COVID

Review

Evaluating the Impact of Climate and Early Pandemic Policies on COVID-19 Transmission: A Case Study Approach

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Abstract: The COVID-19 pandemic has had profound impact, necessitating a deeper understanding of factors influencing virus transmission. The negative impacts have weakened the economy and changed billions of lives around the world. COVID-19 is a new virus, and a lot of studies have tried to investigate its effect on, for example, the economy or environment. This research reveals new approaches to recognizing and stopping the spread of this virus with its connection to weather conditions and relevant parameters. By analyzing how temperature and humidity affect COVID-19 spread, alongside evaluating the effectiveness of initial public policies, this study addresses the critical gap in research by investigating the interplay between climate conditions and government regulations during the early stages of the pandemic in South Korea. This dual approach provides a comprehensive framework for understanding how environmental and policy factors jointly influence pandemic dynamics, offering valuable lessons for future global health crises. Although it focuses only on the first phase of South Korea COVID-19 regulations, outcomes show that these regulations were notably effective against the COVID-19 pandemic. The outcomes prove that higher temperature and higher relative humidity lead to lower transmission. Hence, based on the results during winter, the number of infections would be expected to speed up again.

Keywords: COVID-19; government regulation; global economy; virus spread; AIC; BIC

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1. Introduction

The pandemic and its associated lockdown regulations worldwide substantially shocked the global economy's supply and demand, which most countries were not immune to or ready for, as all economy sectors were affected by the pandemic. The tourism industry is a good example, as it was banned by both government regulation and people's own demand [1,2]. The COVID-19 pandemic has transformed worldwide health and economic landscapes, emphasizing the critical need for research into factors influencing virus transmission. While much research has been conducted on the economic and social consequences of the epidemic, the interaction between climate conditions and government policies remains unexplored. Understanding how environment impacts the spread of respiratory viruses such as COVID-19 can help public health officials respond more effectively and prepare for future pandemics [2–4].

The effect of weather conditions on respiratory diseases is one of the most critical factors indicated by researchers. Respiratory diseases are widespread globally and are the third cause of non-communicable mortality [5]. Many studies have confirmed positive connections between public health and weather indicators, such as temperature, humidity, or wind speed [6,7]. One crucial question during the COVID-19 pandemic is whether there is a connection between weather conditions and the COVID-19 virus spread. This study tries to answer that question. Determining this connection could help governments make more informed policy decisions and become more prepared for the next waves and next pandemics.

Some previous studies have shown that seasonal and geographic climatic change could affect the spread of respiratory diseases, the concentrations of those studies were mostly on influenza, SARS, and MERS-COV but not COVID-19, which is distinctive from other recognized viruses in its spread and pathogenicity. From another angle, there are several studies about government policy and its effects on controlling respiratory diseases. A close relationship between government and society is not inevitable during abnormal conditions like the COVID-19 pandemic. This study also tries to identify the effect of government regulations on controlling COVID-19 transmissions.

To answer the research questions, first, we tried to find the correct number of lag variables by applying the Akaike information criterion (AIC) and Bayesian information criterion (BIC), as most previous studies about the relationship between respiratory diseases and weather conditions have used lag variables [8–10].

Second, the generalized additive model (GAM) was applied to answer the research question. The GAM was selected for this study because it can work with many distributions, such as gamma, normal, and Poisson, and the distribution of dependent variables in this study is Poisson.

This study, which focuses on South Korea's initial regulation period, innovates by merging climate data with an analysis of the consequences of public policy on COVID-19 transmission. Our work incorporates these components to give a comprehensive picture of their combined impact on virus distribution, in contrast to other research that frequently separates climate factors or policy effects. This study provides an improved method for simulating COVID-19 transmission by utilizing the generalized additive model (GAM), which takes into account a variety of distributions and incorporates nonlinear interactions. Together with an analysis of South Korea's early intervention tactics, this methodological development offers fresh perspectives on the policy-driven and environmental aspects of pandemic management. Compared to previous studies, this research uses more features that can affect the spread of the COVID-19 virus. This study is different since it tries to connect two different literature angles by applying climate indicators and government regulation in the same regression as right-hand-side variables. The Infectious Disease Alert level 4 (red) policy caused a decrease in mobility of more than 10% for the whole country; this policy can help control the mobility effect in this study since the city-level mobility data for South Korea are not available. Other contributions of this study include finding reliable predictive models for daily COVID-19 positive cases in countries with the most advanced health care systems and forecasting numbers of infections by applying the GAM. By addressing the gap in understanding the interaction between climate and policy, this study not only enhances current knowledge but also provides a framework applicable to other pandemic scenarios, paving the way for more informed and effective public health strategies globally.

1.1. Literature Review

Coronaviruses (CoVs) belong to the Coronaviridae family, a group of enveloped, positive-sensed, single-stranded RNA viruses [11]. These types of viruses are named CoVs due to their crown shape [12]. Coronaviruses are a widespread group of viruses that are prevalent among animals. Zoonotic transmission, in which viruses travel from animals to humans, has played a crucial role in recent pandemics, including COVID-19, which was initially discovered on 31 December 2019, in Wuhan, China. According to research conducted in China and South Korea, personal contact is the predominant mechanism of

COVID-19 transmission. This highlights the need of understanding both environmental and behavioral factors that influence disease spread [13].

Since 31 December 2019, when the first positive case of COVID-19 was detected in Wuhan, China, people worldwide have struggled with this disease [14]. Based on recent studies, COVID-19 transmission has been mostly happening through physical contact; for example, a study in China reported that 41% of patient infections were due to person-to-person hospital visits [15]. Furthermore, our results are consistent with this fact in the case of South Korea during the timeline of this study (Figure 1).

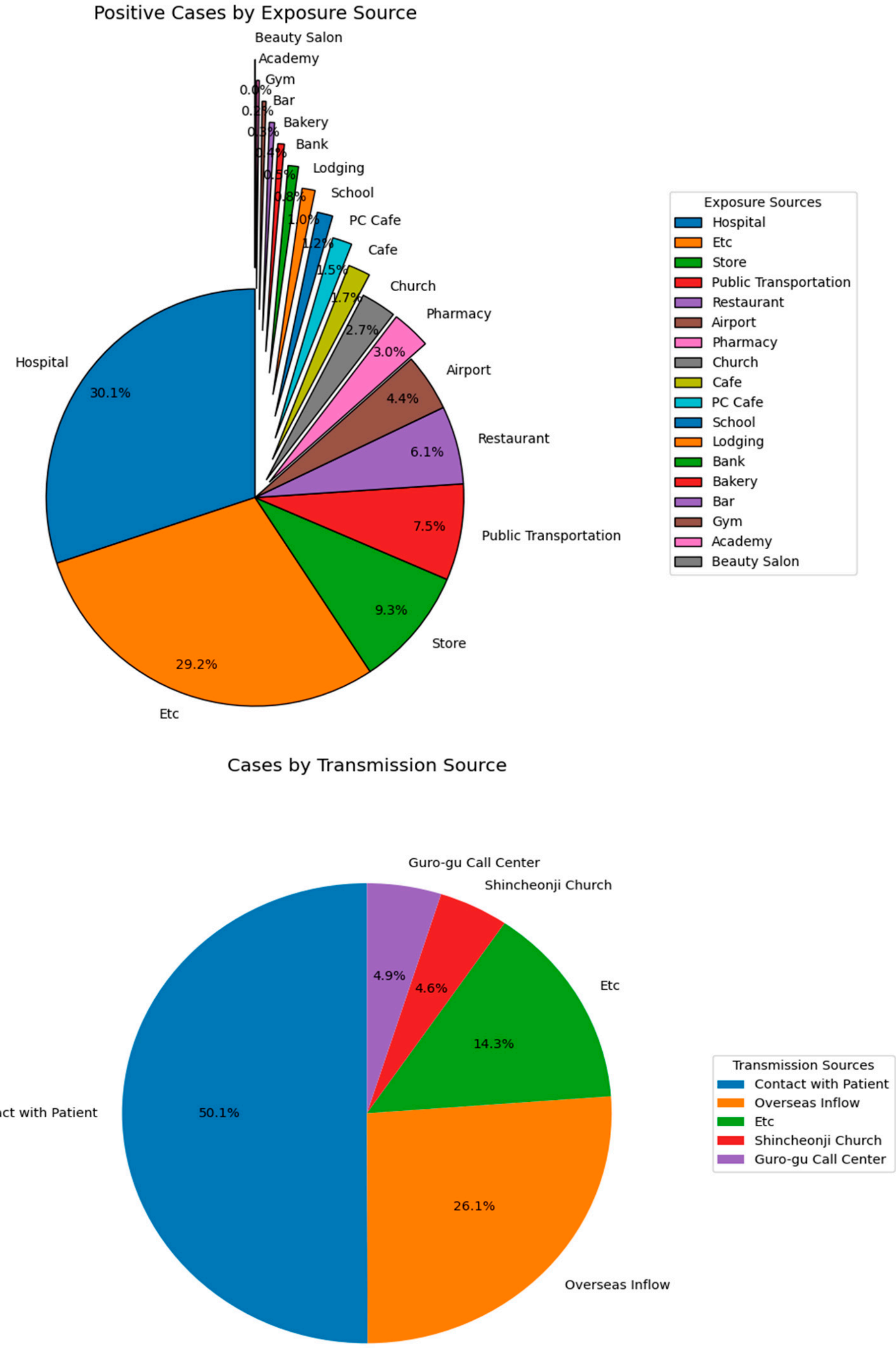


Figure 1. Places and methods of infection in South Korea.

The literature has two strands: disease spread patterns and weather connection and public policy. First, let us focus on the literature on the relationship between weather conditions and respiratory disease. Epidemiological and laboratory research has recognized a connection between weather conditions and respiratory diseases [8,16]. Weather conditions have an essential role in human health. A study was performed by Cheng et al. [17] in the five most populated Australian cities (Sydney, Melbourne, Brisbane, Adelaide, and Perth) from 2000 to 2009, which analyzed the relationship between mortality rate and temperature variability. The results show that any significant temperature change can be associated with a higher mortality rate.

The risk of transmission can differ based on weather conditions related to respiratory diseases' durability on various surfaces [18,19]. There is extensive literature about patterns between weather conditions and virus mortality.

In 2003, Bi et al. [20] tried to estimate how weather conditions could change the speed of spread by applying data for a daily number of positive SARS cases in Beijing and Hong Kong during the 2003 pandemic. This study indicated that higher temperatures could decrease infection; air pressure, however, was positively correlated with the number of positive SARS cases. Likewise, a study in South Korea showed that the number of positive influenza cases increased significantly on days with lower temperatures and relative humidity [21].

In 2020, Bashir [22] conducted a study to analyze the relationship between weather indicators and the COVID-19 mortality rate in New York City. The weather condition variables in this study included average temperature, minimum temperature, maximum temperature, rainfall, average humidity, wind speed, and air quality. The outcome indicated that average temperature, minimum temperature, and air quality were significantly associated with the COVID-19 pandemic. Existing literature reveals a complex relationship between weather conditions and respiratory diseases. Research, such as that by Cheng et al. [17], has shown that temperature variability can influence mortality rates. However, studies specifically connecting weather conditions to COVID-19 transmission are still emerging. For example, Bashir [22] explored the impact of various weather indicators on COVID-19 mortality in New York City, while Hossain et al. [23] examined similar factors across South Asia, highlighting the role of climate indicators like rainfall and air pollution. These studies point to a significant association between climate factors and the spread of respiratory diseases, yet the precise mechanisms remain unclear. This research aims to bridge this gap by investigating how climate conditions interact with social behaviors to affect COVID-19 transmission.

In 2021, Hossain et al. [23] aimed to investigate the effect of weather-condition factors on the number of COVID-19 infected cases in South Asian countries—India, Afghanistan, Pakistan, Bangladesh, and Sri Lanka—from the day of the first infection case to 31 August 2020 in each country. The climate indicators in this study included aggregate rainfall, relative humidity, surface pressure, maximum and minimum temperature (in °C), maximum air pollutants, and maximum wind velocity (m/s). The autoregressive integrated moving average with explanatory variables (ARIMAX) model was applied as an estimator model. The outcomes show that aggregated rainfall, air pollution, and maximum wind velocity play an essential role in spreading coronavirus in these countries.

In 2021, Zhang et al. [24] tried to estimate the effect of temperature and humidity on COVID-19 infection numbers for 1236 areas worldwide. The weather data were collected from a large-scale satellite, and the results indicate that temperature and relative humidity have a negative relationship with the global spread of COVID-19.

Most previous research in this section has indicated that temperature and humidity negatively affect respiratory disease infections [25,26]. The mucus produced in cold weather, however, is especially concentrated and dense, which can lead to obstructions in the respiratory system and raise the likelihood of catching a cold or other respiratory diseases [2].

There is another relevant strand of respiratory disease literature. There are several studies on government policy and its effects on controlling respiratory diseases [27,28]. For example, Nidhi and Jayaraman [29] tried to estimate the effect of Indian government regulations on the amount of carbon dioxide released by factories. They used the information of people who had been hospitalized for respiratory illnesses in seven Delhi hospitals between 1998 and 2004. For the patient population, they applied the Poisson regression model. Their results indicate that the regulations caused a notable reduction in the monthly average density of sulfur dioxide; the monthly average density of nitrogen dioxide, however, increased by 2%. These changes in air quality reduced the number of respiratory patients significantly, by about 12%.

A study in Vietnam examined the effectiveness of government policy during the coronavirus pandemic. The study's timeline was divided into four periods based on four principal government regulations: emergency responses, border and entry control measures, social isolation, and financial support. The findings show that the Vietnamese policy system responded quickly, proactively, and virtually at multiple authority levels [30]. Another research by Wielechowski et al. [31] in 2020 tried to determine how government lockdown regulations in Poland affected mobility and the spread of COVID-19 between 2 March and 19 July 2020. The results indicated that lockdown decreased the number of positive COVID-19 cases in Poland but that social distance regulations were more effective than lockdown. In addition to environmental factors, government policies and social behaviors play crucial roles in disease spread. Research on government regulations, such as those by Nidhi and Jayaraman [29] and Wielechowski et al. [31], demonstrates the impact of policy interventions on respiratory diseases and COVID-19. However, the interaction between these policies and environmental factors, particularly in the context of a pandemic, requires further exploration.

This study seeks to integrate these diverse strands of research by examining how climate variables, social activities, and public policies interact to influence COVID-19 transmission. By focusing on both climatic conditions and social behaviors and employing advanced statistical methods like the Generalized Additive Model (GAM), this research aims to provide a comprehensive understanding of the factors affecting pandemic dynamics. This approach addresses gaps in current literature and offers actionable insights for future public health strategies.

1.2. Data Set Description

The data set includes 11,000 observations, including all the confirmed positive coronavirus cases. The South Korean data set is a reliable source because of the country's aggressive testing protocol and sizable testing capacity. During this study's timeline, around 500,000 individuals were tested—1% of South Korea's population. Sub-national level data and spatial variation in weather within the country were used. We collected daily COVID-19 confirmed case data from the official website of the KCDC (the Korea Centers for Disease Control and Prevention, which is South Korea's main public health agency responsible for managing disease outbreaks and collecting health data) and daily weather data from NASA's website. City-level panel data analysis was used for this research. The data covered the information of nine provinces as well as 95 cities in South Korea (Figure 2).

The COVID-19 data set consists of the following three categories: patient data, policy data, and local data. The patient data category includes per-patient symptom onset date, confirmed date, and state deceased. The symptom onset date is when each patient first displayed symptoms of COVID-19, and the confirmed date is the date that the patient was diagnosed. An age-specific number of patients was also indicated in this category. As shown in Figure 3, people in their twenties have the highest infection rate, but the lowest rate belongs to infants and kids.

The second category is regional data, which includes number of screening centers, land size, and population of each province. It also includes 178 cities in 17 South Korean provinces (126.30–129.47° east longitude and 33.45–38.19° north latitude).

Among these 15 provinces, Gyeongsangbuk-do had the highest COVID-19 spread rate (35.2% of all cases detected during that study period), and the first COVID-19 case was seen in this province. Figure 4 shows more details about this.

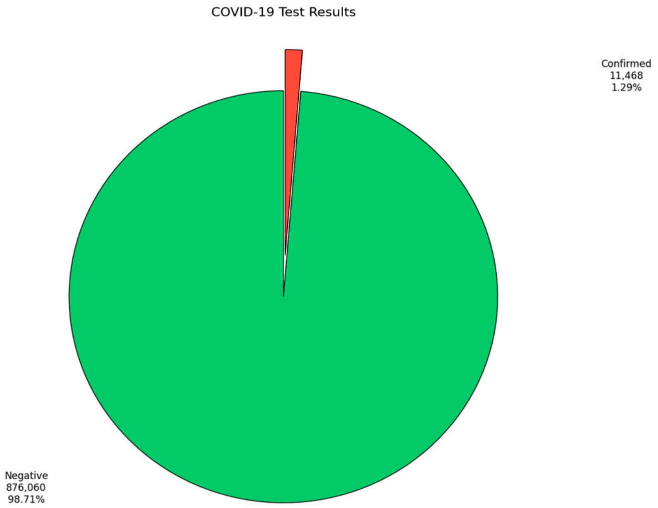


Figure 2. Test results during the timeline of this study.

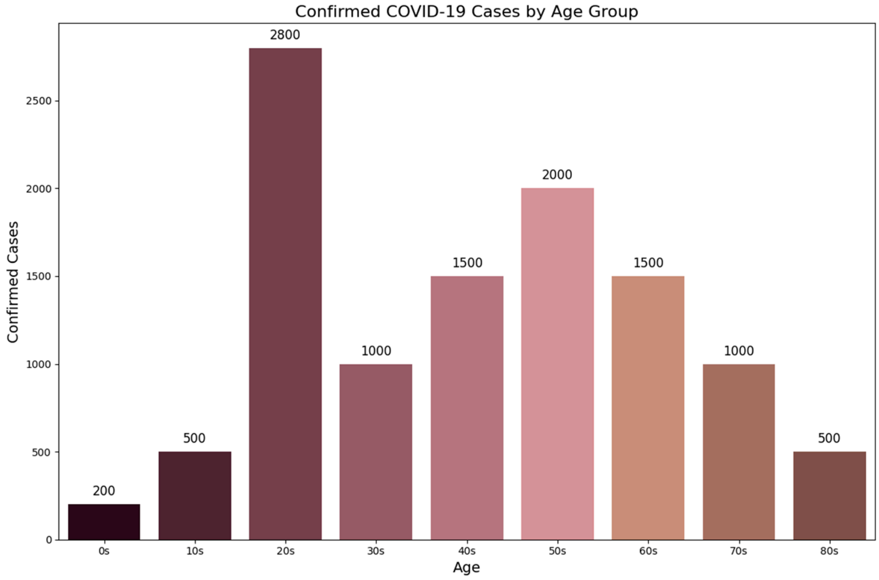


Figure 3. Age-specific number of patients.

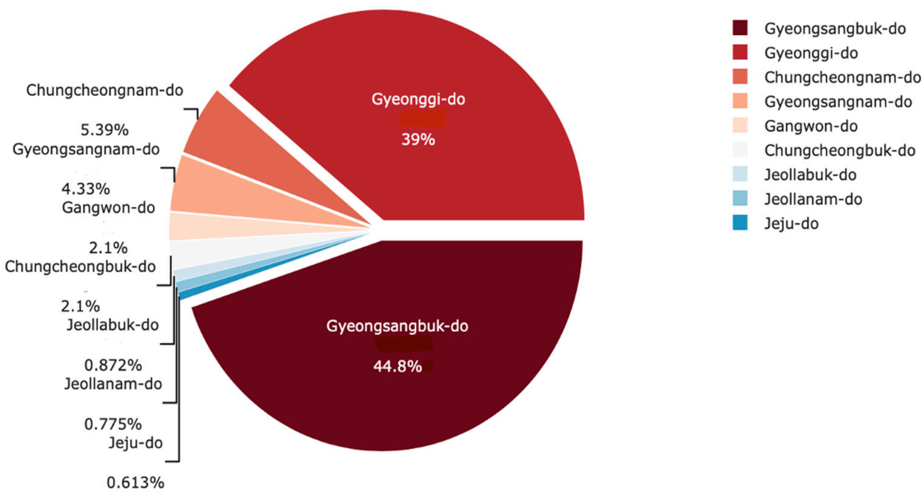


Figure 4. The 9th highest number of infection cases by regions in South Korea.

Lastly, policy data include descriptions and the start and end dates of eight preventative policies enacted by the Korean government [28]. These eight policies include a broad range of policies, such as social, educational, and immigration policies. To help understand the policies' effectiveness, the cumulative number of confirmed patients is appended as part of the data set.

The timeline of this study is 20 January to 28 June 2020; during the timeline of this study, from 19 May to 12 June 2020, South Korea faced the highest number of infections in almost all provinces, as shown in Figure 5.

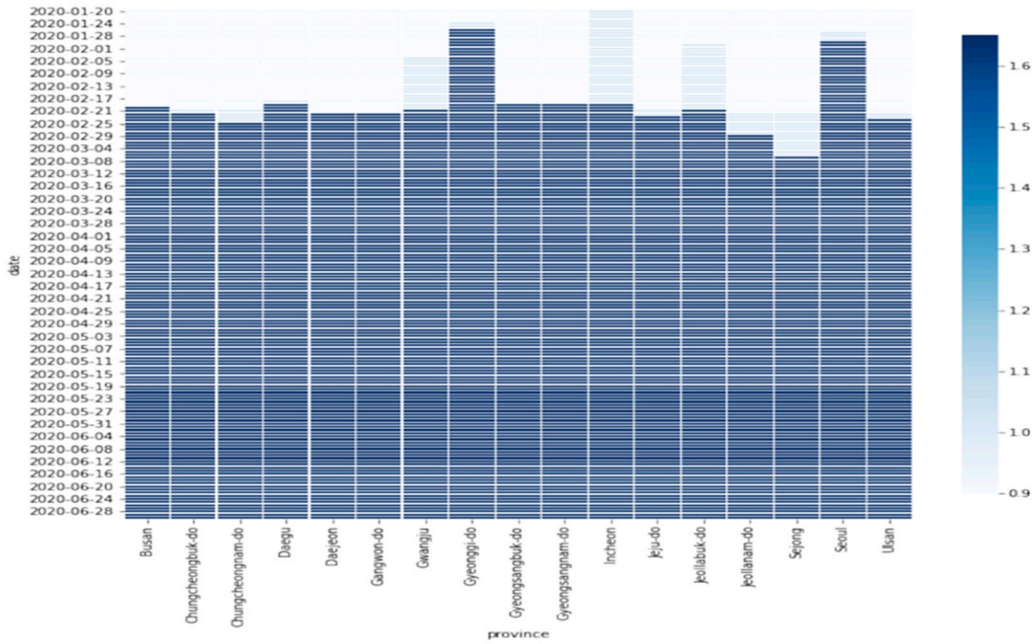


Figure 5. Number of infections for every province (time series plot).

The model also controlled for population density, the number of hospitals per 1000 people, the elderly population ratio, social distance order, the day of the week, and the young population ratio. Table 1 shows summary statistics of selected variables in this study.

Table 1. Descriptive statistics of newly confirmed cases.

Variable	Mean	Min	Max
Confirmed cases	0.36	0	92
Humidity	73.6	49.1	100
Min-temperature	0.85	−16.89	14.71
Min-wind	2.3	0.01	12.15
Pressure	100.11	94.05	103.28

Although other weather condition variables applied in the regression are useful for explaining the relationship between weather conditions and the number of positive coronavirus cases, the minimum temperature is the variable of interest for this study for the following reasons. Firstly, among all explanatory variables, it has the highest correlation with the independent variable.

Secondly, there is a strong correlation between temperature and health, as critical temperatures can jeopardize health conditions by affecting the body's ability to control its internal temperature [25,26]. There are also strong relationships between extreme temperature and cardiovascular disease, respiratory disease, cerebrovascular disease, and diabetes-related conditions [32].

Lastly, since temperature varies by season, it is more predictable than other climate variables [25,26]. Hence, governments can be more prepared and face an issue more effectively based on temperature data. Furthermore, this study's dependent variable is count data, which is reflected in the number of occurrences of behavior in a fixed period, such as the number of positive COVID-19 cases [33]. A proper model, then, is required to work with this type of data, which will be explained in more detail in the Section 2.3.1.

This research innovatively combines weather conditions with COVID-19 transmission dynamics to analyze the impact of temperature and humidity on virus spread. It highlights how higher temperatures and humidity can reduce transmission and examines the effectiveness of South Korea's initial regulatory measures. This dual-focus approach enhances our understanding of both environmental factors and policy responses in managing the pandemic [27,28].

2. Methods

The study was conducted in accordance with the ethical standards of journals, and informed consent was obtained from all participants, ensuring that they were aware of the study's objectives and procedures and their right to withdraw at any time without consequence. The data collected were anonymized to protect participants' privacy and confidentiality. This section discusses selecting an optimal number of lags for some selected variables and addressing the multi-collinearity issue.

2.1. Lag Variables

According to WHO [34], COVID-19 symptoms appear on average 5–6 days after infection. To accommodate the disease onset and detection lag, we used The Akaike information criterion (AIC) and Bayesian information criterion (BIC) to determine the appropriate number of lags to include in the model. In addition, most previous studies on the relationship between respiratory diseases and weather conditions have used lag variables. One study tried to estimate the relationship between weather conditions and varicella (chickenpox) cases using lag variables between seven and 21 days in Guangzhou (South China). The results showed positive relationships between aggregate rainfall, air pressure, sunshine hours, and the number of positive varicella cases [35]. In this research, the cumulative lag effects (lag0_2, lag0_3, lag0_4, lag0_5, lag0_6, lag0_7, lag0_8, lag0_9, and lag0_10) were examined, and seven-day lags were the best fit based on AIC and BIC.

AIC [36] and BIC [37] are valuable methods for estimating a predicted model's likelihood or estimating anticipated values (Table 2). Among model selection methods for this second class of competing models, AIC statistic and its variants [36,38] are one of the most popular. Schwarz [37] proposed the BIC to assist as an asymptotic approximation to a modification of the Bayesian posterior expectation of an applicant model. It is one of the most studied and extensively used tools in statistical model selection. For model selection criteria, minimum BIC and AIC were applied. The most suitable model is a model with the minimum AIC and BIC [39].

Table 2. Results of AIC and BIC tests.

Number of Lags	AIC	BIC
MA (0–2)	20,571.99	21,056.61
MA (0–3)	20,442.46	20,919.61
MA (0–4)	20,410.02	20,886.82
MA (0–5)	20,332.09	20,809.71
MA (0–6)	20,297.28	20,774.08
MA (0–7)	20,089.09	20,565.89
MA (0–8)	20,186.12	20,721.02
MA (0–9)	20,198.24	20,831.02
MA (0–10)	21,187.04	20,941.15

2.2. Variable Selection

To avoid multiclonality, only one variable among minimum, maximum, and average temperature was selected for the regression. Choosing the variable with the highest correlation with the dependent variable (the number of COVID-19 confirmed cases) can solve this problem and increase the predictive power of the model [40]. The same logic was applied for the wind speed variables. The daily minimum temperature and minimum wind speed were selected since they have a higher correlation with COVID-19 infection rate than the mean or maximum temperature and wind speed in the data set. Table 3 shows the summary statistics of these variables.

Table 3. Variable selection based on covariance between the variables.

	Confirmed Cases	**Avg_Temp**	**Max_Temp**	**Min_Temp**	**Avg_Wind**	**Max_Wind**	**Min_Wind**
Confirmed Cases	1	−0.04	−0.04	−0.05	−0.03	−0.03	−0.04
Avg_Temp	−0.04	1	0.92	0.91	0.03	0.57	0.51
Max_Temp	−0.04	0.92	1	0.72	−0.09	−0.05	−0.1
Min_Temp	−0.05	0.91	0.72	1	0.15	0.12	0.14
Avg_Wind	−0.03	0.03	−0.09	0.15	1	0.94	0.83
Max_Wind	−0.03	0.57	−0.05	0.12	0.94	1	0.68
Min_Wind	−0.04	0.51	−0.1	0.14	0.83	0.68	1

2.3. Estimation Models

2.3.1. Model Selection

The counted number of occurrences is the dependent variable of this study (number of COVID-19 infections). This class of data set is known as count data, which is non-negative and discrete. Ordinary linear regression models cannot fully explain this type of model for the following reasons. First, there is a high chance that the model provides negative predicted values, and these results are impossible in theory.

Second, this type of data is skewed positively since many non-negative or zero values are in the data set. Thus, the data set distribution will be far from the normal distribution because of the zero values [41]. Count data define how often an event occurs; frequently, Poisson distribution is applied for this kind of data [42]. It is done the opposite way of the normal distribution of data [43]. Figure 4 shows the distribution of the number of positive COVID-19 cases in South Korea.

For the following reasons, the GAM was applied for this study. First, GAM implements a great fit for nonlinear and linear relations since it is easily adaptable. Second, GAMs can work with many distributions, such as gamma, normal, and Poisson. Lastly, it is very prevalent in epidemiology, air quality, and medicine [44] The main models applied in environmental epidemiology are GAM and GLM, especially when the dependent variable is the count data (Figure 6). Moreover, in these models, Poisson distribution is usually preferred with the logarithmic responding variable [45].

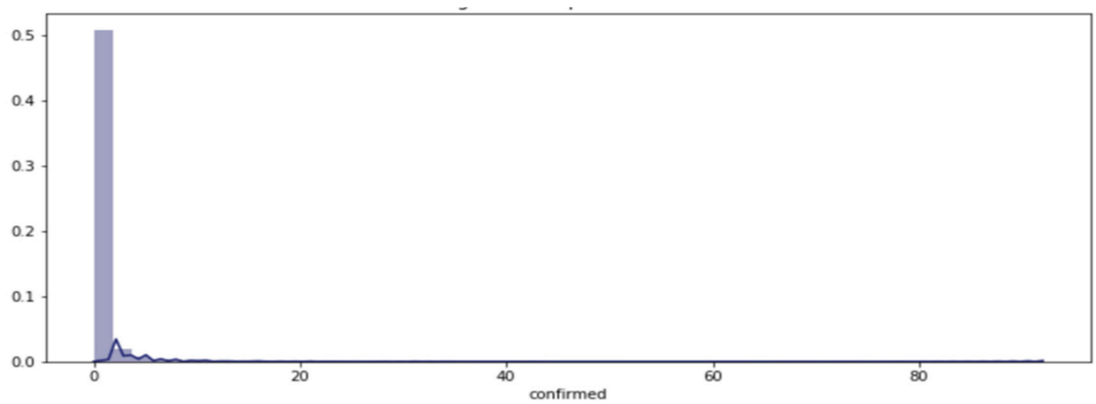


Figure 6. Distribution of the dependent variable.

2.3.2. Regression Analysis

The GAM with Poisson distribution was applied in this regression based on earlier studies [46,47]. The following regression was applied in this study:

$$LogE(y_{it}) = \alpha_0 + Humidity_{it\_7} + Pressure_{it\_7} + Min\_Temperature_{it\_7} + Min\_Wind_{it\_7} + IDA\_RED_i + day_t + city_i + city \times time + \Sigma_{it}$$

GLM stands for the general linear model.

In this model, the dependent variable ($E(y_{it})$) is the expected number of new daily infections on day t for city i. To control population density for each city, we divided the dependent variable by the population. The GAM model uses the logarithmic dependent variable to fix the residuals' non-normality [48,49]. Since there are several days in the data set with zero number of infections, and logarithm zero is undefined, the dependent variable was increased by one to solve the algorithm zero issue [50].

The intercept of the model is α_0, and IDA_RED is a dummy variable; it is zero from 20 January 2020 to 23 February 2020 and otherwise is one. In this study, we focused on the COVID-19 pandemic from the perspective of weather conditions, but other essential factors, like mobility, can affect the COVID-19 epidemic. We could not use these data in our model since the mobility data is not provided at the city level for South Korea by Google or Apple. Both companies solely present country-level data for South Korea. So, instead of using Google or Apple mobility data, the IDA_RED is a dummy variable used to control mobility. IDA stands for Contagious Disease Alert, level 4 (red), which the government announced on 23 February 2020 for the whole country. It is zero from 20 January 2020 to 23 February 2020 and otherwise is one. Based on the KCDC, it caused a more than 10% decrease in mobility for the whole country on average after the government implemented this regulation, even taking into account that South Korea never expected strict limitations or lockdowns like in Germany, Italy, and other countries.

At Infectious Disease Alert, level 4 (red), the government can restrict foreigners from entering the country and force all schools, universities, restaurants, bars, and public facilities to cease operating. It also gives the government the ability to control public activities. The last time alert level 4 was announced was in 2009, to control influenza A (H1N1) [51]. Finally, to control for day and city fixed effects, day_t and $City_i$ are added to the model [52].

3. Results

The results indicate a negative relationship between minimum daily temperature and the daily number of COVID-19 confirmed cases, and the same pattern exists between the dependent variable and humidity. Most previous studies support the results about the negative relationship between temperature and respiratory diseases [15,53], although there is no agreement about the effect of humidity. Some studies show that low humidity aggravates asthma and allergic rhinitis [54,55], and others indicate that high humidity can increase the chance of infection by influenza and respiratory syncytial virus (RSV) [56,57].

The reason behind these results relates to the survival of respiratory viruses (e.g., influenza, flu) in cold weather with very low humidity being close to 24 h, whereas in high humidity and temperatures, it survives for less than one hour [58]. Moreover, as shown in Table 4, a 1 °C rise in minimum daily temperature (lag0–7) led to a 0.88% decrease in the daily number of COVID-19 confirmed cases. For example, when the temperature decreased by 1 °C in a city with a population of 1 million, 880 people could get infected.

Table 4. The main regression results.

	Model (1)	Model (2)	Model (3)
Variables	Coef		
Min_Temp	−0.68 *	−0.81 **	−0.88 ***
Humidity		−1.02 ***	−1.12 ***
Min_Wind		1.31 **	1.49 ***
IDA_RED	−0.51	−0.69 ***	−0.78 ***
Pressure			2.2 ***
R-sq.(adj)	0.57	0.64	0.68
Observations	18,334	18,334	18,334

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

However, the statement suggesting a general pattern of lower infection rates in colder, low-humidity environments may not universally apply. For instance, Mediterranean climates have experienced significant COVID-19 cases despite their relatively mild conditions, which could be attributed to other factors such as population density, public health responses, and healthcare infrastructure.

Furthermore, one should note that putting into effect the Infectious Disease Alert, level 4 (red) policy decreased the number of infections by 0.78%. Other studies confirm that government regulations lead to fewer infections worldwide, especially some implemented rules to decrease mobility, such as a lockdown. For example, in 2020, Méndez-Arriaga showed that a Mexican lockdown phase 1 reduced the number of COVID-19 infections by more than 36%. Moreover, in 2020, Yilmazkuday [59] implied that less mobility led to fewer COVID-19 disease cases and deaths in 130 countries.

Other findings show a negative relationship between relative humidity and the number of COVID-19 infections: a 1 °C increase in humidity caused a 1.12% decrease in risk of getting the disease. This phenomenon happened because the virus, which stays in the air, fades more quickly when the humidity is higher. In environments with faster virus reduction, fewer virus elements survive in the air, a condition associated with a decreased risk of infection [15].

The results confirm that one-inch mercury (inHg) increases in pressure lead to a 2.2% higher chance of COVID-19 infection. The outcomes further show a positive relationship between minimum wind speed (km/h) and positive coronavirus cases. With a 1 km/h upsurge in wind speed, COVID-19 infection risk rises by 1.49%. Other studies confirmed these results in other parts of the world [18,60].

In summary, the finding is to some extent consistent with the previous outcomes of studies on influenza [61,62] and SARS [8].

3.1. Robustness Check

For a robustness check, we ran the same regression on different country locations based on population density. Among all cities, the highest population density was in Yangcheon-gu in Seoul, with a population density of 26,553.00/km^2, and the lowest was in Bonghwa-gun in Gyeongsangbuk-do, with 27.02/km^2, as shown in Figure 7.

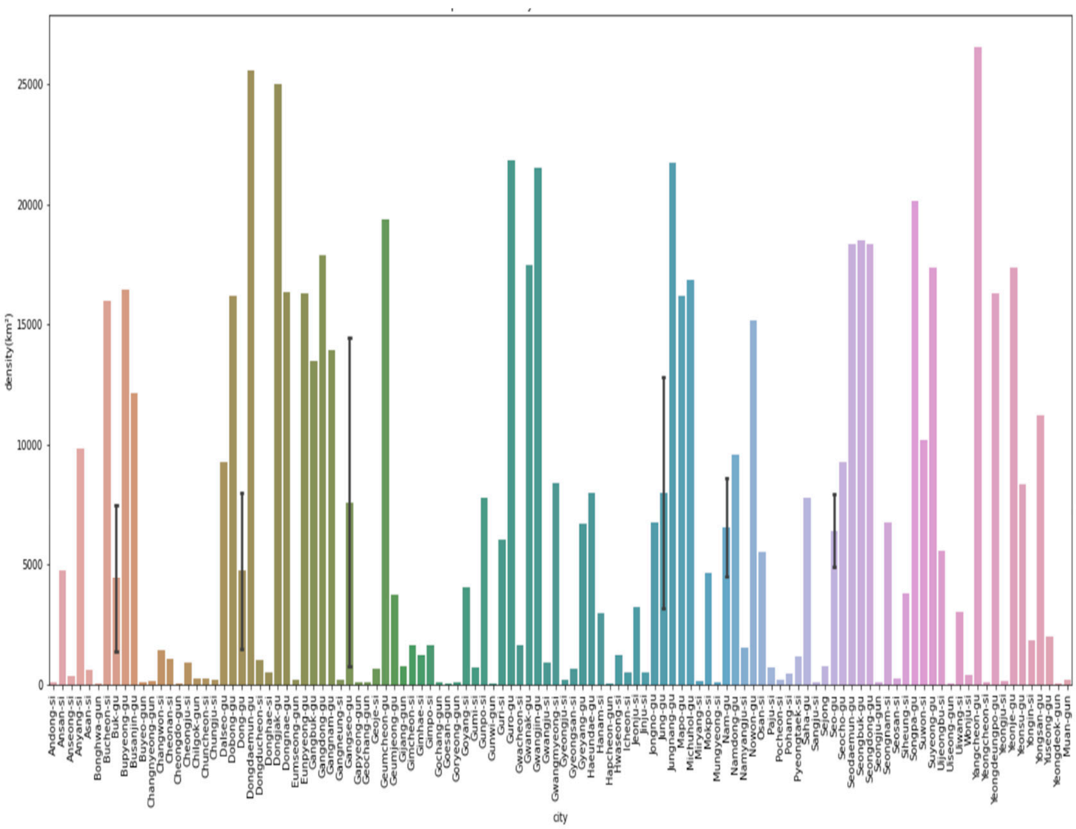


Figure 7. Population density for all cities in South Korea.

The whole data set is divided into four even groups based on population density. The first quantile (0–25%) has the lowest population density, and the last quantile (75–100%) has the highest one. The results of these regressions are indicated in Table 5. The results show a negative relationship between the dependent variable and humidity in all four groups, with the lowest in the first quantile (0–25%). The strongest relationship, however, belongs to the last quantile (75–100%), with the highest population density.

Table 5. Four different quantiles regression results based on population density.

Variables	The Main Regression	0–25%	25–50%	50–75%	75–100%
Humidity	−1.12 ***	−0.99 ***	−1.02 **	−1.15 ***	−1.20 ***
Pressure	2.2 ***	4.19 ***	3.12 ***	4.88 *	2.64
Min_Temp	−0.88 ***	−0.53 ***	−0.48 ***	−0.83 *	−0.90 **
Min_Wind	1.49 ***	1.52 ***	0.11 **	1.07 *	0.98 *
IDA_RED	−0.78 ***	−0.41 *	−0.48 ***	−0.7 *	−0.96 ***
R-sq.(adj)	0.67	0.58	0.58	0.67	0.49
Observations	18,334	4532	4632	4635	4532

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Weather pressure and the number of positive COVID-19 cases have a positive relationship in all groups, but it is not statistically significant for the last quantile. The results regarding the relationship between minimum temperature with a seven-day lag and the dependent variable support our findings, which indicate that a lower temperature causes a higher number of infections. Higher wind speed also increases the number of positive cases for all four groups, like the results of the main regression indicate.

The same regression was applied for maximum and average temperature instead of minimum temperature to check the accuracy of the main regression. Similar processes for maximum and average wind speed were employed instead of for minimum wind speed. The results are shown in Table 6. Thus, four regressions were executed for the first model, and maximum temperature was adopted instead of minimum temperature. The results are the same for all variables when compared to the main regression. The maximum temperature has a negative relationship with the dependent variable, as does the minimum temperature.

Table 6. Regression results for the robustness check.

Variables	Model_1 (Max_Temp)	Model_2 (Avg_Temp)	Model_3 (Max_Wind)	Model_4 (Avg_Wind)
Humidity	−0.11 ***	−0.02 **	−0.11 ***	−1.10 ***
Pressure	2.18 ***	1.98 ***	2.11 *	2.30 ***
Min_Temp	N/A	N/A	−0.45 **	−0.45 **
Max_Temp	−0.52 ***	N/A	N/A	N/A
Avg_Temp	N/A	−0.19 **	N/A	N/A
Min_Wind	1.48 ***	1.48 **	N/A	N/A
Max_Wind	N/A	N/A	0.16 **	N/A
Ave_Wind	N/A	N/A	N/A	−0.96 *
IDA_RED	−0.84 **	−0.59 **	−0.65 *	−0.74 *
R-sq.(adj)	0.63	0.61	0.59	0.54
Observations	4532	4632	4635	4532

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Model 2 employed average temperature in the regression rather than minimum temperature, and the results for all other variables were nearly the same compared to the main regression. The relationship between the number of infections and the average temperature was negative.

In Model 3, maximum wind speed was replaced with minimum wind speed and applied in the regression. The results for all other variables are almost the same compared to the main regression. The relationship between the number of positive COVID-19 cases and the maximum wind speed is positive, as is the relationship between minimum wind speed and the number of infections.

In the last regression, average wind speed was applied instead of minimum wind speed. We got almost the same results for this regression compared to the main regression, and based on these results, it can be concluded that higher average wind speed can increase the number of infections. Hence, all four models support the main results and show high-grade accuracy for this study.

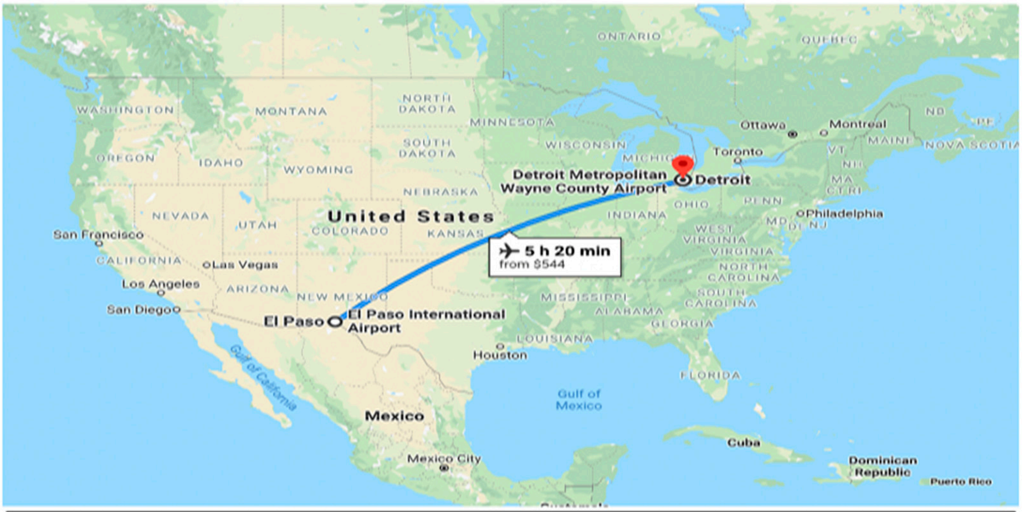
3.2. Prediction

To check the accuracy of the model, the province of Gyeongsangbuk-do in South Korea was selected to predict the number of infections between 2 May and 9 May 2020, and to compare the results with the actual number of positive COVID-19 cases during the same timeline for this province. According to Table 7, the model accuracy is around 70%.

Table 7. Gyeongsangbuk-do predicted number of COVID-19 positive cases.

Date	Min-Temp	Humidity	Min-Wind	Pressure	Predicted Number	Actual Number	Error	Accuracy
02/05/2020	10.4	75.43	0.67	97.78	976	1266	290	77%
03/05/2020	9.04	81.3	0.39	98.2	982	1360	378	72%
04/05/2020	88.0	66.31	1.37	98.35	923	1350	427	68%
05/05/2020	6.0	60.72	2.89	98.85	918	1261	343	73%
06/05/2020	7.32	60.08	2.27	98.56	932	1192	260	78%
07/05/2020	13.82	90.24	3.02	97.7	901	1336	435	67%
08/05/2020	10.06	77.72	2.8	97.55	912	1366	454	67%
09/05/2020	8.78	61.49	2.78	97.75	981	1266	285	77%

Additionally, to help governments make better decisions and become more efficient in responding to the pandemic, two cities with nearly the same population were selected: Detroit, Michigan, with 670,031 people in the midwestern United States, and El Paso, Texas, with 681,728 people in the southern United States (Figure 8). The respective numbers of COVID-19 cases in the fall of 2020 were forecasted based on weather information from 1, 2, and 3 November 2019. Based on the results, the pandemic should be more challenging for Detroit than El Paso.



Detroit, MI	Date	Tempreture	Celsius	pressure	Humidity	Wind	Confirmed
	1-Nov	35°	1.66	29.5	69.8	8	1.41293047
	2-Nov	35°	1.66	29.4	72	7	1.42312847
	3-Nov	37°	2.77	29.4	67.8	6	1.36039747

El Paso, TX	Date	Tempreture	Celsius	pressure	Humidity	Wind	Confirmed
	1-Nov	54	12.22	26.2	15.8	1	0.61837847
	2-Nov	57	13.88	26.2	29.2	2	0.74970247
	3-Nov	55	12.77	26.1	32.2	0	0.76728147

Figure 8. Prediction based on the results.

The results indicated that a 1 °C decrease in minimum daily temperature led to a higher chance of infections for Detroit; therefore, this kind of climate and geographical information can be used by governments to prioritize locations and make more effective decisions regarding contributing resources.

4. Conclusions

To help governments fight the COVID-19 pandemic, this study tried to identify how different weather conditions affected the number of confirmed COVID-19 cases in South Korea. The GAM was applied as the estimation model.

The analysis started by finding the correct number of lags for weather condition variables, since there is a delay between infection and symptoms. The right variables had to be selected to avoid multi-collinearity. The outcomes prove that higher minimum temperature and higher relative humidity lead to a lower transmission rate.

Thus, based on the results, during winter, the number of infections should be expected to speed up again. Therefore, governments need to be prepared and pass regulations to reduce the COVID-19 infection rate. Moreover, minimum wind speed and atmospheric pressure have a negative relationship with the dependent variable. There are some limitations to this study, which are mentioned in the following section.

First, controlling city-level mobility can make results more accurate and help predict previous outcomes [63], but data on this are not available. Secondly, the results are determined based on the specific period in South Korea, which means that the outcomes were estimated under the assumption of no COVID-19 vaccine availability.

Finally, our results are described on statistical patterns, but random control experiments or epidemiological analyses are required to explore more accurate outcomes.

This study's results are aligned with previous studies on the transmission of SARS and other respiratory illnesses based on climate conditions [16,21,64,65].

This research provides valuable results for decision-makers to efficiently combat the COVID-19 pandemic. The outcomes can be applied to increase general awareness and recognize critical factors that affect the transmission of COVID-19. Furthermore, it is desirable to extend social distancing and lockdowns until the vaccine becomes available or the temperature increases, which can reduce infection numbers.

Weather conditions are not the main determining factor in the spread of the COVID-19 virus. Government regulations and public awareness could all contribute to controlling the transmission speed. As temperature decreases in the fall and winter, the spread will probably speed up. Therefore, governments can control the COVID-19 pandemic with a dynamic policy.

Moreover, in light of recent research, it is clear that while weather conditions such as temperature and humidity play a role in influencing COVID-19 transmission rates, they are not the sole determinants. Studies confirm that higher temperatures and humidity can reduce transmission rates, but these effects are moderated by factors like air pollution and social behaviors. Thus, while the data suggest that warmer and more humid conditions could slow the spread, the overall impact of weather is less significant compared to public health measures and policy interventions. Governments should thus focus on dynamic and responsive strategies, including social distancing, travel restrictions, and vaccination campaigns, rather than relying solely on weather-based predictions to manage COVID-19 effectively. Continued adaptation of policies based on emerging data and comprehensive epidemiological models will be crucial in combating the pandemic.

Finally, to address the future direction of this study, it is crucial to extend the research to include various geographical regions and seasonal variations to validate the findings across different climates. Future studies should incorporate real-time data on city-level mobility and behavioral changes, as these factors significantly impact transmission dynamics. Additionally, integrating vaccine coverage and its interaction with weather conditions will provide a more comprehensive understanding of how combined factors influence the pandemic. Further research should also explore the role of emerging variants and their potential interactions with environmental factors to enhance predictive models and inform adaptive public health strategies.

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Conflicts of Interest: Mohammad Javad Mehregan is employed by Holdings, Inc. (EIG) company. Jalil Ghassemi Nejad and Iman Janghorban Esfahani are employed by Glopex Co., Ltd. company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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