.15	612.3	612.85	617.92
	drift	6.648	1.28			
Single vehicle crashes	ma1	−0.890	0.06	548.56	548.83	552.26
Fatalities	ar1	0.239	0.14	478.65	479.58	486.14
	sma1	−0.635	0.28			
	drift	0.941	0.30			
Fatal crashes	ar1	0.303	0.14	455.39	456.32	462.87
	sma1	−0.371	0.22			
	drift	0.999	0.32			
Speeding crashes	sar1	−0.498	0.13	598.78	599.32	604.39
	drift	4.073	0.99			
Speeding crashes (10 pm - 04 am)	sma1	−0.634	0.24	459.19	459.74	464.81
	drift	1.236	0.19			
Drunk driving crashes (10 pm - 04 am)	ma1	0.244	0.14	246.86	247.41	252.48
	sma1	−0.735	0.38			

Most models are considered highly accurate except for drunk driving crashes due to a smaller number of drunk driving crashes in the analysis.

The purpose of interrupted time series (ITS) analysis was to evaluate how the intervention implementation affected an interesting outcome that is simply referred to as the intervention effect. This can be done by putting the intervention parameters into the best-fitting SARIMA model

Table 8
Performance metric on test set of objective 2's indicators.

Variable	MAE	RMSE	MAPE	sMAPE	R^2
Total crashes	165.53	193.37	11.46	11.28	0.689
Single vehicle crashes	63.74	85.05	7.58	7.30	0.575
Fatalities	33.63	39.41	16.26	16.09	0.510
Fatal crashes	36.45	43.06	20.02	19.10	0.625
Speeding crashes	106.55	131.45	10.57	10.21	0.624
Speeding crashes (10 pm–04 am)	25.12	28.15	10.94	10.62	0.160
Drunk driving crashes (10 pm–04 am)	2.21	2.85	68.94	64.91	0.579

Table 9
Timeline of COVID-19 monthly response measures in Thailand in 2020–2021.

Response measures		Duration	Dependent variable
Curfew (10 pm–04 am)		April–June 2020	Speeding crashes (10 pm–4 am)
Prohibition of cross-provincial travel	1st	April–May 2020	Total, fatalities, fatal, single vehicle, and speeding crashes
	2nd	January–February 2021	
	3rd	April–August 2021	
Ban for alcoholic sale and consumption on the premises, and closure of entertainment places	1st	April–June 2020	Drunk driving crashes (10 pm – 4 am)
	2nd	April–June 2021	
	3rd	August–December 2021	

and estimating them as well as including the post-intervention data to evaluate whether the intervention parameters are statistically significant. Intervention effects in ARIMA are normally modelled using dummy variables, dichotomously coded "1" for the implementation of the event and "0" for normal operations.

Table 9 presents the list of interventions that were used during COVID-19 and their possible impacts on the related road crash indicators.

This section summarizes the findings of an interrupted time series analysis, highlighting the interventions that have a significant effect on each road crash indicator and showing the estimated coefficient in each model. A positive coefficient means the intervention is increasing road crash indicators. In contrast, a negative coefficient indicates that the intervention caused a reduction in the number of road crashes. The following section presents the time series forecasting of each variable.

Table 10 shows that the first prohibition of cross-provincial travel significantly affects all road crash indicators, which include total crashes, single vehicle crashes, fatalities, fatal crashes, and speeding crashes. All these indicators tend to decrease when the intervention is implemented. The third prohibition of cross-provincial travel results in a reduction of the number of total crashes, fatalities, and fatal crashes with the same trend as in the first prohibition.

In Table 11, the curfew intervention has a major impact on speeding crashes at nighttime, as with the curfew, the speeding crashes tend to decrease.

Table 12 illustrates that only the first intervention, which included

Table 11
Mean prevalence of speeding crashes (10 pm–04 am) variable and changes due to curfew.

Variable	Curfew	
	Significant	Parameter coefficient
Speeding crashes (10 pm–04 am)	Yes	−133.29

the prohibiting the sale and consumption of alcohol as well as closing entertainment venues from April to late June 2020, significantly reduced the number of drunk driving crashes. The same intervention during the other time periods had no discernible effect. This may be because the first period of intervention took place during the Songkran Festival, when the number of drunk driving crashes was high in the normal period. The difference due to the intervention was therefore clearly seen during this period.

5. Discussion and conclusion

The main purpose of this study is to investigate the impact of the COVID-19 pandemic on different road crash indicators in Thailand using the time series and interrupted time series analysis. In this study, the SARIMA models are used to forecast the number of road crash data points in the absence of the COVID-19 pandemic and compare those predictions to the actual observed data to highlight any differences. The second objective of this study is to determine which interventions significantly influence the changes in the number of road crash data points.

Similar to the findings from other countries as discussed in the literature review section [11–13], the first wave of the COVID-19 pandemic in Thailand resulted in a reduction in the number of crashes across all indicators and had the greatest impact for several reasons. The government had to announce many measures to prevent the spread of the disease, which could have devastating consequences for the nation's public safety and economy. Some measures affect mobility and traffic volume. After the lockdown measures were relaxed, the number of crashes increased and was higher than the predicted values, then fell back to the pre-forecast level. It was evident that crashes tended to increase a few months after lockdown restrictions were loosened. Finally, the third wave, which took the longest to spread (7 months), caused a considerable reduction in all road crash indicators, particularly fatalities and fatal crashes. Though it took much longer, this wave did not have the greatest impact on the number of crashes.

The Thai government announced several countermeasures to combat the COVID-19 pandemic, but this study only takes into account those that could reduce the number of road crashes, including three different interventions: cross-provincial travel restrictions, curfews, and the banning alcohol consumption and closure of entertainment venues. The first prohibition of cross-provincial travel significantly decreased the overall number of crashes, single vehicle crashes, fatalities, fatal crashes, and speeding crashes. Similarly, the third prohibition is also causing a reduction in road crashes for total crashes, fatalities, and fatal crashes. However, the second prohibition did not have a significant impact on any crash indicators as it was a short outbreak and only happened in

Table 10
Mean prevalence of each variable and changes due to prohibition of cross-provincial travel.

Variable	First prohibition		Second prohibition		Third prohibition	
	April–May 2020		January–February 2020		April–August 2021	
	Significant	Parameter coefficient	Significant	Parameter coefficient	Significant	Parameter coefficient
Total crashes	Yes	−800.68	–	–	Yes	−247.30
Single vehicle crashes	Yes	−0.29	–	–	–	–
Fatalities	Yes	−87.49	–	–	Yes	−63.94
Fatal crashes	Yes	−0.45	–	–	Yes	−0.35
Speeding crashes	Yes	−547.67	–	–	–	–

Table 12
Mean prevalence of drunk driving crashes (10 pm - 04 am) variable and changes due to closure of entertainment places.

Variable	First ban		Second ban		Third ban	
	Significant	Parameter coefficient	Significant	Parameter coefficient	Significant	Parameter coefficient
Drunk driving crashes (10 pm–04 am)	Yes	−9.43	–	–	–	–

certain areas. For the nighttime, curfews and close of entertainment places during the first wave of the COVID-19 pandemic reduced the number of speeding crashes and drunk driving crashes between 10 p.m. and 4 a.m., respectively. This is consistent with the findings of the analysis in Objective 1, which indicate that the number of all road crash indicators will sharply decline in April 2020.

As mentioned in the results, although the announcement of measures to cope with the first wave of COVID-19, which include the first prohibition of cross-provincial travel, curfew, and close of entertainment places, could reduce the number of road crashes across all indicators, single vehicle crashes and speeding crashes were decreased in lower proportion when comparing to the decrease in total crashes. After releasing the lockdown measure, the number of road crashes were higher than the forecasting numbers across all indicators, especially speeding crashes which have increased in higher proportion than the overall crashes. Moreover, the third prohibition was associated with reduction in total crashes, fatalities, and fatal crashes, but did not result in the reduction of single vehicle crashes and speeding crashes. It can be hypothesized that speeding crashes remains the most concern regarding road safety management in Thailand even during COVID-19 pandemic. Strict law enforcement should be considered to address excessive speed driving behavior in the next pandemic event.

Finally, it can be observed that curfews and ban on alcohol sales result in a drop in the number of speeding crashes and drunk driving crashes, respectively. These countermeasures have been proved that if they are seriously taken into practice during normal operations, the number of crashes can be reduced significantly.

For further study, Traffic volume, monthly VKT, or fuel consumption data should be considered for the future study to calculate accident rate. If the number of accidents decreases, but the exposure data decrease in greater portion, accident rate might be increase which mean safety performance is worse, or more people die on the road compared to the same amount of traffic. In addition, daily, weekly, and biweekly data might give better forecasts, more detail, and more accuracy. Furthermore, from the report of Office of Transport and Traffic Policy and Planning in 2019, it indicated that the total mileage of roads under the responsibility of the Department of Highway accounts for only 7.39%. Most of the rest are under the responsibility of the Department of Rural Highway and the Department of Local Administration for 6.84% and 85.16%, respectively. Therefore, the accident data from DOH may not be representative of the entire country's accident data. It would be better if there was a database that collected accident data across the country. Lastly, other methodologies or more sophisticated models might predict more precisely such as spatial analysis. In addition, other forecasted methods should be compared to select the best model for future similar studies such as exponential smoothing, time series regression, dynamic regression models.

Declaration of competing interest

Authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) or belief that could affect the objectivity in the subject matter or materials discussed in this manuscript.

References

[1] Department of Disease Control, A Situation Report on COVID-19 and Mitigation Measures to Control COVID-19 in Thailand, Department of Disease Control, 2021.

[2] World Health Organization, Global Status Report on Road Safety 2018. https://www.who.int/publications/i/item/9789241565684, 2018 (accessed 10 October 2020).

[3] World Health Organization, Global Status Report on Road Safety 2015. https://www.afro.who.int/publications/global-status-report-road-safety-2015, 2015 (accessed 10 October 2020).

[4] A.E. Retallack, B. Ostendorf, Relationship between traffic volume and accident frequency at intersections, Int. J. Environ. Res. Public Health (2020), https://doi.org/10.3390/ijerph17041393.

[5] R. Elvik, A.K. Hoye, Changes over time in the relationship between road accidents and factors influencing them: the case of Norway, Accid. Anal. Prev. 183 (2023), https://doi.org/10.1016/j.aap.2023.106989.

[6] A. Tucker, K. Marsh, Speeding through the pandemic: perceptual and psychological factors associated with speeding during the COVID-19 stay-at-home period, Accident Anal. Prev. 159 (2021), https://doi.org/10.1016/j.aap.2021.106225.

[7] D. Stavrinos, B. McManus, S. Mrug, H. He, B. Gresham, M. Grace Albright, A. M. Svancara, C. Whittington, A. Underhill, Adolescent driving behavior before and during restrictions related to COVID-19, Accident Anal. Prev. 144 (2020), https://doi.org/10.1016/j.aap.2020.105686.

[8] A. Hakkert, L. Braimaister, The Use of Exposure and Risk in Road Safety Studies, SWOV, Leidschendam, 2002.

[9] J. Lee, A. Porr, H. Miller, Evidence of Increased Vehicle Speeding in Ohio's Major Cities during the COVID-19 Pandemic, Transport Findings. 10.32866/001c.12988.

[10] W.G.M. Vanlaar, H. Woods-Fry, H. Barrett, C. Lyon, S. Brown, C. Wicklund, R. D. Robertson, The impact of COVID-19 on road safety in Canada and the United States, Accident Anal. Prev. 160 (2021), https://doi.org/10.1016/j.aap.2021.106324.

[11] M. Gupta, N.M. Pawar, N.R. Velaga, Impact of lockdown and change in mobility patterns on road fatalities during COVID-19 pandemic, Int. J. Transp. Res. 13 (2021), https://doi.org/10.1080/19427867.2021.1892937.

[12] M. Sutherland, M. McKenny, A. Elkbuli, Vehicle related injury patterns during the COVID-19 pandemic: what has changed? Am. J. Emerg. Med. 38 (2020) 1710–1714, https://doi.org/10.1016/j.ajem.2020.06.006.

[13] Ò. Saladié, E. Bustamante, A. Gutiérrez, COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain, Transport. Res. Interdisc. Perspect. 8 (2020), https://doi.org/10.1016/j.trip.2020.100218.

[14] M.L. Doucette, A. Tucker, M.E. Auguste, A. Watkins, C. Green, F.E. Pereira, K. T. Borrup, D. Shapiro, G. Lapidus, Initial impact of COVID-19's stay-at-home order on motor vehicle traffic and crash patterns in Connecticut: an interrupted time series analysis, Inj. Prev. 27 (2020) 3–9, https://doi.org/10.1136/injuryprev-2020-043945.

[15] M.L. Doucette, A. Tucker, M.E. Auguste, J.D. Gates, D. Shapiro, J.P. Ehsani, K. T. Borrup, Evaluating of motor vehicle crash rates during and after the COVID-19-associated stay-at-home order in Connecticut, Accident Anal. Prev. 162 (2021), https://doi.org/10.1016/j.aap.2021.106399.

[16] M.J. Rapoport, J.N. Chee, N. Aljenabi, P.A. Byrne, G. Naglie, F. Ilari, Y. Elzohairy, E. Vingilisf, B.H. Mulsant, Impact of COVID-19 on motor vehicle injuries and fatalities in older adults in Ontario, Canada, Accident Anal. Prev. 157 (2021), https://doi.org/10.1016/j.aap.2021.106195.

[17] S.R. Barnes, L.-P. Beland, J. Huh, D. Kim, The Effect of COVID-19 Lockdown on Mobility and Traffic Accidents: Evidence from Louisiana. Global Labor Organization (GLO) 616. http://hdl.handle.net/10419/222470.

[18] H. Inada, L. Ashraf, S. Campbell, COVID-19 lockdown and fatal motor vehicle collisions due to speed-related time-series, Inj. Prev. 27 (2020) 98–100, https://doi.org/10.1136/injuryprev-2020-043947.

[19] A.I. Qureshi, W. Huang, S. Khan, I. Lobanova, F. Siddiq, C.R. Gomez, M. Fareed, K. Suri, Mandated societal lockdown and road traffic accidents, Accident Anal. Prev. 146 (2020), https://doi.org/10.1016/j.aap.2020.105747.

[20] J. Catchpole, F. Naznin, Impact of COVID-19 on fatal crashes in Australia, J. Integrated Mobil. (2020) 29–33.

[21] M. Sekadakis, C. Katrakazas, E. Michelaraki, F. Kehagia, G. Yannis, Analysis of the impact of COVID-19 on collisions, fatalities and injuries using time series forecasting: the case of Greece, Accident Anal. Prev. 162 (2021), https://doi.org/10.1016/j.aap.2021.106391.

[22] C. Katrakazas, E. Michelaraki, M. Sekadakis, G. Yannis, A descriptive analysis of the effect of the COVID-19 pandemic on driving behavior and road safety, Transport. Res. Interdisc. Perspect. 7 (2020), https://doi.org/10.1016/j.trip.2020.100186.

[23] A. Latif Patwary, Asad J. Khattak, Crash harm before and during the COVID-19 pandemic: evidence for spatial heterogeneity in Tennessee, Accident Anal. Prev. 183 (2023), https://doi.org/10.1016/j.aap.2023.106988.

[24] X. Dong, K. Xie, H. Yang, How did COVID-19 impact driving behaviors and crash severity? A multigroup structural equation modeling, Accident Anal. Prev. 172 (2022), https://doi.org/10.1016/j.aap.2022.106687.
[25] A. Shahlaee, M. Shirazi, E. Marshall, J.N. Ivan, Modeling the impact of the COVID-19 pandemic on speeding at rural roadway facilities in Maine using short-term speed and traffic count data, Accident Anal. Prev. 177 (2022), https://doi.org/10.1016/j.aap.2022.106828.
[26] N. Dong, J. Zhang, X. Liu, P. Xu, Y. Wu, H. Wu, Association of human mobility with road crashes for pandemic-ready safer mobility: a new York City case study, Accident Anal. Prev. 165 (2022), https://doi.org/10.1016/j.aap.2021.106478.
[27] R. Hyndman, George Athanasopoulos, Forecasting: Principles and Practice, 3rd edition, OTexts, Melbourne, Australia, 2021.
[28] M.G. Karlaftis, E.I. Vlahogianni, Memory properties and fractional integration in transportation time-series, Transport. Res. Part C Emerg. Technol. 17 (2009) 444–453, https://doi.org/10.1016/j.trc.2009.03.001.
[29] C. Katrakazas, E. Michelaraki, M. Sekadakis, A. Ziakopoulos, A. Kontaxi, G. Yannis, Identifying the impact of the COVID-19 pandemic on driving behavior using naturalistic driving data and time series forecasting, J. Safety Res. 78 (2021) 189–202, https://doi.org/10.1016/j.jsr.2021.04.007.
[30] K. Pattrawiwat, Interrupted time series design: evaluating of the intervention for applications in behavioral science research, J. Behav. Sci. 22 (2016).
[31] R. Hyndman, A. Koehler, Another look at measures of forecast accuracy, Int. J. Forecast. 22 (2006) 679–688, https://doi.org/10.1016/j.ijforecast.2006.03.001.
[32] C. Lewis, Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting, Butterworth Scientific, London, 1982.