THE IMPACTS OF COVID-19 PANDEMIC ON BEHAVIORAL CHANGES IN TRANSPORTATION ACTIVITY TO A FOREST RECREATION AREA AND CAUSALITY ANALYSIS IN TURKEY

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Abstract. With COVID-19, increased vehicle use for recreational purposes was observed. This study examines monthly changes in the number of transportation vehicles to a recreation area between 2018–2019, compared to 2020 in Turkey. Also, based on 17 weeks of data between 1 June-27 September 2020, causality relationships were investigated between the number of COVID-19 cases and deaths and the number of vehicle entries to the recreation area using digital card payment. According to the results, in 2018-2019, a similar seasonal trend was observed in the total number of vehicles. However, the number doubled at the end of 2020. Also, results showed a causal relationship between the number of deaths caused by COVID-19 and the number of vehicles entering the forest recreation area. However, there was no relationship observed between the number of COVID-19 cases and the number of vehicles. Furthermore, a causal relationship was found between the number of times the digital card was used to pay fees and the number of cases, but not the number of deaths. Therefore, a general evaluation results of the study concluded that the COVID-19 pandemic affected activity in the forest recreation area, and thus, it should be considered a factor in transportation management.
Keywords: *number of cases, forest area, green areas, mobility, time series analysis*

Introduction

The global spread of novel coronavirus-infected pneumonia (COVID-19) was unexpected. The first cases were reported to the World Health Organization (WHO) on 31 December 2019 in Hubei Province of China (Haider et al., 2020). On 30 January 2020, WHO declared COVID-19 a public health emergency of international concern (Tezer and Demirdag, 2020). On 11 February 2020 WHO named the novel coronavirus COVID-19 (Wang et al., 2020). As of 13 February 2020, there were approximately 47,000 confirmed COVID-19 cases (WHO, 2020), and on 11 March 2020, WHO declared COVID-19 a global pandemic. The first case was recorded in Turkey on 11 March 2020, and the first death was recorded on 17 March 2020 (MH, 2021) (*Fig. 1*).

The coronavirus pandemic caused unpredictable daily life changes, especially in economic activities and mobility (Venter et al., 2020), as many European countries implemented national lockdowns, restrictions on daily activities (Jarvis et al., 2021), and constraints on movement and social interaction (Davies et al., 2020). These significant and sudden disruptions to everyday life impacted human well-being (Samuelsson et al., 2020), and it was thought that the risks of cardiovascular disease (Peçanha et al., 2020), metabolic disease (Martinez-Ferran et al., 2020), and other health issues might increase due to the decline in physical activity and the restrictions (Doubleday et al., 2021).

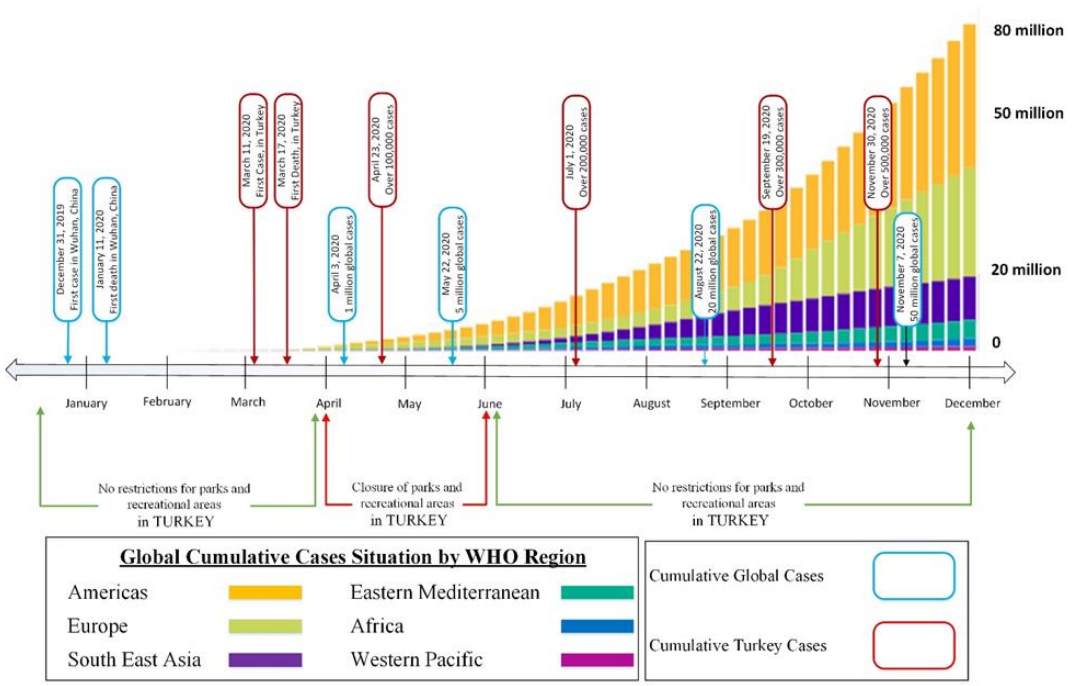

Figure 1. *The cumulative number of cases globally and during the COVID-19 outbreak in Turkey*

During the COVID-19 pandemic, parks, green spaces, recreational areas, and forests became popular and positively affected human psychology and physical wellness (Freeman and Eykelbosh, 2020; Rice and Pan, 2020; Geng et al., 2021).

Green areas were vital to meet various requirements and allowed safe entertainment while maintaining social distancing (Freeman and Eykelbosh, 2020). In addition, they helped visitors to reduce their stress levels (Thompson et al., 2012), provided exercise opportunities (Mitchell, 2013), and had beneficial effects on physical and mental health (Fong et al., 2018).

In addition, school closures due to COVID-19 enabled families to visit parks and entertain their children during the pandemic (Rundle et al., 2020; Viner et al., 2020). For this reason, parks became popular areas of isolation and were mentally beneficial (Matias et al., 2020; Rice et al., 2020) for adults and children alike. Rice and Pan (2020) reported that parks, green spaces, recreational areas, and forests functioned as significant and irreplaceable, healthy, and isolated places from the coronavirus. As green infrastructure, they also provided transition zones between rural and urban life (Wolff et al., 2020) and supported people's health (Chen et al., 2018). As a result, forests became critical infrastructures for society to maintain social distancing during the pandemic (Derks et al., 2020).

Due to the lack of open and green areas in cities with dense populations such as Istanbul, people living in the city tend to go to forest areas, which are very limited for recreational activities. Consequently, intensive human activity, which has increased significantly during the pandemic, forest degradation occurs in terms of vegetation, wildlife, natural, and aesthetic features. In this context, reducing the pressure caused by urban people's use of natural forests, especially for recreational purposes, is necessary.

During the COVID-19 pandemic, peak periods of cases and deaths occurred in Turkey and many other countries, and various restrictions and strict lockdown measures

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were applied. After a while, lockdowns have been less severe and people have been permitted to go outside during restricted hours while keeping to social distance recommendations go outside. Urban green space, including parks and forest areas, had a key impact on how inhabitants responded to the pandemic containment measures despite this Turkish lockdown regulation. As a result of the restrictions, decreasing cases and deaths instigated the normalization process. The normalization process created increased mobility and human activity, due to the people's need for relaxation.

Forests are used for seasonal recreation by people and people many of whom use vehicles. Due to the benefits mentioned above, green areas gained importance during the pandemic, especially in large urban areas. This study served two purposes. First, the study revealed the monthly change in the total number of vehicles used for transportation to a recreation area from 2018–2019 and compared it with the COVID-19 pandemic period in 2020. Second, the study revealed the relationships during the normalization period of the COVID-19 pandemic, between COVID-19 cases and deaths, the number of vehicles entering the forest, and the digital payment method for vehicles in the forest recreation area. In this context, during the post-peak normalization period, relationships between the related variables were revealed using weekly data (seven-day mean) between 1 June 2020 and 27 September 2020, using the Toda–Yamamoto causality test.

Materials and methods

Study area and data descriptions

The research area was in Belgrade Forest near the Sarıyer district of Istanbul in Turkey (41°11′40″N 28°57′05″E) (*Fig. 2*). The total area of forest is 5,444 ha, and constitutes 0.03% of the total forested areas in Turkey (Coban et al., 2016). Belgrade Forest contains well-known recreation areas for many activities, such as jogging, hiking, and cycling.

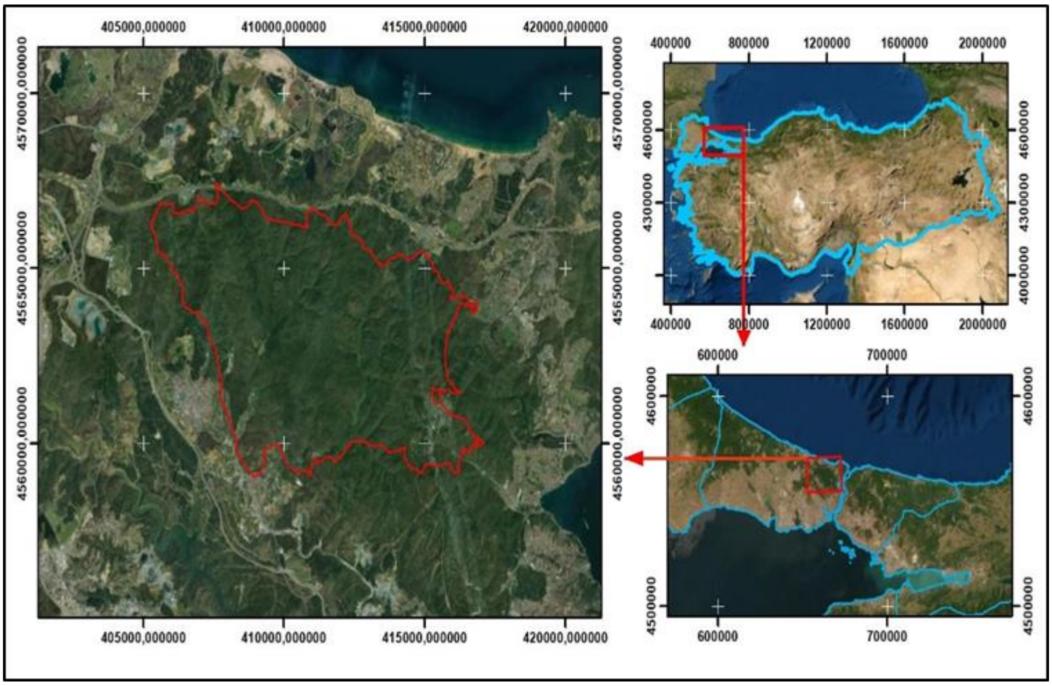

Figure 2. *The study area location map*

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Weekly data were recorded for 17 weeks, from 1 June 2020 to 27 September 2020, at the end of the restrictions. The data for the number of vehicles (The number of vehicles was counted with the car counting system automatically) and the rate of digital card usage from the recreation area in Istanbul's Belgrade Forest belonged to the Istanbul Metropolitan Municipality-ISPARK organization. The COVID-19 cases and deaths were obtained from the COVID-19 data of the Republic of Turkey Ministry of Health (MH, 2021). The data analyses and calculations were performed with EViews 11 and Minitab 19 software.

According to data obtained from the ISPARK company for Belgrade Forest between 2018–2020, a similar seasonal trend was observed in the total number of vehicles for 2018 and 2019. However, with the end of the restrictions in 2020, an approximately two-fold increase was observed (*Fig. 3*).

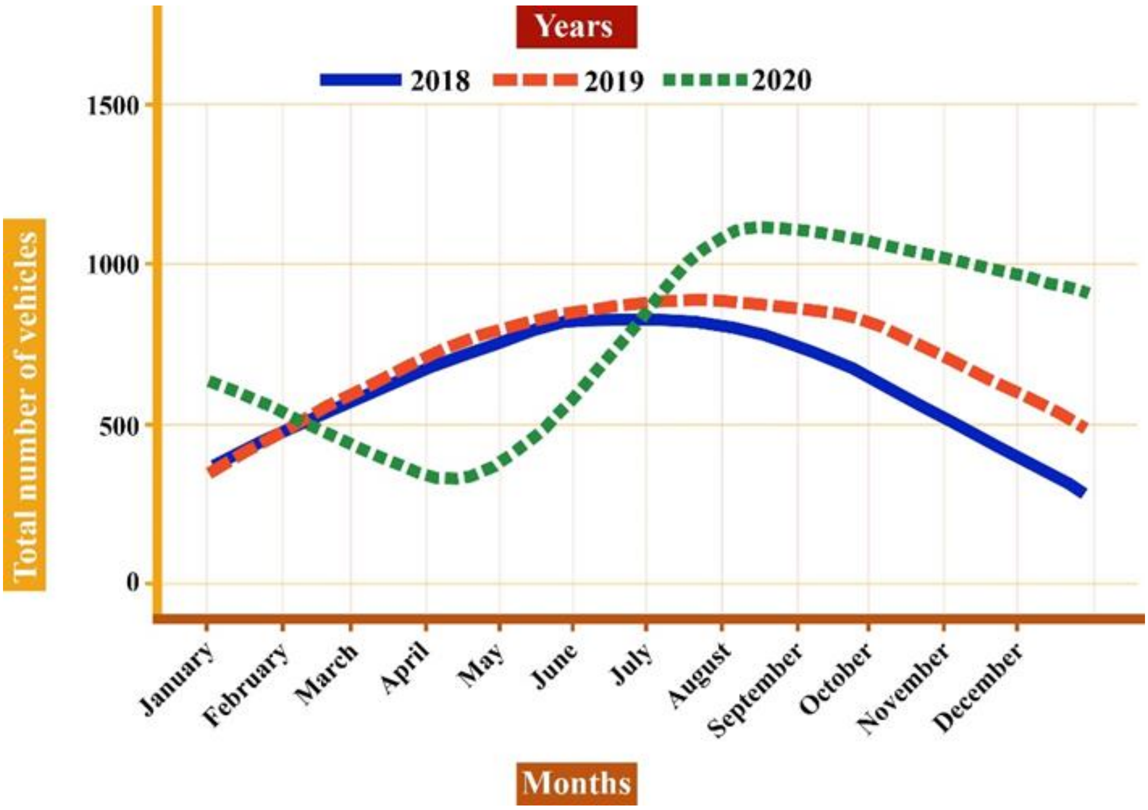

Figure 3. *The monthly difference in the total number of vehicles for the years 2018–2020*

Table 1 provides descriptive statistics for data analysis covering the period 1 June 2020 to 27 September 2020 based on weekly data.

Table 1. *Descriptive statistics (weekly data)*

Variables	Minimum	Maximum	Mean	Standard deviation
Number of cases (CN)	884.28	1672.14	1264.63	269.15
Number of deaths (DN)	16.42	70.14	29.05	18.21
Number of vehicles (VN)	953.85	1465.57	1146.68	152.81
Digital card utilization rate (%) (DCUR)	93.10	98.89	97.61	1.47

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The descriptive statistic values of the variables were examined with results as follows (*Table 1*):
Number of COVID-19 cases: minimum 884.28; maximum 1672.14; average 1264.63.
Number of deaths caused by COVID-19: minimum 16.42; maximum 70.14; average 29.05.
Number of vehicles: minimum 953.85; maximum 1465.57; average 1146.68.
Digital card utilization rate (%): Digital cards (credit cards) are an alternative payment option for recreation area entry instead of cash payment. Digital cards are used to pay vehicle fees: minimum 93.10%; maximum 98.89%; average 97.61%.

Two vector autoregressive models (VAR) were created in the study. The first model determined the effect of the number of cases and deaths on the number of vehicles. The second model investigated the effect of COVID-19 cases and deaths on the number of digital cards (%) used to pay for entrance to the recreation area. Relevant VAR models are as follows:

VAR Models:
Model VAR 1 $VN = f\,(DN, CN)$
Model VAR 2 $\mathrm{DCUR} = f\,(DN, CN)$

Method

A Toda–Yamamoto causality test was used to determine the causality relationship in the related VAR models. The Toda–Yamamoto causality test developed through Wald test statistics is not affected, unlike Granger causality (Granger, 1969), by the series integration order or the co-integration properties (Toda and Yamamoto, 1995). Hatemi-J and Irandoust (2000) stated that when a VAR is estimated in the Toda– Yamamoto test, it has an asymptotic chi-square distribution. The relevant literature noted that the Toda–Yamamoto causality test was used in areas such as econometrics (Jain and Ghosh, 2013; Ghosh and Kanjilal, 2014; Shammugam et al., 2019; Udemba et al., 2021), occupational accidents (Liang and Fung, 2019), waste management (Lee et al., 2016), and energy consumption (Lee and Chong, 2016). The advantage of the Toda–Yamamoto causality test (Toda and Yamamoto, 1995) is that it can be applied to non-stationary series without first recording the time series differences in the VAR system, thus preventing loss of information in the long run Mavrotas and Kelly (2001) emphasized another advantage; the risks arising from wrongly determining the integration degree of the series are eliminated. Using this approach, a standard VAR model was created by using the level values of the series. In the next step, the lag length (k) of the VAR model was changed to ($k + d_{max}$) by adding the maximum degree of integration (d_{max}) of the series. Relevant VAR models were estimated by using the seemingly unrelated regression (SUR) method. In this context, in the study, unit root tests (Augmented Dickey-Fuller test and Phillips Perron test) were used to determine the stationarity levels of the variables, and the diagnostic tests (normality test, auto-correlation test, and heteroskedasticity test) were performed to check the validity of the VAR models. Also, variance decomposition and impulse response analyzes were performed to determine how one unit shock affects the other among the variables in the short run.

The Toda–Yamamoto causality method steps are listed below (Lotfalipour et al., 2010).

1. Determine the maximum order integration of variables by applying unit tests (d).
2. Determine the optimum lag length in the VAR model (k).
3. Lag-augmented VAR ($k + d$) model estimation.
4. Augmented VAR ($\underline{k} + d$) robustness of augment checking.

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5. Implement Wald test on the first *k*.

According to the Toda and Yamamoto (1995) test, the general equation form (*Eqs. 1* and *2*) was listed as shown below:

$$Y_t = \alpha_0 + \beta_{1i} \sum_{i=1}^{k} Y_{t-i} + B_{2j} \sum_{j=k+1}^{d_{max}} Y_{t-j} + \gamma_{1i} \sum_{i=1}^{k} X_{t-i} + \gamma_2 \sum_{j=k+1}^{d_{max}} X_{t-j} + \varepsilon_{1t} \quad \text{(Eq.1)}$$

$$X_t = \alpha_1 + \lambda_{1i} \sum_{i=1}^{k} X_{t-i} + \lambda_{2j} \sum_{j=k+1}^{d_{max}} X_{t-j} + \delta_{1i} \sum_{i=1}^{k} Y_{t-i} + \delta_{2j} \sum_{j=k+1}^{d_{max}} Y_{t-j} + \varepsilon_{2t} \quad \text{(Eq.2)}$$

where *k* is the optimal log order, *d* is the maximum order of integration of the series, and ε_{1t} and ε_{2t} are error terms.

In this study, VAR model 1 and VAR model 2 were created according to the Toda–Yamamoto causality criterion. These VAR models are given in *Equations 3* and *4*.

VAR Model 1

$$\ln VN_t = \alpha_0 + \sum_{i=1}^{k} \beta_{1i} lnVN_{t-i} + \sum_{j=k+1}^{dmax} \beta_{2i} lnVN_{t-j} + \sum_{i=1}^{k} Y_{1i} lnDN_{t-i} + \sum_{j=k+1}^{dmax} Y_{2i} lnDN_{t-j} + \sum_{i=1}^{k} \delta_{1i} lnCN_{t-i} + \sum_{j=k+1}^{dmax} \delta_{2i} lnCN_{t-j}\ \mu_{1t} \quad \text{(Eq.3)}$$

H0: $Y_1 = 0$ (There is no causal relationship between the number of deaths and the number of vehicles).

H0: $\delta_1 = 0$ (There is no causal relationship between the number of cases and the number of vehicles).

VAR Model 2

$$ln\ DCUR_t = \alpha_1 + \sum_{i=1}^{k} \theta_{1i} lnDCUR_{t-i} + \sum_{j=k+1}^{dmax} \theta_{2i} lnDCUR_{t-j} + \sum_{i=1}^{k} \mu_{1i} lnDN_{t-i} + \sum_{j=k+1}^{dmax} \mu_{2i} lnDN_{t-j} + \sum_{i=1}^{k} p_{1i} lnCN_{t-i} + \sum_{j=k+1}^{dmax} p_{2i} lnCN_{t-j}\ \mu_{2t} \quad \text{(Eq.4)}$$

H0: $\mu_1 = 0$ (There is no causal relationship between the number of deaths and digital card utilization).

H0: $p_1 = 0$ (There is no causal relationship between the number of cases and the digital card utilization).

The methodology usage steps explained in detail above are shown in *Figure 4.*

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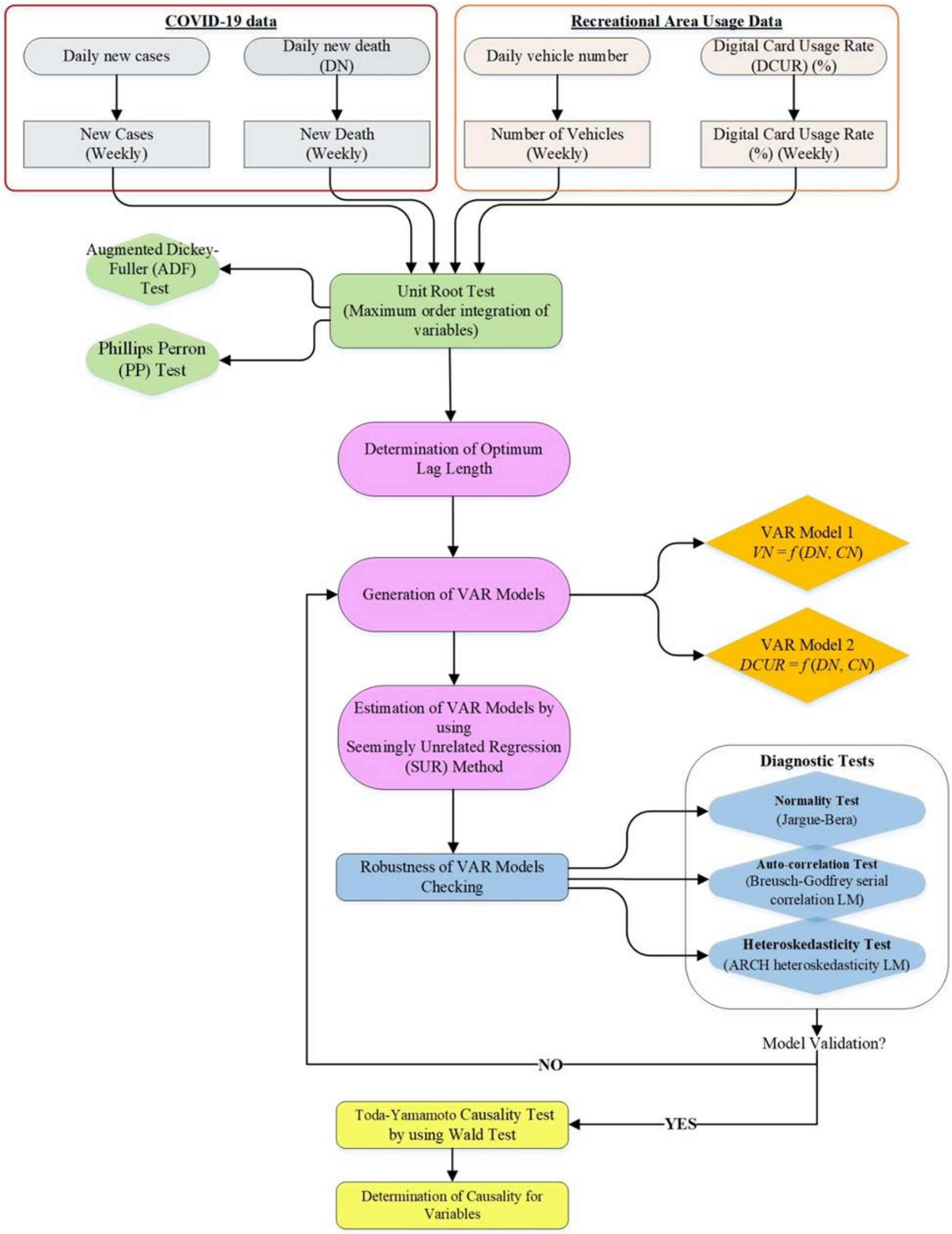

Figure 4. *Methodology adopted for the study*

Results

Unit root test results

The natural logarithms of all variables used in the study were recorded and included in the analysis. Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips–Perron (PP) (Phillips and Perron, 1988) unit root tests were performed for data analysis. Unit root test results are demonstrated in *Table 2*. According to the unit root

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test results, case number, death number, digital card number variables I (1), and vehicle number variable I (0) were determined. The maximal integration order was determined as 1 (d_{max} = 1) for all variables.

Table 2. *Unit root tests*

Variables / Level		ADF	PP*
Intercept	Number of cases (CN)	-1.66 (0.42)	-1.58 (0.46)
	Number of deaths (DN)	-2.29 (0.18)	0.65 (0.98)
	Number of vehicles (VN)	-3.91 (0.01)[b]	-3.91 (0.01)[b]
	Digital card utilization rate (%) (DCUR)	-2.42 (0.15)	-2.42 (0.15)
Intercept and trend	Number of cases (CN)	-4.90 (0.00)[a]	-1.83 (0.63)
	Number of deaths (DN)	-1.05 (0.90)	-1.05 (0.90)
	Number of vehicles (VN)	-0.21 (0.98)	-3.78 (0.04)[b]
	Digital card utilization rate (%) (DCUR)	-2.87 (0.19)	-2.90 (0.18)
1st difference			
Intercept	Number of cases (CN)	-4.03 (0.01)[b]	-2.54 (0.12)
	Number of deaths (DN)	-3.22 (0.03)[b]	-3.23 (0.03)[b]
	Number of vehicles (VN)	-6.06 (0.00)[a]	-9.13 (0.00)[a]
	Digital card utilization rate (%) (DCUR)	-4.33 (0.00)[a]	-4.87 (0.00)[a]
Intercept and trend	Number of cases (CN)	-3.04 (0.16)	-2.57 (0.29)
	Number of deaths (DN)	-3.36 (0.09)	-3.36 (0.09)
	Number of vehicles (VN)	-6.21 (0.00)[a]	-16.32 (0.00)[a]
	Digital card utilization rate (%) (DCUR)	-4.14 (0.02)[b]	-5.29 (0.00)[a]

*Bartlett Kernel and Newey-West Bandwidth were used
[a]Null hypothesis rejected at 1% level of significance
[b]Null hypothesis rejected at 5% level of significance

Determination of optimum lag length

Clarke and Mirza (2006) stated that determining the appropriate lag length has an important role in preventing bias in the causality relationship. In this study, for VAR model 1 and VAR model 2, the optimum lag selection is given in *Tables 3* and *4*, respectively.

Table 3. *Optimal lag length selection for VAR model 1*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	13.45291	NA	5.44e-05	-1.306615	-1.161755	-1.299197
1	41.74045	42.43130*	5.04e06*	-3.717557*	-3.138115*	-3.687884*

*Lag order selected by the criterion

Table 4. *Optimal lag length selection for VAR model 2*

Lag	LogL	LR	LPE	AIC	SC	HQ
0	49.69579	NA	5.86e-07	-5.836975	-5.692114	-5.829557
1	79.66286	44.95061*	4.40e-08*	-8.457858*	-7.878417*	-8.428186*

*Lag order selected by the criterion

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The optimum lag length number for VAR model 1 and VAR model 2 was determined as 1, considering sequential modified LR Test Statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criteria (SC), and Hannan Quinnin (HQ) lag order selection criteria (*Tables 3* and *4*).

Roots of characteristic polynomial

As seen in *Figures 5* and *6*, for VAR model 1 and VAR model 2, all inverse roots are within the unit circle and are less than 1.

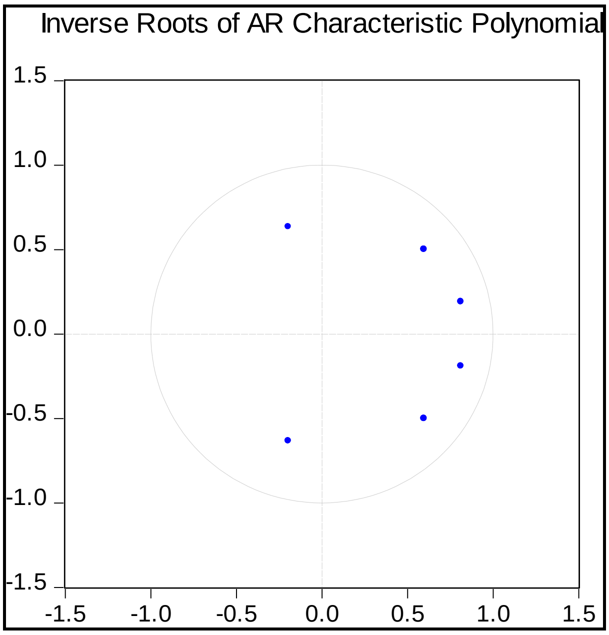

Figure 5. *Inverse roots of AR characteristic polynomial for VAR model 1*

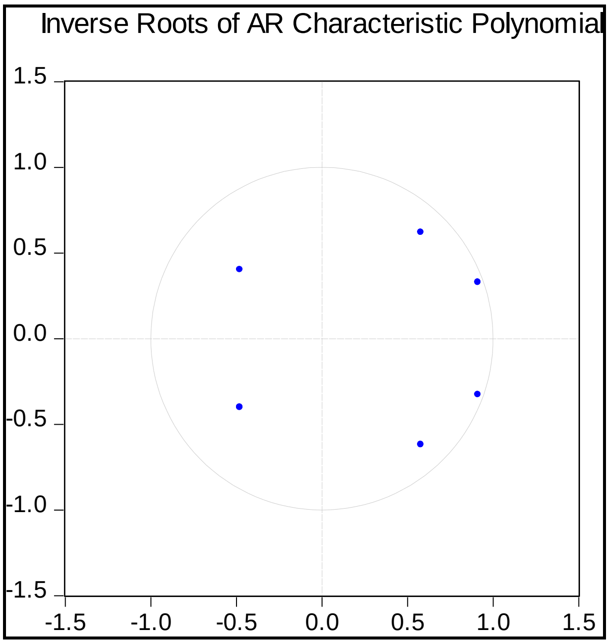

Figure 6. *Inverse roots of AR characteristic polynomial for VAR model 2*

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Diagnostic test results

Autocorrelation test (Breusch–Godfrey serial correlation LM), normality test (Jargue–Bera), and heteroskedasticity test (ARCH heteroskedasticity LM) were performed for VAR model 1 and VAR model 2. The results are given in *Table 5*. According to the results obtained, no problems with autocorrelation or varying variance were seen, and in both models, the assumption of normality was met for VAR model 1 and VAR model 2.

Table 5. *Diagnostic test results for VAR model 1 and VAR model 2*

Diagnostic tests	Toda-Yamamoto VAR model 1	Toda-Yamamoto VAR model 2
Breusch-Godfrey serial correlation LM test	0.8361*	0.6988*
Normality Jargue-Bera test	0.9064*	0.9680*
ARCH heteroskedasticity LM test	0.3868*	0.3405*

*p > 0.05

Causality test results

Related causality analyses for VAR model 1 and VAR model 2 were made according to the Toda and Yamamoto (1995) causality test. Causality test results are given in *Table 6.*

Table 6. *Toda–Yamamoto causality test results*

VAR model	Null hypothesis	Mwald statistics	p-values	Causality
VAR model 1 *VN* = f (*DN*, *CN*)	lnDN → lnVN	4.17	0.04*	Yes
	lnCN → lnVN	0.33	0.56	No
VAR model 2 *DCUR* = f (*DN*, *CN*)	lnDN → lnDCUR	1.44	0.22	No
	lnCN→ lnDCUR	6.67	0.00**	Yes

*p < 0.05 **p < 0.01

The relationship between the number of deaths and the number of vehicles was determined according to the Toda–Yamamoto causality test results. In addition, the causality relationship was determined for the number of cases and the use of digital cards. No causality was found between the number of cases and the number of vehicles. Similarly, no causality was found between the number of deaths and the use of digital cards (*Table 6*).

Variance decomposition and impulse response results

In determining how a one-unit shock between variables affects the other in the short-run (Koop et al., 1996; Pesaran and Shin, 1998), variance decomposition and impulse-response function approaches were used in the study. Variance decomposition results are presented in *Tables 7* and *8* for VAR model 1 and VAR model 2.

Table 7. *Variance decomposition results for VAR model 1*

Period	S.E.	Number of vehicles	Number of deaths	Number of cases
1	0.077	100.000	0.000	0.000
2	0.085	83.918	15.736	0.345
3	0.094	79.210	14.649	6.140
4	0.107	62.402	28.038	9.559
5	0.118	56.212	34.828	8.959
6	0.133	53.430	39.432	7.136
7	0.146	49.101	44.934	5.963
8	0.154	46.771	47.617	5.611
9	0.158	45.999	48.451	5.548
10	0.160	45.516	48.974	5.509

Table 8. *Variance decomposition results for VAR model 2*

Period	S.E.	Digital card use rate (%)	Number of deaths	Number of cases
1	0.009	100.000	0.000	0.000
2	0.010	88.666	0.012	11.320
3	0.010	83.945	2.985	13.068
4	0.010	81.017	3.082	15.900
5	0.011	77.194	3.190	19.615
6	0.011	75.250	3.416	21.332
7	0.011	75.159	3.412	21.427
8	0.011	73.158	3.973	22.867
9	0.011	69.658	5.165	25.176
10	0.012	67.558	6.347	26.093

According to the variance decomposition results, in VAR model 1, 45% of the number of vehicles is self-explained in the 10th period, 48.97% is explained from the number of deaths, and 5.50% from the number of cases. In VAR model 2, 67.55% of digital card usage is self-explained, 26.09% is explained by the number of cases, and 6.34% by the number of deaths in the 10th period.

Impulse response analysis is presented in *Figures 7 and 8* for VAR model 1 and VAR model 2, respectively. As seen in *Figure 7*, while the number of vehicles gave a negative response to the number of deaths in the initial period, they gave a positive response in later periods. There was no significant general reaction in the number of cases.

When examining the impulse response situation, as seen in *Figure 8*, the usage of digital cards initially gave a negative reaction to the number of cases but had a positive effect until the 7th period and a positive effect in the following periods. Although the reaction of digital card usage to the number of deaths was initially negative and positive, it did not give a significant reaction to the number of deaths in general.

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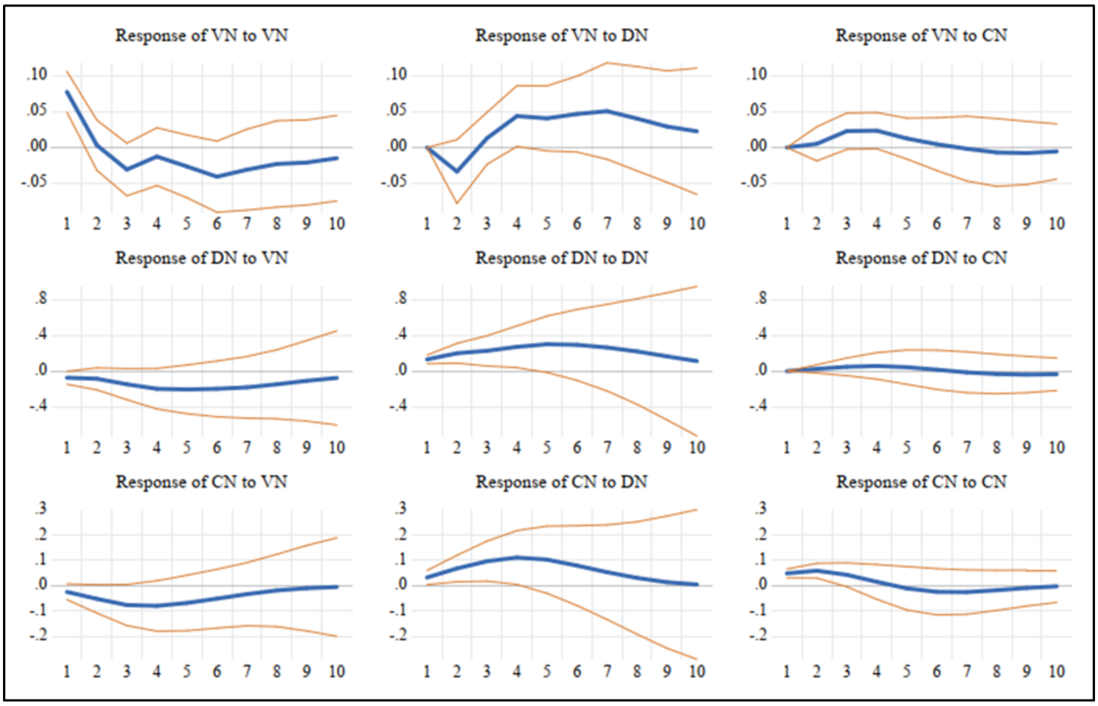

Figure 7. *Impulse response function results for VAR model 1*

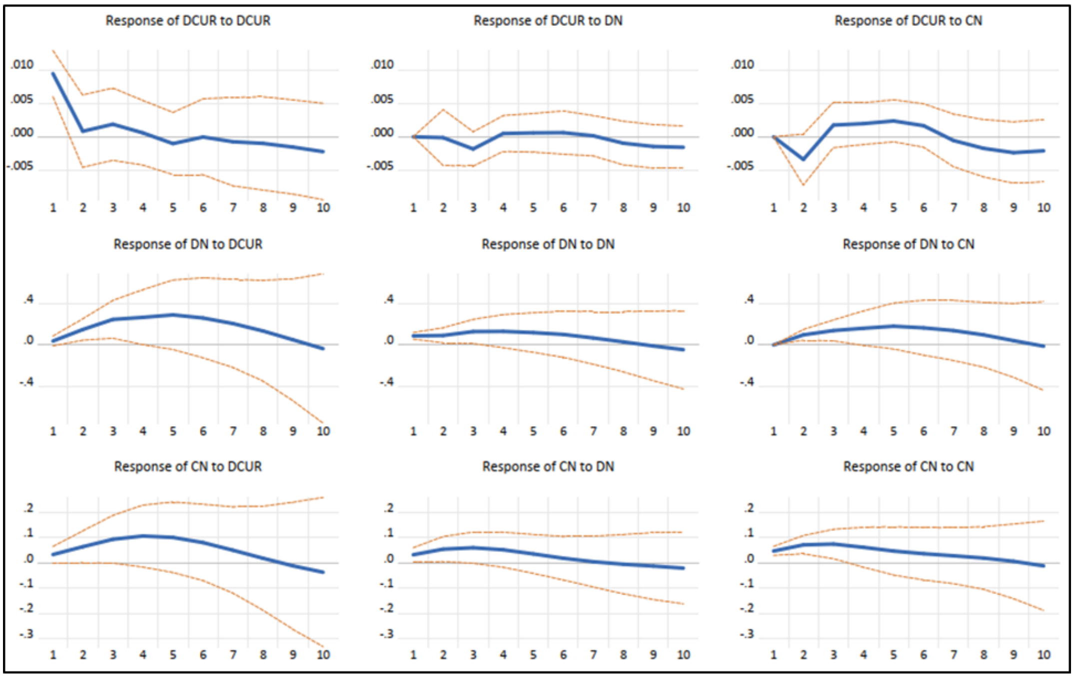

Figure 8. *Impulse response function results for VAR model 2*

Discussion and conclusion

The study compared monthly changes in the total number of vehicles used for transportation to the recreation area in 2018–2019 and the COVID-19 pandemic period in 2020. In addition, the causality relationships between changes in the total number of

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vehicles used by visitors to access the recreation area, related to the number of cases and deaths in Turkey due to COVID-19, and the use of digital cards during entrance fee payment were examined.

Numerous studies were conducted during the COVID-19 pandemic. According to a survey study conducted with about 1000 people in Austria, 45% of the participants did not use green spaces before the pandemic but began using them during restriction periods (Berdejo-Espinola et al., 2021). Venter et al. (2020) noted that outdoor recreational activities increased more than 290% during lockdowns, relative to the three-year average of typical days in Norway. Derks et al. (2020) stated that people visiting parks in Germany increased twice during the COVID-19 period. Another study conducted by Grima et al. (2020) in Vermont found that visits to the natural areas and urban forests in Vermont increased by 69%. Similarly, according to the results of this study, it was determined that the number of visitors and the total number of vehicles used for transportation to the recreation area in the 2020 COVID-19 pandemic period increased approximately three-fold compared to 2018–2019.

In a long-term study, Jiao et al. (2021) measured passenger behavior in Texas during the COVID-19 pandemic (1 March 2020–11 November 2020) and found no significant relationship between the number of cases and mobility. In another study, Kim and Kwan (2021) stated that mobility status decreased from March to June in the United States but returned to pre-pandemic mobility from April to June. They also emphasized that when the number of cases increased between June and September, there was a partial decrease in mobility. Lamb et al. (2021) concluded that the change in mobility during April 2020 in New York City was not related to the rate of the number of cases caused by COVID-19. Geng et al. (2021) conducted a study that examined the impact of the COVID-19 pandemic on urban park visits. They emphasized that trends are demonstrated in the relationship between COVID-19 cases and park visits, and the trends differ between countries. For example, park visits in Denmark increased continuously throughout the pandemic, but there was no significant change in Sweden and Japan. Their study also found that different restriction policies taken according to the severity of the COVID-19 pandemic in a country may affect the situation. In Turkey, increased interest in recreational areas during the pandemic period and the change in vehicle usage preferences were thought to be caused by the restrictions applied and the pandemic management process.

In addition, it was found that the decreasing global trend towards national parks varied considerably between countries throughout the pandemic. Public interest in many national parks in Africa and Asia declined significantly, while public interest was retained in the USA, Europe, and Australia (Souza et al., 2021). However, Rice and Pan (2020) conducted a study based on google mobility in West America, stating that the mobility in parks during the COVID-19 period was partly due to the pandemic. Lu et al. (2021) conducted a study in Asian cities (Hong Kong, Singapore, Tokyo, and Seoul) and found that the tendency to visit urban green spaces increased as the number of confirmed COVID-19 cases per week increased during the pandemic period. This study’s results showed no causal relationship between the weekly number of COVID-19 cases announced and the number of vehicles used as transport to recreational areas. However, a significant causal relationship was found between the number of deaths due to COVID-19 and the total number of vehicles used to reach recreational areas. It was concluded that the emerging situation increased travel behavior and the use of

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individual vehicles in transportation to recreation areas, as the number of deaths caused by COVID-19 caused anxiety.

Regarding the digital card usage rates of recreational visitors during vehicle entry, a significant causal relationship was reached with the number of cases originating from COVID-19, while no causal relationship was found between the number of deaths caused by COVID-19. In this context, supporting our results, a study by Shishah and Alhelaly (2021) stated that contactless payment methods have increased significantly due to the COVID 19 pandemic and are now the most common payment method used. In addition, it was emphasized that 65% of users stated the reasons for preferring contactless payment methods as health and safety and hygiene.

This study provided the opportunity to reveal the extent of people's interest in recreational forest areas, changes in individual vehicle preferences and entrance fee payment methods, and the number of cases and deaths during the COVID-19 pandemic. The study results revealed that the number of deaths caused by COVID-19 was more determinative of vehicle mobility than the number of cases. In addition, it was revealed that the number of cases caused by COVID-19 was determinant in the use of digital cards at the entrance to recreational areas. When the study results were evaluated in general, it was concluded that the COVID-19 pandemic affected transportation activity in the forest recreation area. For this reason, it should be considered as a factor in the management of transportation in the forest recreation area. In future studies, in addition to the number of cases and deaths caused by the COVID-19 pandemic, and depending on the size and type of the data set, more comprehensive results can be obtained by considering seasonal variables and demographic variables that may affect people's transportation behaviors for in forest recreation areas.

In addition, during the COVID-19 global pandemic, it was observed that interest in relatively isolated places such as urban forests, green spaces, and parks that could be used for recreational purposes increased. Therefore, it is concluded that it would be beneficial to remove restrictions on green areas during epidemic periods, to increase self-isolation, and provide mental health benefits.

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