Analysis of the impact of COVID-19 on collisions, fatalities and injuries using time series forecasting: The case of Greece

Marios Sekadakis [a], Christos Katrakazas [a,*], Eva Michelaraki [a], Fotini Kehagia [b], George Yannis [a]

[a] National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., GR-15773 Athens, Greece
[b] School of Civil Engineering, Division of Transportation and Construction Management, Highway Laboratory, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece

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ABSTRACT

The current study aims to investigate the impact of the COVID-19 pandemic on road traffic collisions, fatalities, and injuries using time series analyses. To that aim, a database containing road collisions, fatalities, and slight injuries data from Greece were derived from the Hellenic Statistical Authority (HSA) and covered a ten-year timeframe (from January 2010 to August 2020. The chosen time period contained normal operations, as well as the period of the first COVID-19-induced lockdown period in Greece. Three different Seasonal Autoregressive Integrated Moving Average (SARIMA) time series models were implemented in order to compare the observed measurements to forecasted values that were intended to depict assumed conditions; namely, without the appearance of the COVID-19 pandemic. Modelling results revealed that the total number of road collisions, fatalities, and slightly injured were decreased, mainly due to the sharp traffic volume decrease. However, the percentage reduction of the collision variables and traffic volume were found to be disproportionate, which probably indicates that more collisions occurred with regard to the prevailing traffic volume. An additional finding is that fatalities and slightly injured rates were significantly increased during the lockdown period and the subsequent month. Overall, it can be concluded that a worse performance was identified in terms of road safety. Since subsequent waves of COVID-19 cases and other pandemics may reappear in the future, the outcomes of the current study may be exploited for the improvement of road safety from local authorities and policymakers.

1. Introduction

The coronavirus pandemic (COVID-19) was declared as such by the World Health Organization (WHO) in March 2020, after the first confirmed case was identified in the city of Wuhan in China in December (Jiang et al., 2020). To date, COVID-19 has infected several million individuals, with recent data reporting more than 122 million confirmed cases globally, including over 2.69 million fatalities (ECDC, 2020). At the same time, road collisions continuously consist one of the most crucial problems of transportation globally, resulting in material damage, economic losses as well as physical injuries and casualties (Hsu et al., 2015; Kopits and Cropper, 2005). According to WHO, road traffic fatalities claim more than 1.35 million lives each year around the world and count up to 50 million injuries every year (WHO, 2020). As a result, road collisions may be considered a significant but neglected global public health issue, constituting the eighth leading cause of death

worldwide as well as the first leading cause of death between children and young adults aged 5 and 29 (WHO, 2020).

Given the way of transmission of the COVID-19 virus, social distancing along with other mobility restriction measures were implemented, such as stay-at-home policies by closing shopping centers, bars, restaurants, and educational institutions, suspension of cultural events, businesses, workplaces, and all religious services, in the affected areas. The purpose of these measurements was to control the spread of the COVID-19 disease by reducing interactions among people and restricting mobility to mitigate the risk of healthcare system capacities being exceeded (Klein et al., 2020). The aforementioned countermeasures consequently had a significant impact on traffic volumes and travel behavior. Specifically, road traffic volumes, public transport users, and overall mobility activity has been reduced massively (Apple, 2020; Google LLC, 2020; Moovit, 2020). Moreover, the restrictions on mobility appeared to have a significant effect on driving behavior. It was revealed

that driving indicators, such as average speed, the exceedance of speed limits, and harsh acceleration or braking per distance, changed radically (Katrakazas et al., 2021, 2020; Stavrinos et al., 2020). All the related to this study aspects are analyzed further in literate review sections as it is important to understand the impact of COVID-19 pandemic on traffic-related areas.

Considering all the aforementioned facts, this study aims to investigate and model the impact of the COVID-19 pandemic on road traffic fatalities and injuries. Greece was chosen as a study case due to data availability (i.e., collision data are open-access from the Hellenic Statistical Authority-HSA) and the exposure data were extracted from the mobility trend report of Apple (Apple, 2020). Four different collision-related variables were measured, i.e., the number of collisions, fatalities, seriously and slightly injured. It is expected that the current work contributes new evidence to the growing literature on the multiple effects of the COVID-19 pandemic on transportation around the world.

On that basis, the research questions that this study attempts to answer are the following:

1. How was the total number of road collisions, road fatalities, and slight injuries affected due to the COVID-19 pandemic in Greece and especially in combination with traffic volume?
2. How were the fatality and slightly injured rates affected due to the COVID-19 pandemic in Greece?

Based on the aforementioned research questions, more light is shed on the effect of the pandemic and a weighted rate of collisions and related injuries taking into account exposure is calculated. In that way, the study evolves on the state-of-the art literature, which is mainly based on before/after comparisons and visual or descriptive statistics and performs a time series analysis of the COVID-19 effect on critical indicators for road safety such as collision and injury rates. As a result, in-depth explanations and conclusions can be drawn with regards to collisions and injuries in a health-critical and dynamically changing time period.

The rest of this paper is structured as follows: Section 2 provides a brief literature review of studies regarding the COVID-19 pandemic and its corresponding impact on driver performance, traffic volumes, and road collisions, focusing on studies that explored travel behavior changes globally during the pandemic period. Then, in Section 3, a description of the methodological approach is provided, including the theoretical background of time series forecasting analysis. Section 4 presents the data collection, and then Section 5 includes the utilized analysis method. Section 6 provides the results of the analysis method performed in the framework of the current study. Lastly, discussion on the impact of the COVID-19 pandemic on road fatalities and injuries is highlighted in Section 7. In the last section, conclusions on the originality, innovation, contribution to practice and knowledge of the study are revealed.

2. Literature review

A literature review was carried out to investigate the impact of the COVID-19 pandemic on traffic-related areas. The search was conducted in the databases ScienceDirect, ResearchGate, Scopus, PubMed, and Google Scholar. Relevant literature was documented and summarized, and the most associated papers with the investigating topic were included in this review.

2.1. COVID-19 pandemic and road collisions

During lockdown restrictions, the number of road collisions and road traffic fatalities has been found to decrease significantly during the first months of 2020. For instance, during lockdown from March 16th 2020 to April 26th 2020 in Spain, the number of road collisions per day fell by 74.3% compared to the normal period in February (i.e., reference week).

At the same time, a 76% reduction was identified in respect to the equivalent period in previous years of 2018–2019 (Saladié et al., 2020). Moreover, the study of Aloi et al. (2020) indicated that the total number of road collisions during the lockdown period was reduced by up to 67% in relative terms compared to the normal period.

Reduced traffic volume may have played a significant factor in collisions reduction found in major global cities. For example, during the three months of the COVID-19 pandemic (i.e., August - October 2020), road collisions in Milan, Madrid, and Paris remained lower than miles-traveled by 51%, 33%, and 29%, respectively, compared to 2019, indicating a decrease in the collision rate per mile (Pishue, 2020). In addition, motorways, as opposed to A-roads and arterials, appeared to have a larger reduction in road crashes outside of New York (Pishue, 2020). It was also revealed that road collisions and especially injury-causing and fatal collisions had been reduced by half, from approximately 1,000 crashes and roughly 400 injury-causing/fatal crashes per day to 500 and 200 per day, respectively (Shilling and Waetjen, 2020).

With regards to road fatalities, according to the International Traffic Safety Data and Analysis Group (IRTAD), an overall decrease was identified in 2020 in most countries compared to 2019. Specifically, some interesting descriptive results were summarized, and a 58% reduction in road fatalities was identified in April 2020 compared to April 2019 in Greece (IRTAD, 2020). On a global level, most countries saw a decrease in the total number of road deaths during the first months of 2020 (i.e., the lockdown period), with a drop in fatalities up to 80%. Results also indicated that fewer people were involved in fatal road crashes, but, unfortunately, the rate of reduction had slowed.

2.2. COVID-19 pandemic and traffic volumes

In general, existing studies revealed a great change in mode choice patterns and, by extension, in traffic volumes. More specifically, Vanlaar et al. (2020) demonstrated that 42.2% of people used to travel by their individual vehicle and 41.2% by public transit prior to the pandemic. On the contrary, during the COVID-19 restrictions, 69.9% preferred using their own vehicle, while only 4.4% of people tended to use public transit. In the same study, it was found that walking as a preferred method was increased by 121.2% and cycling by 152.1%, as well as the use of taxi or rideshare services was decreased by 55.7%. Additionally, Aloi et al. (2020) identified a 76% overall reduction in traffic volumes, which was proved to be less great in the case of the private car. At the same time, public transport users dropped by up to 93%. Furthermore, during the lockdown period in California, there were statistically significant reductions in traffic volumes about 80% in certain counties from early March to mid-April compared to the normal period, before the appearance of the COVID-19 pandemic (Shilling and Waetjen, 2020). Traffic volumes of North Carolina and Virginia declined about 40% and 50%, respectively.

In general, travel demand decreased, and many countries have already witnessed sizeable drops in car traffic and public transport ridership. Along the same lines, the total number of trips and the distance traveled were also reduced considerably. In particular, Bucsky (2020) found that COVID-19 measures decreased traffic volumes and transport demands by half in the city of Budapest almost immediately after the introduction of mobility restrictions. Mode choice patterns were also changed during the pandemic with car usage growth in the modal share from 43% to 65%. Meanwhile, a significant reduction was revealed regarding the share of public transport from 43% to 18%. Hence, traffic volumes stabilized at this lower level, while the number of daily trips dropped approximately 60% compared to 2018. Moreover, during the lockdown period, New Zealand, France, and South Africa achieved the most significant reductions in traffic volumes by 74%, 75%, and 77%, respectively (IRTAD, 2020). Another interesting approach, aiming to investigate the impact of COVID-19 disease on travel behavior, revealed that during the lockdown period in the Netherlands, the total amount of trips and distance travelled dropped by

55% and 68%, respectively, when compared to the fall of 2019 (Haas et al., 2020). During the implementation of several COVID-19 restrictive measures, particular focus was given in the case of Italy, where a remarkable 50% reduction in driving volumes was highlighted (Pepe et al., 2020).

2.3. COVID-19 pandemic and driver behavior

The restrictions on mobility have also fostered certain changes in driver behavior. It should be noted that there was not a large variety of published studies investigating the link between driving indicators (e.g., harsh acceleration, harsh braking, or mobile phone use during driving) and the pandemic. On the other hand, particular emphasis was given to changes in average speed, speeding, and driving distance per trip during the pandemic. In particular, Katrakazas et al. (2020) indicated that reduced traffic volumes due to COVID-19 restrictions led to an increase in average speed by 6–11% in Greece and the Kingdom of Saudi Arabia (KSA). At the same time, a higher (up to 12%) rise in harsh events (i.e., harsh acceleration and harsh braking) as well in mobile phone use (up to 42% increase) was identified during March and April 2020, which were the months when COVID-19 spread was at its peak.

Focusing on changes in commuting behavior due to the COVID-19 pandemic in California, it was revealed that unsafe driving behaviors, such as speeding and stunt driving were increased according to police enforcement data (Shilling and Waetjen, 2020). Specifically, the authors indicated that maximum and average traffic speeds increased slightly on certain California highways. Average travel speeds in Toronto were dramatically increased within the first four months of the COVID-19 pandemic and still maintain much of the gains through October. In addition, a notable increase in the average level of speeding was also observed in three major urbanized areas in Ohio, USA: Columbus, Cincinnati, and Cleveland (Lee et al., 2020). It was also revealed that the mean differences in speeding after the COVID-19 outbreak were statistically significant compared to the same period last year.

2.4. Review conclusions, motivation, and research gap

The majority of literature studies examined the effect of COVID-19 on road safety and driving behavior by performing exploratory or before/after descriptive analyses with the aim to quantify the differences in road safety and mobility. To date, no similar study exists that attempts to model the evolution of collision and injury data conjointly with the COVID-19 evolution (apart from Katrakazas et al. (2021). This fact forms the motivation for the current paper, which aims at quantifying the effect of the COVID-19 pandemic on collisions, fatalities, and injuries, utilizing time series forecasting techniques in order to compare and contrast the "expected" collision and injury rates with the actual ones observed during the pandemic.

3. Methodology

For the purpose of modeling road collision data, as well as the number of fatalities and slightly injured drivers, Seasonal Autoregressive Integrated Moving Average (SARIMA) models are utilized. With regards to SARIMA time series analysis, the following steps are followed according to Bisgaard & Kulahci, (2011), Box & Jenkins, (1976) and Essi, (2018):

- Decomposition of time series
- Autocorrelation and Partial Autocorrelation
- Stationarity test
- SARIMA modelling
- Residual test
- Test set error
- Forecasting

An ARIMA model is generally denoted as:

$$ARIMA(p, d, q) \tag{1}$$

where the non-seasonal part of the model: p denotes the number of autoregressive terms (number of time lags), d denotes the number of differences (i.e., the number of non-seasonal differences required for stationarity), and q is the number of lagged forecast errors in the prediction equation (Nau, 2020)

A SARIMA model is suggested when the time series data presents seasonality, such as the available collision data. SARIMA is denoted as:

$$ARIMA(p, d, q)(P, D, Q)m \tag{2}$$

where the seasonal part of the model: P denotes the seasonal autoregressive order, D denotes the number of seasonal differencing, Q denotes seasonal moving average, and m is the number of observations per year.

The parameters of p, d, q of the no-seasonal part of *the S*ARIMA model and *P, D, Q* of the seasonal part as mentioned in Eq. (2) were estimated with an algorithmic search. This specific search uses aspects of the Hyndman-Khandakar algorithm, which combines unit root tests, minimization of the Akaike information criterion (AIC), and maximum likelihood estimation (MLE) to obtain the optimal SARIMA model (Hyndman and Athanasopoulos, 2018). This automatic algorithmic search is implemented based on popular packages in R and Python programming languages (Hyndman and Khandakar, 2007; Smith et al., 2017).

In results, two criteria are used, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), which are typically used as a criterion for model selection (Mohammed et al., 2015), as exactly in the present study. AIC is a method for model selection, and it is based on the log-likelihood of model fit and the number of independently adjusted parameters within the model (Akaike, 1974). Following the same logic, BIC is another criterion for model selection which is based on the likelihood of the tested model (Schwarz, 1978). A lower value of AIC and BIC indicates a better model fit.

After developing the ARIMA models on the testing and validation sets, forecasts are evaluated using popular forecasting evaluation metrics such as:

- Mean Error (ME)
- Mean Absolute Error (MAE)
- Mean Percentage Error (MPE)
- Mean Absolute Percentage Error (MAPE)
- Root Mean Squared Error (RMSE)

Moreover, the statistical significance of SARIMA model components is checked, and the desired confidence interval (CI) should be equal to 95%.

4. Data collection

For each of the investigated variables (i.e., road collisions, road fatalities, slightly injured) derived from the HSA, the monthly time series were obtained for a 10-year timeframe, i.e., from January 2010 to August 2020. HSA processes collision data exploiting reports, which are filled by police authorities after road collision occurrence. Collision data give the opportunity to compare road safety performance taking into account the COVID-19 spread, the lockdown measures as well as the prevailing traffic volumes. Table 1 provides a brief description of the examined variables, while Table 2 provides descriptive statistics (i.e., mean, standard deviation, maximum, minimum value, and sample size) for each one of the corresponding variables.

With regard to traffic volume, data were extracted from the mobility trend report of Apple (Apple, 2020), in which route requests are measured and categorized depending on people driving, walking, and use public transport. All user requests to the Apple Maps service were

Table 1

Examined Variables Description.

Variables	Description
Road Collisions	Monthly reported road collisions (count) (Source: HSA, 2020)
Road Fatalities	Monthly reported road fatalities due to road collisions (Source: HSA, 2020)
Slightly Injured	Monthly reported slightly injured road users due to road collisions (Source: HSA, 2020)
Seriously Injured	Monthly reported seriously injured road users due to road collisions (Source: HSA, 2020)
COVID-19 cases	Daily reported cases due to COVID-19 (Source: Our World in Data, 2020)
COVID-19 casualties	Daily reported casualties due to COVID-19 (Source: Our World in Data, 2020)
Traffic Volume	Change in driving routing requests since January compared to a baseline of 100% before the COVID-19 spread. (Source: Apple, 2020)

Table 2

Descriptive statistics of the examined variables (monthly).

Variable	Mean	Standard deviation	Maximum value	Minimum value	Sample size (N)
Road Collisions (count)	986	177.4	1424	326	128
Road Fatalities (count)	72	21.5	149	21	128
Slightly Injured (count)	88	40	210	21	128
COVID-19 cases (count)	1267	1878.9	5733	0	8
COVID-19 casualties (count)	33	33.1	96	0	8
Traffic Volume (%)	108	60.8	217	29	8

stored randomly, fully compliant with EU GDPR data protection legislation. In the present study, such data were used as a surrogate for the prevailing traffic volume conditions. The data consists of daily reports of the driving traffic volume in Greece and are expressed as a percentage equal to the change compared to a 100% baseline volume on January 13th, 2020. For instance, as depicted in Fig. 2, if the traffic volume equals 60%, this indicates that a 40% reduction occurred in traffic volume compared to the 100% baseline traffic volume.

In Table 2, COVID-19 cases, casualties, and traffic volumes have a small sample size since they refer to monthly measurements from January 2020 to August 2020. On the contrary, collision data consist of monthly observations within a 10-year time period (i.e., from January 2010 to August 2020), and the sample size is greater. Regarding the monthly measurements of COVID-19 statistics and traffic volume, the average values were also calculated for consistency reasons. The variable of serious injuries is not included in the present study since it yielded statistically insignificant results.

Furthermore, in Fig. 1, the examined variables of road collisions, road fatalities, and slightly injured are plotted within a 10-year time period.

Table 3 summarizes the timeline of COVID-19 response measures that the Greek government has announced. Specifically, in March, gradual closure restrictions were applied. Firstly, the Greek government restricted educational activities and then leisure activities (i.e., shopping, restaurants, and cafes). After three days, the religious services were suspended, and finally on April 23rd, a complete lockdown was imposed. In contrast, the entire April was under lockdown restrictions. Consequently, two different situations of road safety in terms of

measures are investigated.

Fig. 2 presents the monthly change in COVID-19 cases and fatalities, and traffic volumes. During the lockdown period (i.e., March and April), an initial outcome is that traffic volumes were reduced by about 42% and 71%, respectively. It is quite reasonable that a greater reduction was observed in April since it was a month of complete lockdown, as mentioned before. Traffic volume is defined as a percentage of people driving compared to the 100% baseline of the non-COVID-19 period. After the end of the lockdown, traffic volume was increasing steadily. In June, the volume approximately reached a baseline of 100%. In August, a 100% increase in driving was identified compared to the baseline period, probably due to passengers' choice to avoid using public transport and human contact. Another significant reason is that there was a seasonal increase in moving vehicles due to summer tourism.

5. Time series modelling

5.1. Time series decomposition

For the purpose of analyzing the obtained data, there are three components that need to be initially examined; trend, seasonality and randomness. The following definitions of "trend", "seasonality" and "randomness" are used, as illustrated in the multiplicative model decomposition plots of Fig. 3 (Hyndman and Athanasopoulos, 2018):

- Trend: a trend exists when there is a long-term trend (i.e., increase or decrease) in the observations.
- Seasonality: is a seasonal pattern that occurs when a time series is affected by seasonal factors, e.g., the time of the year or the day of the week, and usually follows a fixed and known frequency.
- Randomness: is the distribution of residuals over time.

These three components (i.e., trend, seasonality, and randomness) of the time series of the considered indicators are shown separately in Fig. 3, which depicts the multiplicative model decomposition plots. A mutual trend, seasonality, and randomness were observed between the variables, which is quite understandable since road collisions induce fatalities and injuries. With regard to the trend, all variables present a similar decreasing trend from 2010 to 2020. Concerning seasonality, it can be concluded that the maximum values were observed in the first and third quarters of each year for each variable, creating a pattern of two spikes per year, and these were observed within the 10-year timeframe. With regard to the randomness, a random spreading was observed, and it is noteworthy that randomness in 2020 was increased dramatically, which is justifiable since the equilibrium of mobility has changed due to COVID-19.

5.2. Autocorrelation and Partial autocorrelation

Fig. 4 illustrates the Autocorrelation Function (ACF) plots for the 1st difference of the examined variables. ACF gives auto-correlation values of the time series with its lagged values, and Partial Autocorrelation Function (PACF) gives the correlation of the remaining residuals (Salvi, 2019). The blue dashed line in the following figures indicates the level of when the autocorrelation is significant.

The 1st difference was chosen for all the final models due to the existence of high autocorrelation on non-differencing variables. More specifically, ACF for non-differencing variables was highly autocorrelated since many lag values were over the blue dashed line. Highly autocorrelated series indicate that they are non-stationary and hence it is suggested be differenced (SAGE, 2017). To that aim, in order to avoid high autocorrelation in final models, the 1st difference of the same variables was chosen and tested for the final models. Investigating the autocorrelation and partial autocorrelation plots of 1st difference, both ACF and PACF were presented relatively lower values compared to the non-differencing, and consequently the 1st difference presents
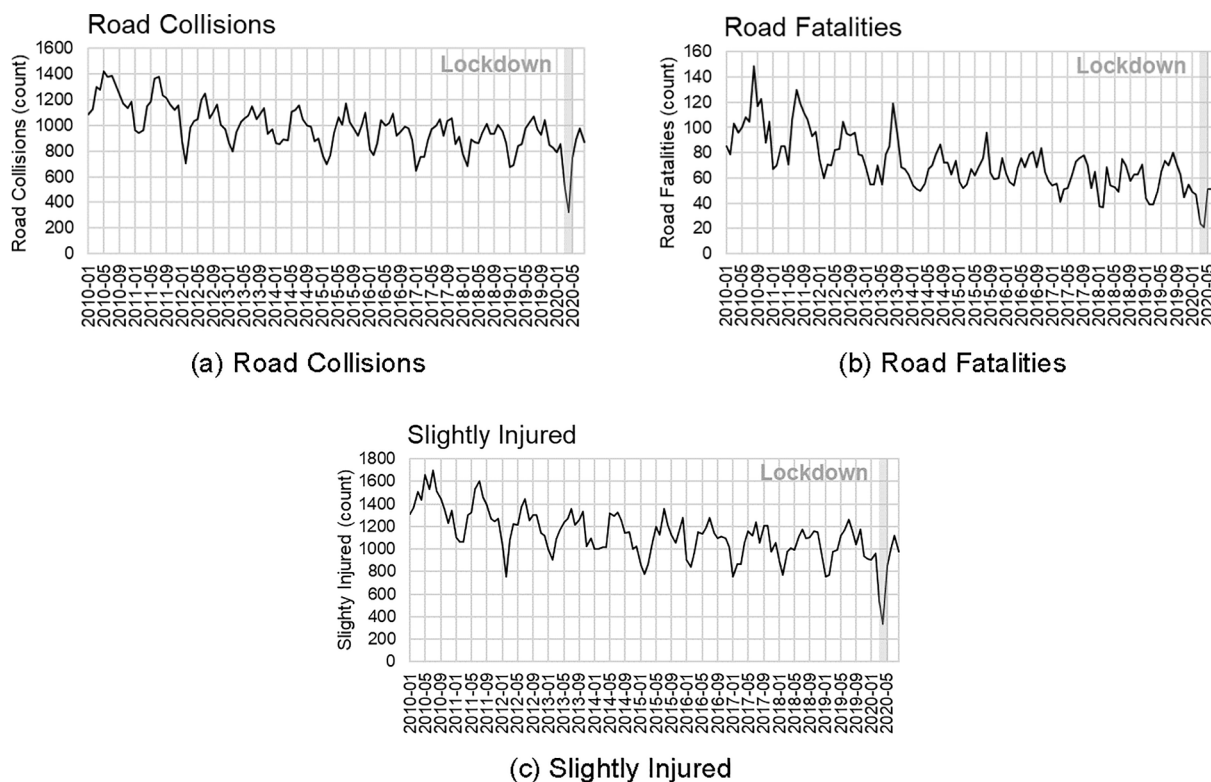
Road Collisions

(a) Road Collisions

Road Fatalities

(b) Road Fatalities

Slightly Injured

(c) Slightly Injured

Fig. 1. Collision data of (a) Road Collisions, (b) Road Fatalities, (c) Slightly Injured.

Table 3
Dates of lockdown measures in Greece.

Measure	Date
Appearance of COVID-19	26–2-2020
Closure of educational institutions	10–3-2020
Closure of shopping centers and cafes	13–3-2020
Suspension of religious services	16–3-2020
Lockdown of non-essential movements	23–3-2020
End of lockdown	4–5-2020

COVID-19 cases & Traffic Volume

Fig. 2. COVID-19 cases and Traffic Volume Change.

appropriate autocorrelation values, as depicted in the following ACF plots.

5.3. Stationarity

For stationarity checking, the Augmented Dickey-Fuller (ADF) test

was performed for the final model of 1st difference (Y_t - Y_{t-1}) of road fatalities, road collisions, and slightly injured. ARIMA differencing is a method of transforming a non-stationary time series into a stationary one, and it is used in this study to eliminate non-constant trend. A seasonal differencing was implemented in the same context, and an attempt was made to remove the seasonal effect or trend from the time series observations.

As mentioned in section 5.2, it was necessary to choose the 1st difference of each examined variable and include them in the final models due to the existence of high autocorrelation on non-differencing variables. Consequently, the non-differencing variables were rejected due to the aforementioned autocorrelation test, and a transformation was needed regardless of the fact that all of them were stationary.

Table 4 includes the ADF test for the 1st difference of each variable, which again shows that all variables are significantly stationary at 99% CI, and therefore sufficient for the SARIMA models.

Moreover, the Box-Ljung Test was conducted to examine if the variables take the form of white noise. This test was performed on the 1st difference of road fatalities, road collisions, and slightly injured, and none of them was found to be "white noise".
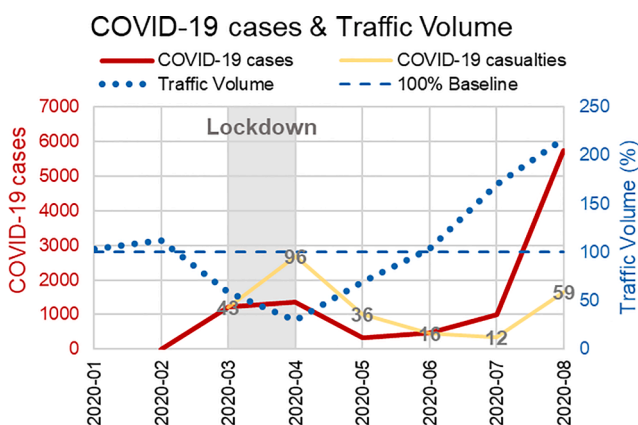
5.4. Time series modelling

In order to test the performance of the models, a train-test split of the collected data was implemented. The split consists of 75% training data (i.e., from January 2010 to July 2017) and 25% testing data (i.e., from August 2017 to February 2020, when COVID-19 appeared in Greece). The results of performance metrics on the test set are presented in Table 7. In order to obtain the best SARIMA specifications, the *auto-arima* package in R was used (Hyndman et al., 2021). Table 5 provides an overview of each SARIMA model parameters, as stated in Eq. (2). It can be observed that a non-seasonal and seasonal differencing equal to 1 was accomplished for each model, while m = 12 denotes the number of observations per year that was used for model specification.

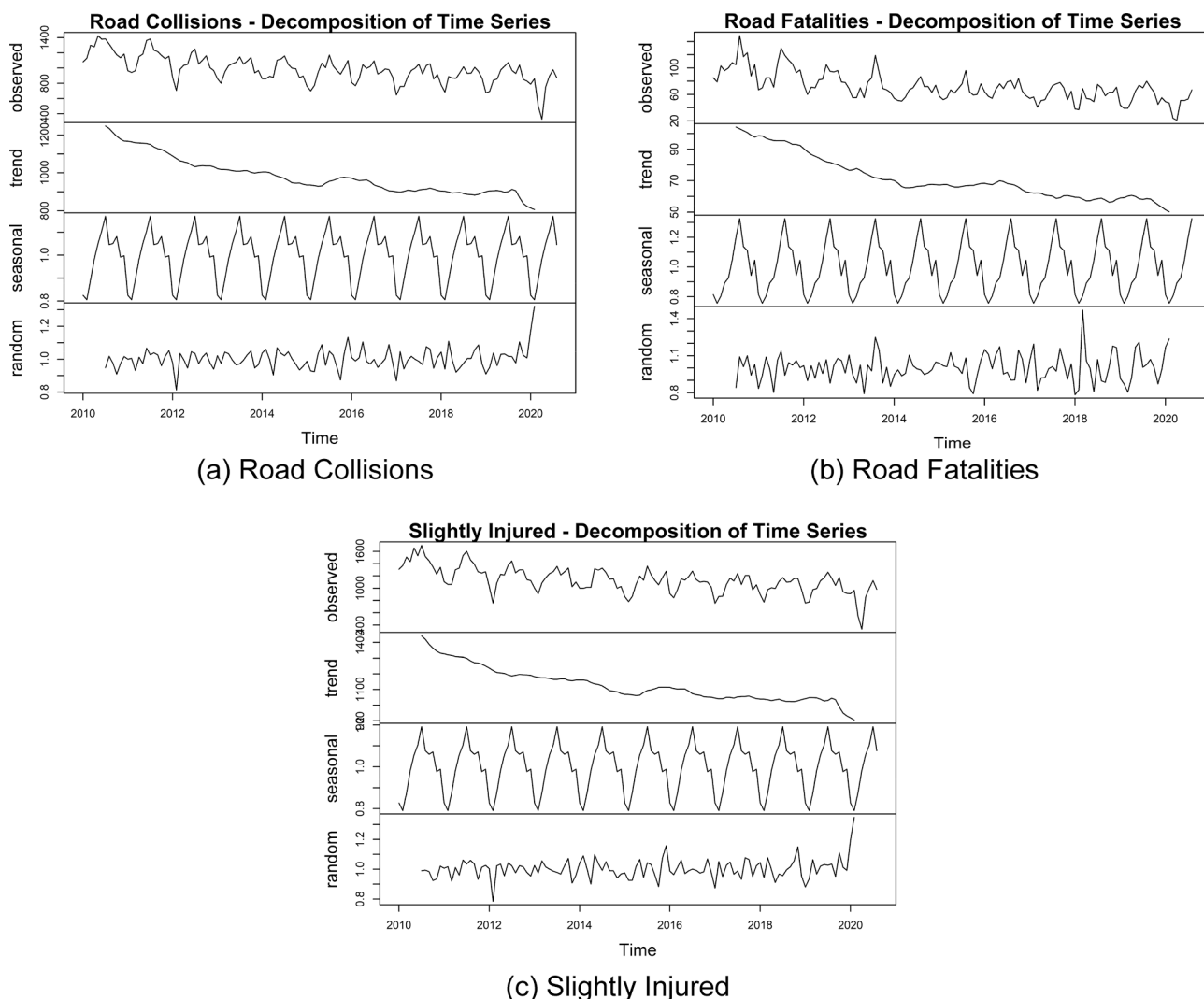In Table 6, the model specification for each of the corresponding

Fig. 3. Multiplicative Decomposition of Time Series: (a) Road Collisions, (b) Road Fatalities, (c) Slightly Injured.

models is presented. Statistical performance of the coefficients is also presented by including metrics of estimate, standard error, z-value, and p-values. Taking into consideration the p-value for each parameter, it is demonstrated that all parameters are statistically significant. The estimators of AIC and BIC are included to have a clear picture for each model.

5.5. Residuals test

Along with the coefficients of the models and for the purpose of model verification, a residuals test was also conducted. The residuals should be randomly scattered without the existence of any pattern within the investigated timeframe in order to approve the residuals test. An additional criterion for the residuals is the ACF test which checks the autocorrelation of potential lags. All lags are lower than the desired threshold, which indicates significant autocorrelation. The final residuals approval criterion is to be normally distributed.

5.6. Performance metrics

Table 7 shows the performance metrics on the test set of the estimated SARIMA models. More specifically, in the following table, the error between the observed and forecasted (test set) values is included to estimate the performance metrics. ME, RMSE, and MAE are included in order to estimate the performance of the test set. Nevertheless, in the

current study, only MPE and MAPE are used to compare the results since these are percentage errors and have the advantage of being unit-free (Hyndman and Athanasopoulos, 2018). Concerning MAPE values, it can be concluded that the model on the frequency of slightly injured performs better with only an 8.33% difference from the observed measurements. In the final column, the first-order autocorrelation coefficient (ACF1) is presented (Hyndman and Athanasopoulos, 2018), and it can be concluded that all SARIMA models perform quite well. It is worth mentioning that as the autocorrelation function can provide the correlation among different points separated by various time lags, ACF1 is a measure of how much is the current value influenced by the previous values in a time series.

Focusing mainly on the MAPE, the forecasting performance of a model is considered highly accurate if the MAPE value is<10% and good for<20% (Lewis, 1982). Therefore, time series of road collisions and slightly injured are lower than 10% MAPE, and the forecasting performance can be considered highly accurate. Similarly, regarding the performance of road fatalities model is<15% and is considered acceptable. This can be confirmed given the fact that in existing transportation studies with SARIMA models, the evaluated MAPE ranged from 3.4 to 13.5% in Xu et al. (2019) and 10.6 to 37.5% in Guo et al. (2013).
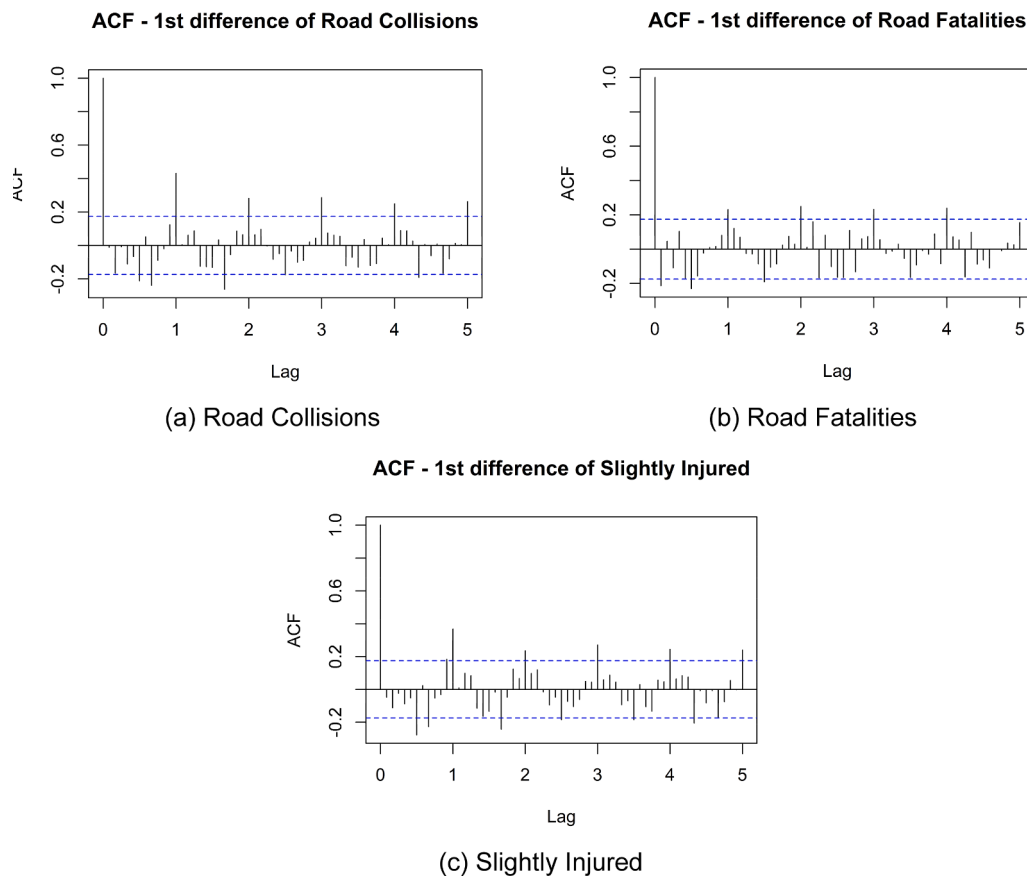
ACF - 1st difference of Road Collisions

ACF - 1st difference of Road Fatalities

(a) Road Collisions

(b) Road Fatalities

ACF - 1st difference of Slightly Injured

(c) Slightly Injured

Fig. 4. ACF plots of the frequency for the 1st difference of the examined variables: (a) Road Collisions, (b) Road Fatalities, (c) Slightly Injured.

Table 4
Augmented Dickey-Fuller Test of the 1st difference of each variable.

Variable	Augmented Dickey-Fuller Test		
	Test statistics	Lag order	p-value
diff(**Road Collisions**)	−7.37	5	<0.01
diff(**Road Fatalities**)	−7.17	5	<0.01
diff(**Slightly Injured**)	−7.65	5	<0.01

Table 5
SARIMA models parameters.

Variable	SARIMA Model
diff(**Road Collisions**)	ARIMA(0,1,2)(1,1,0)[12]
diff(**Road Fatalities**)	ARIMA(0,1,1)(0,1,1)[12]
diff(**Slightly Injured**)	ARIMA(3,1,0)(1,1,0)[12]

6. Results

6.1. Road collisions

Fig. 5 presents a plot of the forecasted road collisions based on the (0,1,2)(1,1,0)[12] SARIMA model. It is demonstrated that road fatalities were decreased sharply over the lockdown period, while in assumed conditions without the appearance of COVID-19, more road collisions would have been observed depending on the forecasted values. An initial result is that road safety was improved over the lockdown period.

Table 7
Performance metrics on test set.

Variable	ME	RMSE	MAE	MPE	MAPE	ACF1
diff(**Road Collisions**)	67.97	103.36	82.08	7.40	9.08	0.08
diff(**Road Fatalities**)	5.07	10.48	8.21	7.14	13.59	0.06
diff(**Slightly Injured**)	51.86	106.81	86.45	4.76	8.33	−0.03

Table 6
Summary of the optimal SARIMA models.

Dependent Variable	Model parameters	Estimate	Std. Error	z value	Pr(>|z|)	AIC	BIC
diff(**Road Collisions**)	ma1	−0.50	0.11	−4.23	2.278e-05 ***	913.68	923.11
	ma2	−0.34	0.12	−2.84	0.0046 **		
	sar1	−0.34	0.12	−2.94	0.0033 **		
diff(**Road Fatalities**)	ma1	−0.84	0.06	−12.95	< 2.2e-16 ***	601.96	609.03
	sma1	−0.62	0.12	−5.13	2.88e-07 ***		
diff(**Slightly Injured**)	ar1	−0.67	0.11	−6.19	5.907e-10 ***	950.93	962.71
	ar2	−0.59	0.12	−5.05	4.402e-07 ***		
	ar3	−0.30	0.11	−2.75	0.0059 **		
	sar1	−0.32	0.12	−2.59	0.0095 **		

Significance codes: 0 '***' | 0.001 '**' | 0.01 '*' | 0.05 '.' | 0.1 ' ' | 1
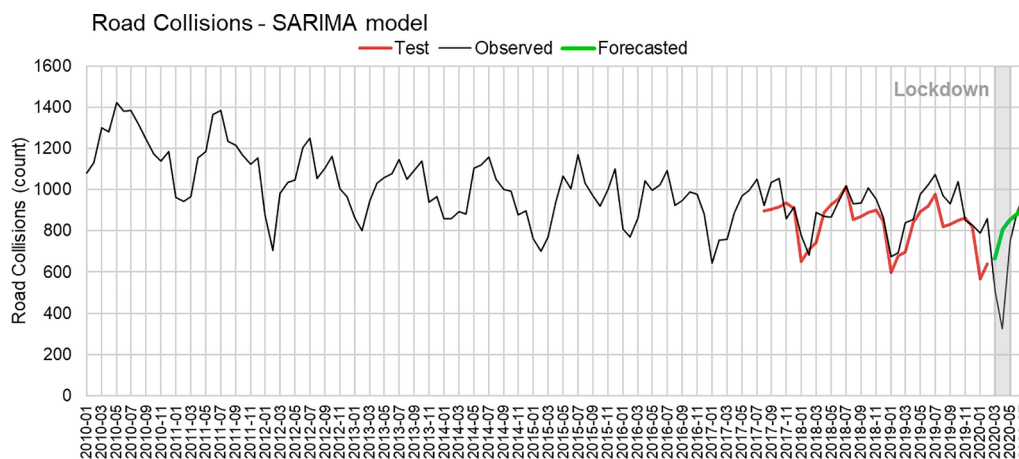
Fig. 5. SARIMA forecast of Road Collisions.

Nevertheless, this improvement is important to be validated by combining the change in traffic volume at the same period.

In Fig. 6, the comparison between forecasted and observed values reveals that during the lockdown period, about 160 (24%) and 480 (60%) fewer road collisions were observed compared to the SARIMA forecasts in March and April, respectively. For the entire lockdown period, the corresponding drop is about 42%. At the same time, as it is also illustrated in the same figure, traffic volume was reduced by 42% and 71% in March and April, respectively, while 56.5% less traffic was on the roads during the lockdown period.

In general, there is a clear proportional relationship between the number of road collisions or fatalities and traffic volume (Dickerson et al., 2000; Blokpoel; Appel in Oppe, 1989). Consequently, the percentage reduction of road collisions and traffic volume under the same traffic conditions should be approximately the same. However, a 42% reduction was observed in road collisions, and a greater decrease of 56.5% in traffic volume was found. These percentages were disproportionate, and this indicates that more collisions occurred considering the prevailing traffic conditions. Hence, with regards to road safety, a worse performance was identified.

After the lockdown period and investigating the subsequent months, road collisions seem to fit to the forecasted values regardless of the fact that traffic volume was increased over the baseline. It should be noted that observed collision data were available until August 2020. However, the SARIMA forecast was implemented up to December 2020 in order to compare and validate the performance of the model with future observations.

It is worth mentioning that the reduction of road collisions and traffic volumes are not directly comparable since they refer to different reference date-points. However, this comparison probably gives the

opportunity to investigate the road safety performance more thoroughly in future studies.

6.2. Road fatalities

Fig. 7 presents the plot of road fatalities forecasts based on the ARIMA $(0,1,1)(0,1,1)[12]$ model. It can be observed that road fatalities were decreased over the lockdown period.

To further investigate the effect of COVID-19 lockdown on road fatalities, the forecasted values were compared to the observed measurements. Fig. 8 depicts the SARIMA model predictions for road fatalities along with the differences between road fatalities observed and predicted values.

During the lockdown period, as depicted in Figs. 8, 6 (21%) and 20 (48%) fewer fatalities were observed in reality compared to the observations in March and April 2020, respectively. This finding can be converted into a reduction of about 0.56 and 1.87 road fatalities per million inhabitants, respectively. On the contrary, the dotted blue line of traffic volume was reduced about 42% and 71% in March and April compared to the baseline of a non-COVID-19 date, whereas a 56.5% for the lockdown period was demonstrated. The percentage reduction of road fatalities and traffic should be approximately proportional as mentioned before, and therefore a worse performance can be concluded in terms of road safety.

Another noteworthy observation was that in May 2020 (i.e., a month after loosening the lockdown restrictions), the observed road fatalities were increased 20% compared to the forecasted, while road collisions were reduced by 12% compared to the baseline. This difference indicates that more fatal collisions have occurred during the re-opening month of May, and subsequently, it is essential to estimate the fatality rate of the investigated months.

As mentioned before, an essential road safety indicator is the ratio of road fatalities to the number of road collisions to understand the fatality rate per collision. In assumed non-COVID conditions, the fatality rate would be equal to 4.6% and 5% in March and April, respectively. However, the observed fatality rate was 4.7% and 6.4%, respectively. Hence, the fatality rate in March was increased by 3% and in April (a complete month of lockdown) by 28%. Additionally, the aforementioned investigation worthy finding that fatalities increased while road collisions decreased in May is confirmed with the greatest increase of 37% in fatality rate compared to the lockdown months. Consequently, the observed collisions in Greece were more fatal during the lockdown period and a month after the restrictions.

6.3. Slight injuries

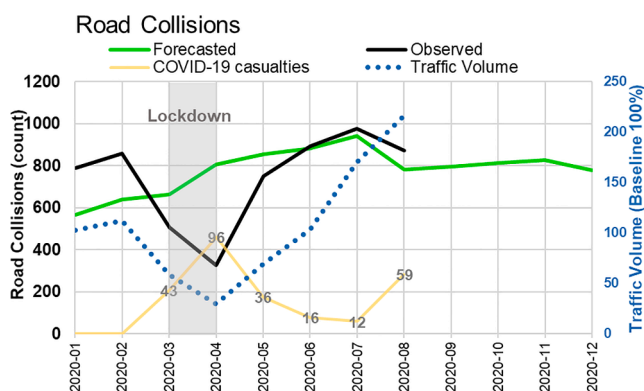In Fig. 9, slight injuries caused by road collisions are depicted based
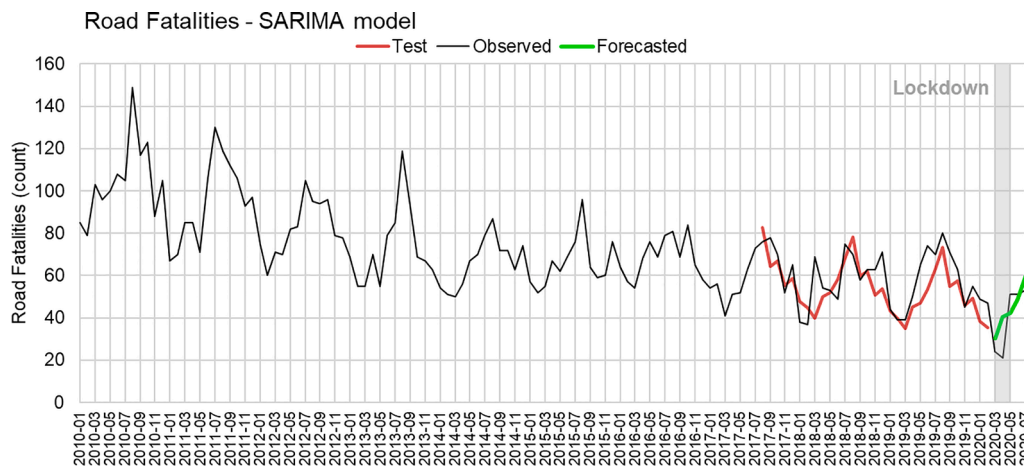

Fig. 6. COVID-19 impact investigation.

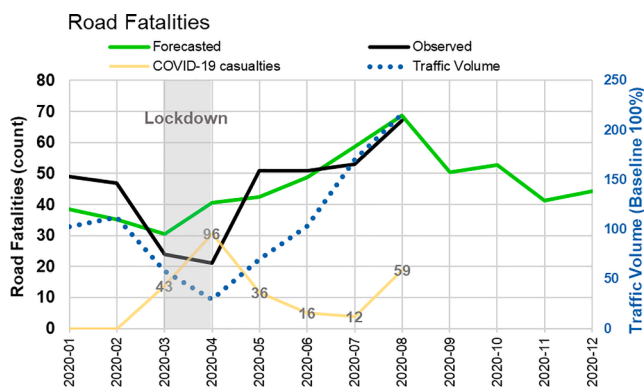**Fig. 7.** SARIMA forecast of Road Fatalities.

Fig. 8. COVID-19 impact investigation.

on the ARIMA (3,1,0)(1,1,0)[12] model. Slightly injured decreased sharply over the lockdown period (identical trend as in the plot of road collisions), compared to what would have been in assumed non-COVID conditions.

During the lockdown period, 240 (30.4%) and 640 (65.8%) fewer slight injuries were observed based on the SARIMA models in March and April, respectively (and 48.1% for the entire lockdown period). The aforementioned reduction in slight injuries can also be expressed as 22.4 and 59.7 fewer slight injuries per million inhabitants in March and April, respectively. On the contrary, traffic volumes were reduced by 42% and

71% in March and April, respectively (and 56.5% for the lockdown period) compared to the traffic volume baseline of a non-COVID-19 date. Similarly with the previous findings, the percentage reduction of slightly injured and traffic volume was disproportionate, and this probably indicates a worse performance in terms of road safety but not to the same degree as the previous variables.

After the lockdown period, the plot of slightly injured seems to fit the forecasted values with approximately the same values and regardless of the fact that the traffic volume was increased. In assumed non-COVID-19 conditions, the slightly injured rate would be 84.9% and 83% regarding the months of March and April, but instead, the observed values were 93% and 98.2%, respectively. Hence, the slightly injured rate was increased by 10% and 18% in March and April. Additionally, in May, the slightly injured rate was increased by about 7%. Therefore, the increase in fatality and slightly injured rates indicate that drivers were involved in more fatal and injury-causing collisions during the lockdown period and a month after loosening the restrictions (i.e., in May).

7. Discussion

In this section, the main outcomes of the current research are discussed. Three SARIMA models were developed in order to forecast the assumed conditions without the appearance of the COVID-19 pandemic, during and after the lockdown period. It should be clarified that assumed "non-COVID" conditions refer to the forecasted values extracted from SARIMA models that would have been observed without the appearance of the COVID-19 pandemic. Then, the forecasted values
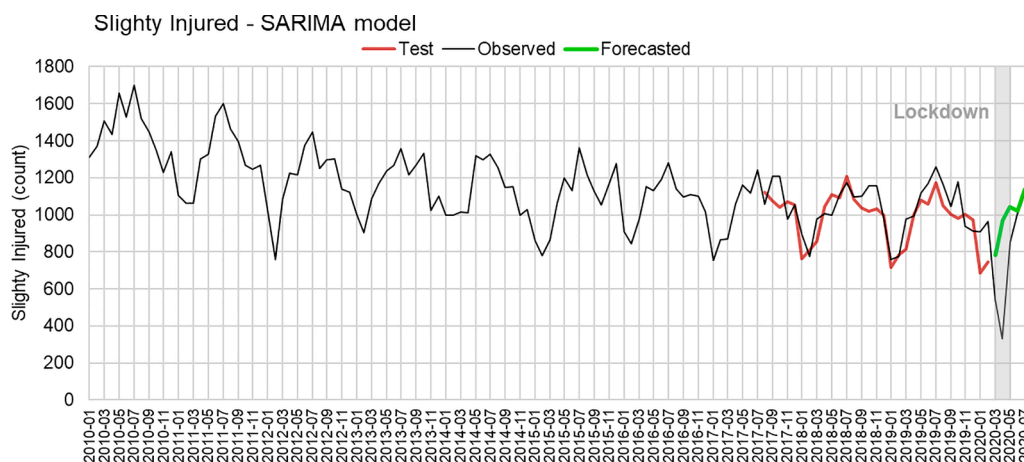

Fig. 9. SARIMA forecast of Slightly Injured.

were compared to the observed measurements (i.e., road collisions, fatalities, and slight injuries). Hence, a key achievement of the current study is that time series were modeled (at 99% CI) for the purpose of investigating the impact of the COVID-19 pandemic on road safety and contrasts with the majority of the existing literature. The lockdown changed this pattern, and findings from the current research are consistent with phenomena reported by Brodeur and Wright (2020) and Shilling and Waetjen (2020), who compared the incidence of road collisions before and during the lockdown period in the United States.

Road collisions, fatalities, and slight injuries were found to be lower than the forecasted values, as the traffic volume was reduced at the same period. Bringing traffic volume into account, however, it can be concluded that road safety performance was worsened. The forecasted values were compared to the observed values, and it was revealed that the reduction of traffic volume was greater than the decrease of the other examined variables. Consequently, a worse performance can be concluded in terms of road safety with regards to the measured disproportional reduction.

The greatest reduction among the examined variables (i.e., road collisions, road fatalities, and slight injuries) was identified in slightly injured (48.1%), followed by road collisions (42%), and then by road fatalities (34.5%). It is worth highlighting that the mobility restrictions led to a reduction in road collisions. This was consistent with the findings reported by Christey et al. (2020), who analyzed road transport-related hospital admissions in New Zealand over two 14-day periods, before and during the lockdown for COVID-19, in which a 74% decrease in admissions due to road collisions was identified. However, this disproportional change among the examined variables and the traffic volume was indirectly compared.

Additionally, the indicators of fatalities and slightly injured rate (defined as the ratio of fatalities or slightly injured to the number of road collisions) were estimated. The fatality rate, as a road safety indicator, is included in several existing studies with different units of measurement and metrics, such as fatalities per traffic volume, fatalities per population, fatalities per million vehicle distance driven, and fatalities per million vehicles (Abdul, 2003; Al-Ghamdi; A. S., 1996; Elvik et al., 2004; Mohan, 2009).

As estimated by the SARIMA models, the rate of fatalities per collision was increased in lockdown months, i.e., March and April. Consequently, the observed collisions during the lockdown period in Greece were more fatal. Furthermore, in the current research, it was found that the slightly injured rate was increased at the same lockdown period. Hence, the likelihood of fatal and slightly injury-causing collisions was increased during the lockdown period; in other words, the trauma impact of the collisions was increased.

Probably a logical explanation for the increased fatality and slightly injured rate is the higher speed, speeding, harsh braking per distance, which were identified during the lockdown period (i.e., April 2020) in Greece (Katrakazas et al., 2020). The increase in the aforementioned parameters was justified by Katrakazas et al. (2020), as empty roads led drivers to be more aggressive and accelerate more, whereas sudden events such as pedestrians crossed the empty road leading to a combination of harsh acceleration and braking. Combining these findings, the increased speed, speeding, harsh accelerations, and harsh braking events led to a higher collision impact of the observed collision and caused more fatalities and slight injuries per collision compared to assumed "non-COVID" conditions. This finding can be supported by previous studies in which it was found that higher driving speeds had a higher probability for a severe collision occurrence (Castillo-Manzano et al., 2019; Farmer et al., 1999; Ossiander and Cummings, 2002).

Investigating the month after the loosening of the restrictions (i.e., May 2020), an additional finding was that road fatalities were higher than in assumed "non-COVID" conditions, whereas the traffic volume was reduced. The greatest increase in fatality rate was forecasted in May compared to the lockdown months of March and April. Additionally, the slightly injured rate was increased, but not to the same degree. These outcomes can be considered as an aftermath effect of the lockdown period. This can probably be explained due to the fact that the drivers coped with new and unfamiliar traffic conditions (e.g., empty roads due to the COVID-19-induced lockdown).

Given the fact that road traffic fatalities are an annual "pandemic" owning to more than 1.35 million lives each year around the world and count up to 50 million injuries every year (WHO, 2020), predicting the evolution of collisions and injuries becomes essential. Road collisions should be examined exhaustively for vital purposes, especially now that mobility and collision trends are disturbed sharply. Firstly, it is important to examine, predict and establish the short- and long-term change and by extension its association with exposure measurements, so as to achieve the mitigation of the road "pandemic". Road safety data during the pandemic (i.e., road collisions, road fatalities, and slight injuries) according to the study outcomes proved to be highly critical in early prognosis and mitigation during the different phases of the COVID-19 crisis. Specifically, the derived findings with regards to road collisions should be considered and directly exploited by safety policymakers for potential subsequent waves of COVID-19 cases and future pandemics in order to improve road safety. Some potential countermeasures for risk reduction in subsequent pandemics are lower speed limits within all road types and traffic law enforcement, especially during the pandemic and the loosening months. Nevertheless, the effectiveness of COVID-19 pandemic massive measures for controlling the spread of the disease can be an excellent example of the need for more serious and massive measures on the road collisions "pandemic". Whereas road infrastructure safety improvement and market penetration of safer vehicles require several years before witnessing major results, traffic behavior can certainly be controlled and improved much faster if social acceptance and political will are strong and sincere. Additionally, the analysis method sets the foundations for further research since it is also capable of investigating the aftermath effect after the loosening of the restriction and generally examining the aftermath effect after the end of the COVID-19 era.

Nevertheless, this paper is not without shortcomings. Regarding the mobility trend report of Apple, a basic limitation of this study was that traffic volume data were available only for a short-time period (i.e., January-August 2020) and no evidence for driving or walking traffic volumes from the previous years, during 2010–2019 was identified. In order to investigate and compare the change between traffic volumes and variables directly, traffic volumes should be forecasted in a similar way using time series models, as described in section 6. It is also worth highlighting that traffic volumes were based on location data of Apple Maps services and referred to a specific sample of drivers (i.e., users of Apple) and not to the entire population of Greece. Another limitation of this study derived from the data source used. The information available made it possible to identify road collisions, fatalities, serious and slight injuries. However, there was no evidence to determine the days on which they occurred (i.e., weekend, workday), the exact time of each collision (i.e., rush hours, risky hours from 00:00 am to 05:00 am), the speed at which it took place, or the type of the vehicles involved. Furthermore, it should be mentioned that rates for seriously injured were not found statistically significant in this work. Still, the implementation of other sophisticated models, such as neural networks, could succeed in forecasting using this variable as well. The main scope of the study is to identify the impact of the COVID-19 pandemic by comparing historic collision data with 2020 data, without considering the influence of other indicators. Possibly, a larger amount of collision and injury data as well as the use of multivariate time series analyses and deep learning might further improve modelling results and insights. Specifically, multivariate time series, such as Vector AutoRegression (i.e., VAR), could provide more insights than the developed SARIMA models (Mercy and Kihoro, 2016). However, exposure data were unavailable (e.g., traffic volumes) and the abrupt dynamics of COVID-19 would lead to imbalanced datasets.

Further research is needed to understand longer-term implications.

Time series analysis using exogenous variables, such as road safety policy measures or weather conditions could be implemented. As mentioned in the limitations, other methodological approaches with more personalized survey methods and sophisticated models might predict more precisely the examined road safety change. Moreover, further analysis for determining behavioral travel changes during lockdown events as well as investigating the impact of the COVID-19 pandemic on road collisions, fatalities, and injuries at a European or global level, could be conducted. Traffic volume information could be combined with other external data of road safety (i.e., driver behavior or performance variables, road layout, time of the day, distraction, or demographic characteristics) in order to gain further insights on whether these specific forms of movement were changed following the measurements implemented at various governmental levels. For instance, the evolution of road collisions after the lockdown period could be studied for each type of road network (i.e., highway, rural, urban environment). In addition, weekly or daily collision data may provide better forecasts and more precise outcomes.

8. Conclusions

This study focused on investigating the impact of the COVID-19 pandemic on collisions and the related fatalities and slight injuries in Greece. Using SARIMA time series models, it was demonstrated that the magnitude of COVID-19 led to less collisions and injuries during 2020, however when taking the additional reduction of traffic volumes into account, the road safety performance was found to be reduced.

As previous literature concerned with COVID-19 and road safety failed in considering the time series nature of collision and injury data as well as exploiting final collision data, the novelty of the current paper is evident. Actual collision data were compared with "expected" collision data, forecasted by the history of corresponding data from previous months. The forecasts were also correlated with traffic volumes and rates of fatality and slight injuries per collision frequency were estimated, advancing on recent studies that fail to take direct exposure into account (e.g Hassouna et al., 2020; Hassouna and Al-Sahili, 2020; Sebego et al., 2014). As a result, the aftermath effect after loosening restrictions was sufficiently investigated and the methodology applied can easily be generalized for the forthcoming months and years when the pandemic will be overcome.

Taking into account that the level of road safety proved to be highly critical in the early prognosis and mitigation of the public health system status during the different phases of the COVID-19 crisis, policymakers and researchers should further exploit the findings of this study. The presented results should be strengthened by combining final collision and injury data with detailed exposure data (e.g. VKMs travelled), the existence of specific COVID-19 countermeasures (e.g. school closures or public events cancellations) and additional road safety indicators such as harsh event frequencies or average speeds. In that way, practitioners and traffic management agencies would be able to proactively assess the evolution of collision rates and offer more time for authorities to apply targeted countermeasures to improve safety and well-being for all community members.

CRediT authorship contribution statement

Marios Sekadakis: Conceptualization, Writing – original draft, Software, Data curation. **Christos Katrakazas:** Conceptualization, Methodology, Writing – review & editing. **Eva Michelaraki:** Writing – original draft, Software. **Fotini Kehagia:** Supervision. **George Yannis:** Supervision, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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