Time-Series Analysis of COVID-19 in Iran: A Remote Sensing Perspective

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This chapter reports on a national study of COVID-19 using remote sensing (RS) indicators in Iran. Time-series analysis is performed on RS indicators ($n=12$) including wind speed, temperature, evaporation, carbon monoxide (CO), nitrogen dioxide (NO₂), Sulphur dioxide (SO₂), ozone (O₃), formaldehyde (HCHO), cloud cover, precipitation, air pressure and soil moisture (SM) to identify remotely sensed products that may contribute to COVID-19 transmission. Mann-Kendall test is employed to summarize time-series observations. Further, a correlation analysis is performed between Z-scores obtained from the Mann-Kendall test and the number of COVID-19 cases. Findings indicated that the precipitation, NO₂, and SO₂ have high correlations with number of COVID-19 cases with Spearman correlation coefficient of -0.39, -0.33, and -0.31, respectively. Findings may provide useful insights for public health decision makers by improving the accuracy of predicative models.

22.1 Introduction

As of 1 July 2020, Iran has been identified as one of the top ten countries with the highest number of reported COVID-19 cases. Several neighboring countries such as Bahrain, Iraq, Georgia, Kuwait, Oman, Afghanistan, Lebanon, and Pakistan reported that their first cases of COVID-19 was imported from passengers traveling from Iran [1]. As of 3 September 2020, over 381,000 confirmed cases and almost 22,000 deaths had been reported from Iran. However, the real figure is largely underestimated [2]. It is predicted that the country will face several waves of the pandemic due to ineffective controlling strategies such as early reopening and ease of restrictions.

Several studies have identified associations between environmental indicators and COVID-19 transmission. For instance, in China, Yongji et al. (2020) examined the relationship between ambient air pollution and daily (confirmed) COVID-19 cases using generalized additive models. They found a positive association between COVID-19 and particulate matter 2.5, carbon monoxide, nitrogen dioxide, and ozone, while Sulphur dioxide was negatively associated with the disease [3]. Ma et al. (2020) modeled the relationship between daily COVID-19 mortalities and temperature and relative humidity variations using time-series analysis. They found a positive association with temperature and negative association with relative humidity [4].

Epidemiological investigations of infectious diseases mostly concentrate on medical aspects and infection control and disregard the geographic components of the diseases [5–7]. Geospatial technologies such as Remote Sensing (RS) and geographic information system (GIS) have been identified useful in monitoring a variety of infectious diseases when they are coupled with

data-driven techniques [8, 9]. GIS and RS have been utilized in the study of COVID-19 across the world. For instance, Liu et al. (2020) used RS data such as nighttime light and air quality index to assess the impact of COVID-19 lockdown on human lives in Mainland, China. Their results suggested that with the implementation of lockdown policies, the nighttime light radiances generally decreased in the entire Mainland, and a significant decline was observed in commercial center regions. Meanwhile, air quality significantly improved [10]. In a GIS-based study in the United States, Mollalo et al., (2020) utilized multi-scale geographically weighted regression to explain the variations of COVID-19 incidence at the county level across the country. They compiled a geodatabase of 35 explanatory variables, including environmental, behavioral, and socio-economic factors. Their results indicated that socio-economic variables, particularly income inequality, could explain more than 68% of variations of disease incidence compared to environmental factors [11, 12].

To our knowledge, there are limited studies that have utilized remotely sensed data to monitor COVID-19 in any region of Iran, especially at the national level. To bridge the gap, we examined the applicability of RS coupled with time-series analysis in Iran as our study area.

22.2 Materials and Methods

In this section, we describe the study area, data used and methodology for identifying time-series relation among COVID-19 and environmental indicators obtained from satellite observations.

22.2.1 Study Area

The study area covers Iran. This country with the area of 648,195 km² is considered as the 17th largest country in the world. Iran is divided into 31 provinces (Figure 22.1). Two types of datasets including the number of COVID-19 cases and remotely sensed data were compiled. Figure 22.1 shows the geographic location of study area together with the normalized number of COVID-19 cases by the population.

22.2.2 Disease Dataset

The number of COVID-19 cases in each province was obtained from the Ministry of Health and Medical Education. The data were only available for 22 provinces, excluding Alborz, Isfahan, Qom, Razavi Khorasan, Semnan, and Tehran provinces, which are shown in Figure 22.1. The actual number of cases is presented in NCD column of Table 22.2. The number of COVID-19 cases is registered from 20 February 2020 to 19 April 2020, which is about 53000 cases.

22.2.3 Remotely Sensed Data

In this study, various satellite data sources and products were obtained from Google Earth Engine (GEE) platform (<https://earthengine.google.com/>). GEE is an efficient cloud computing tool that provides georeferenced and calibrated RS data of a variety of satellite imagery [13]. It allows researchers and users to simultaneously process, visualize, and analyze time-series geospatial data in a simple and quick way [14]. GEE was utilized to provide 12 spatial indicators including wind speed, temperature, evaporation, carbon monoxide (CO), nitrogen dioxide (NO₂), Sulphur dioxide (SO₂), ozone (O₃), formaldehyde (HCHO), cloud cover, precipitation, surface pressure, and soil moisture (SM) (Table 22.1). The selection of parameters is based on literature review and available RS indicators [3, 4, 10–12].

In order to extract time-series RS indicators ($n=12$) from GEE, Terra Moderate Resolution Imaging Spectroradiometer (MODIS), Sentinel-5 Precursor (Sentinel-5P), Global Precipitation Measurement (GPM), Soil Moisture Active Passive (SMAP), National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR), and Global Land Data

FIGURE 22.1

The geographic location of Iran in world map, and the normalized number of COVID-19 cases obtained until 19 April 2020 for each province

Assimilation System (GLDAS) were used. These data were acquired from February 20, 2020 (starting date of COVID-19 outbreak in Iran) to 19 April 2020.

22.2.3.1 MODIS Data

According to previous studies, the number of COVID-19 cases may be influenced by the changes of temperature and evaporation [15, 16]. Terra MODIS MOD11A1 Collection 6 (C6) product provides daily daytime, and nighttime land surface temperature (LST) at a spatial resolution of 1 km [17]. We selected Terra MODIS data, because the atmosphere is more stable at the early hours of the day. Atmospheric instability can influence dispersion of aerosols, pollutants, and smoke plumes in some areas [18, 19]. This product is vastly used and evaluated by many researchers across the world [20, 21]. The MOD11A1 with scientific datasets (SDS) name of “LST-Day-1km” ($^{\circ}K$) was obtained from GEE data catalog during the study period.

Terra MODIS level 4 MOD16A2 C6 product, which provides land surface total evapotranspiration (ET) (kg/m^2) datasets in 8-day at 500 m resolution, have also been used [22]. ET product can be used to calculate regional water and energy balance. Provinces with high ET values may have high COVID-19 cases, therefore researchers believe that ET may be an effective indicator. Hence, change of ET and its effect on COVID-19 are investigated. The MOD16A2 product

with SDS name of “ET-500m” was also downloaded from GEE data catalog. This product has been applied, evaluated, and validated by many researchers [23, 24].

22.2.3.2 GPM Data

Previous studies indicate that precipitation is an important indicator that may lead to an influence on microbial pollution which may effect on the number of COVID-19 cases [25]. For this reason, this indicator is incorporated in the dataset. GPM is an international earth’s precipitation observation science mission that measures amounts of rainfall and snowfall (mm/hr) for every three hours at a spatial resolution of 0.1 arc degrees (≈ 11.1 km). GPM data products can improve analyzing climate data all over the world [26, 27]. The data were previously validated by some researchers [28–31]. GPM version 6 with SDS name of IR (Infrared) precipitation was utilized.

22.2.3.3 NCEP CFSR Data

Surface pressure (SP) is an indicator that effects some respiratory diseases such as chronic obstructive pulmonary disease, therefore it is employed in this study [32]. NCEP CFSR, one of the global reanalysis datasets, designed to compute an estimation of the global interaction between atmosphere, ocean, sea ice, and land surface [33]. Surface pressure (Pa), albedo (%), sea surface temperature ($^{\circ}K$), soil temperature ($^{\circ}K$), snow depth (m), vegetation cover (%), relative humidity (%), planetary boundary layer height (m), and surface roughness (m) were available variables in the datasets at 0.2 arc degrees (≈ 22.2 km) resolution. These reanalysis datasets were widely used and evaluated in many studies [34, 35]. Among these, surface pressure with SDS name of “Pressure-surface” was the only variable used in this study.

22.2.3.4 SMAP Data

Soil Moisture (SM) is an environmental indicator that can be provided by RS data. Change of SM may influence COVID-19 cases. Hence, this indicator is included in this study. SMAP measures surface values and subsurface SM (mm) every 3 days at 0.25 arc degrees (≈ 27.75 km) resolution with the combination of passive (radiometer) and active (radar) instruments [36]. Scientists can use SMAP data products to better investigate different environmental applications, such as drought monitoring, climate change analyzing, flood prediction, and monitoring of agricultural crop growth [37–39]. These data were evaluated and validated in some research projects [40, 41]. In this study, level 3 surface soil moisture (SSM) with SDS name of SSM was acquired.

22.2.3.5 GLDAS Data

Similar to surface pressure, wind speed can be an influential factor that may be associated with the transmission of respiratory diseases [42]. GLDAS utilizes different earth observation satellites and ground-based data. It is mainly used to generate wind speed (m/s), albedo (%), and soil temperature ($^{\circ}K$). These data are provided at 0.25 arc degrees (≈ 27.75 km) resolution every 3 hours, which are used and evaluated in many research projects, such as water resource management, drought monitoring, weather forecasting, and flux cycle studies [42, 43]. In this study, wind speed (WS) was extracted from GLDAS data products using GEE platform.

22.2.3.6 Sentinel-5P Data

Copernicus program provides some environmental parameters that can present appropriate information about diseases [44]. They can show crowded and industrial areas that people have a high interaction. Hence, it is employed to extract some environmental indicators and the their effects on COVID-19. Sentinel-5P sensor called TROPOspheric Monitoring Instrument (Tropomi) is designed to monitor the atmosphere, climate, air quality, and solar radiation, at a spatial resolution of 0.01 arc degrees (≈ 1.11 km), and a spectral range of (270–495), (675–775), and (2305–2385) nm [45]. In this study, Near Real-Time (NRTI) air pollutant concentrations, including CO, NO₂, SO₂, O₃, and HCHO were obtained. Also, cloud cover fraction data among NRTI level 3 cloud products of Sentinel-5P was extracted from GEE data catalog and utilized as explanatory variable.

TABLE 22.1

Remotely sensed data used in this study together with spatial resolution and sources.

Source	Indicator	Spatial resolution	Citation
MODIS	LST	1 km	[15–17, 46]
	Evaporation	500 m	
GPM	Precipitation	11 km	[47]
NCEP CFSR	Surface Pressure	22 km	[32]
SMAP	Soil Moisture	27 km	[40, 41, 48]
GLDAS	Wind Speed	27 km	[32, 49]
Sentinel-5P	CO, NO ₂ , SO ₂ , O ₃ , HCHO, Cloud Cover	1 km	[44]

22.2.4 Methodology

In the proposed method, time-series analysis of 12 spatial indicators including wind speed, temperature, evaporation, NO₂, SO₂, CO, O₃, cloud cover, HCHO, precipitation, surface pressure and SM obtained from GLDAS, MODIS, Sentinel-5P, GPM, NCEP CFSR, and SMAP satellites/datasets. Pre-processing tasks including some scale factors were performed. Further, the average of each indicator was estimated. Mann-Kendall test was employed to produce Z score maps of time-series observations for each indicator. Mann-Kendall test was used to indicate the general trend of a variable resulted from the processing of time series data. Finally, correlation between Z values and the number of COVID-19 cases was calculated to identify the most effective indicators. Figure 22.2 depicts the workflow of the research.

22.2.4.1 Mann-Kendall Test for time-series Analysis

Mann-Kendall test was utilized to study time-series changes of the selected environmental RS indicators. The main advantage of this test is that it is not influenced by observations with the drastic changes [50, 51]. Mann-Kendall test was also employed for two main reasons: 1- To study severe time-series and changes of spatial indicators in the study area, 2- since the number of registered COVID-19 cases have been registered in period of two months, we need to make a parameter from daily and weekly satellite observations to compare it with the number of COVID-19 cases. Z score of Mann-Kendall test provides a change of an indicator in period of two months, therefore it is possible to perform a correlation analysis among them.

Suppose n observations in accordance with $x_1, x_2, \dots, x_n$ in the Mann-Kendall test, S variable is calculated based on Equation (22.1):

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (22.1)$$

where, $\text{sgn}(x)$ is calculated as:

$$\text{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (22.2)$$

The variance of S is calculated as:

$$\text{var}(S) = \frac{[n(n-1)(2n+5) - \sum_{i=0}^m (t_i(t_i-1)(2t_i+5))]}{18} \quad (22.3)$$

where m is the number of groups with similar values and t_i is the number of points in group i . After calculating the variance, the Z score is calculated using the Equation (22.4). Positive Z scores indicate positive changes in the variable trend, while negative Z scores indicate decreasing trend of the studied variable. Values greater than 1.96 and smaller than -1.96 indicate significant changes

FIGURE 22.2

Workflow of the proposed method to identify effective time-series RS indicators on COVID-19

at 95% confidence level.

$$ZScore = \begin{cases} \frac{(S-1)}{\sqrt{Var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{(S+1)}{\sqrt{Var(S)}} & \text{if } S < 0 \end{cases} \quad (22.4)$$

22.2.4.2 Correlation Analysis for Validation

The relation between COVID-19 and spatial indicators was investigated using correlation analysis. Correlation analysis was examined between Z score of each indicator and the number of COVID-19 cases. Three correlation coefficients including Pearson, Spearman, and Kendall were utilized, which were frequently used in previous studies [52]. If at least two correlation methods confirm high correlation values, it can be concluded the spatial indicator may be related to the COVID-19.

Pearson is a linear approach to measure correlation among two variables, which was frequently

used in previous researches. The range of values in Pearson is changing between -1 and 1. Values approaching -1 and 1 show high correlation between variables [53]. Spearman is another correlation estimation method which assesses monotonic relationships between variables [54]. The Kendall rank correlation coefficient is another way to measure correlation of two variables [55]. To assess the significance level of the three correlation approaches, P-values were also computed.

22.3 Results and Discussion

Figure 22.3 shows the map of average time-series of each indicator across Iran. According to cloud cover map, maximum cloud was observed in North and West regions of Iran. Maximum values of CO were seen in regions near Caspian Sea, Persian Gulf and Oman Sea. While, minimum values were observed in central areas. Precipitation of the wettest regions in Iran was higher than other regions. While, precipitation of central and east regions were lower than other regions. Maximum precipitation was occurred in south regions of Iran, where some flood events were also reported during 2020. HCHO over Tehran, Gilan, Mazandaran, Khuzestan, and Bushehr provinces was more than others during the study period. Temperature of north and west regions of Iran was lower than south and east, which is true based on climate of those areas. Wind speed of east regions was more than north and west ones during the study period.

Maximum value of NO₂ was observed in Gilan, Mazandaran, Albourz, Tehran, Qom, Markazi, Isfahan, and Khuzestan. High density population in the mentioned areas may be a possible explanation for this finding. Moreover, a high number of COVID-19 cases were registered in the mentioned provinces. Time-series analysis of O₃ showed a higher density in higher longitude compared to lower altitudes.

According to time-series analysis, the larger amount of SO₂ values were observed in Gilan, Mazandaran, Tehran, Khuzestan, Bushehr, East Azarbaijan, and Kerman provinces. Surface pressure of south, west and central regions of Iran was more than other areas. In addition, SM of north and west regions of Iran was more than other areas, while central regions had the lowest values compare with the other regions.

The Z scores of each indicator obtained from Mann-Kendall test were presented in Table 22.3. Cloud cover time-series analysis shows that the percentage of cloud cover in south and north regions including Alborz, Isfahan, Fars, Hormozgan, Semnan, Sistan and Baluchestan, and Yazd have been significantly increased during study period (Z score < 1.96). While, a significant decrease with Z Score lower than -1.96 in cloud cover was observed over Kordestan and West Azarbaijan (Wazar). Among the mentioned provinces, Alborz, Isfahan, Semnan and Yazd have a high number of COVID-19 cases. In general, according to Z score results, it seems that the cloud cover is not an effective indicator to find provinces with low and high numbers of COVID-19 cases were not detected.

Although the amount of evaporations over all provinces has been increased during the study period, it is not significant ($0 < Z \text{ score} < 1.96$). Therefore, it seems that ET is not a related indicator to COVID-19.

According to satellite observations and Mann-Kendall test, precipitation was significantly increased over Bushehr, Isfahan, Fars, Hormozgan, Kerman, Kohgiluyeh and Buyer Ahmad, North Khorasan (Nkhorsan), Razavi Khorasan (Rkhorasan), Semnan, Sistan and Bluchestan, and South Khorasan (Skhorasan). During the study period, the number of COVID-19 diseases in the mentioned provinces was lower than others. It seems that Z score of precipitation is negatively correlated with the number of COVID-19 cases.

Z score of temperature over all provinces was positive and greater than 1.96, which shows an increase in temperature in all provinces. Since the research period was between winter and spring, the results seem to be correct. There was no significant association between the number of COVID-19 cases and surface pressure and the association has not changed over majority of provinces. Based on SMAP observations, SM of central and east regions of Iran i.e., Fras, Kerman, Razavi Khorasan, South Khorasan, and Yazd were increased. Moreover, the Z scores of west regions

FIGURE 22.3
Average maps of indicators obtained from Iran in time of study(a) Cloud cover (b) CO (c) ET (d) HCHO (e) LST (f) NO2 (g) O3 (h) Precipitation (i) SO2 (j) Surface pressure (k) SM (l) Wind speed

of Iran i.e., Ilam, Kermanshah, Khuzestan, Kordestan, Lorestan, Mazandaran, and Zanjan were decreased. According to the results, a strong relation among SM and the number of COVID-19 cases is not observed.

The values of CO, O₃ and HCHO indicators in all provinces were increasing, decreasing and increasing, respectively. NO₂ was decreased in some provinces, especially in regions that the number of patients was higher than others. Moreover, based on the Z score, SO₂ was decreased over all provinces. Due to several limitations of government on industries, universities, schools, and transportation, it appears that the results of NO₂ and SO₂ were reasonable. Since results of these indicators are complex, we use correlation analysis to find relation among these two indicators and COVID-19.

All the correlation coefficients (i.e., Pearson, Kendall, and Spearman) between spatial parameters and the number of COVID-19 cases, were calculated and presented in Table 22.3. A significant correlation is not observed between number of COVID-19 diseases and spatial indicators including evaporation, cloud cover, SP, SM, temperature, wind, CO, formaldehyde, and O₃ (P value > 0.05). Their correlation values were closer to zero with large P values.

Unlike the study of Yongjian [3] that showed a positive correlation among CO, O₃, and the number of COVID-19 cases, the correlation values of Pearson, Kendall, and Spearman for CO and O₃ were (0.04, 0.06, 0.09) and (0.24, 0.02, 0.04), respectively. This suggests that there is no correlation among the mentioned indicators and the number of COVID-19 cases in Iran.

Based on outcomes of [4], a high correlation among humidity, temperature, and number of death due to COVID-19 is observed. In this study, Kendall and Spearman correlation values for ET are 0.19 and 0.24, respectively, which shows a correlation among them, but it is not significant enough. Also, a low correlation value (<0.1) is obtained between temperature and number of COVID-19 cases in this study.

According to our findings, precipitation, NO₂, and SO₂ are the most effective indicators that were highly correlated with the number of COVID-19 cases. Correlation values of Pearson, Kendall, and Spearman for precipitation were -0.35, -0.28, -0.39, respectively. Based on low P-values of each correlation value (P-P value=0.08, K-P value=0.05, S-P value=0.05), it can be deduced that these associations are not due to the chance alone. Moreover, the P values of two correlation analysis methods confirmed that the correlation between precipitation and COVID-19 cases with confidence level of 95% is meaningful. Moreover, NO₂ with the correlation values of -0.25, -0.24, -0.33 for Pearson, Kendall, and Spearman is another important indicator. Likewise, SO₂ seems to be associated with the number of COVID-19 cases. P-values of NO₂ and SO₂ are higher than precipitation. Based on P-values of Kendall and Spearman, results with a confidence level of 85% are acceptable. This suggests that Kendall and Spearman correlation analysis methods confirm a significant correlation among NO₂, SO₂, and number of COVID-19 cases. Results of [3] are in agreement with our findings about NO₂ and SO₂.

Although this is a new study about the effect of RS indicators on COVID-19 in Iran, there are some limitations that should be considered. As the spatial and temporal resolutions of the used indicators are inconsistent, the integration of those indicators in data level would be a great limitation. Moreover, there are some no-data pixels in products of some days that should be corrected by interpolation methods. Another limitation is that the used products such as SO₂ and NO₂ should be calibrated based on ground observations for Iran to achieve more reliable outcomes. Finally, we employed the number of registered COVID-19 cases for two months. Since satellite observations can be provided on a daily basis, the use of daily statistics regarding COVID-19 cases can help us to perform a more robust validation on environmental indicators. The most important limitation is related to lack of detailed understanding of the nature of COVID individual cases & deaths, or correcting for epidemiological & personal health issues.

TABLE 22.2
The Z scores of spatial indicators over all provinces

Province / Indicators	Cloud cover	Evaporation	Precipitation	Surface pressure	Soil moisture	Temperature	Wind speed	CO	HCHO	NO ₂	O ₃	SO ₂	NCD
Alborz	2.00	1.22	0.36	-0.37	0.53	4.53	-1.22	0.01	-2.35	-4.37	4.37	-1.83	N/A
Ardebil	0.84	0.73	0.19	0.09	0	1.82	1.08	2.60	-1.67	2.48	5.31	-3.61	0.018
Bushehr	0.97	-0.24	3.01	-4.42	0.07	4.24	0.37	0.92	0.01	-2.25	4.60	-1.31	0.006
Ch-Mahal & Bakh*	1.48	1.22	0.76	-0.25	-1.28	2.81	0.47	4.30	-1.88	1.95	5.12	-0.31	0.008
East Azarbaijan	-0.53	1.22	-0.38	-0.79	1.51	5.16	2.07	3.52	-2.21	0.01	4.53	-3.56	0.111
Fars	3.61	1.22	2.74	-0.96	2.34	2.16	0.27	2.22	-1.78	-1.36	4.52	-1.56	0.077
Gilan	-0.11	1.22	-0.56	0.12	-0.30	2.18	1.35	2.88	-0.56	-1.24	5.42	-0.95	0.134
Golsetan	1.71	1.71	0.22	0.08	-1.11	1.62	0.03	2.31	-1.16	-0.20	4.40	-2.80	N/A
Hamedan	-1.17	1.22	-0.14	-0.83	-0.68	3.79	1.05	4.85	-1.19	-0.95	4.70	-2.10	0.023
Hormozgan	2.06	0.73	4.12	-3.03	0.75	2.87	0.67	0.77	-0.67	-1.20	2.44	-1.25	0.024
Ilam	0.24	1.22	0.02	-1.99	-3.78	5.71	-0.17	3.38	-0.38	0.56	4.68	-0.60	0.011
Isfahan	2.60	1.22	2.21	-0.77	0.62	2.72	0.06	3.71	-2.86	-2.81	5.232	-2.55	N/A
Kerman	3.97	1.22	5.39	-1.35	2.27	2.30	0	2.78	-1.23	0.50	3.12	-0.80	0.017
Kermanshah	-0.55	1.22	0.33	-1.04	-2.12	3.61	0.04	3.92	-0.62	-0.81	4.99	-1.37	0.035
Khuzestan	-0.44	0.24	0.95	-4.09	-2.49	4.32	0.61	3.24	0.51	-0.88	4.91	-0.81	0.086
Kohg & B-Ahmad**	0.80	0.73	1.99	-1.47	0.90	3.94	0.54	2.01	-1.26	0.10	4.96	-1.02	0.010
Kordestan	-1.93	1.71	-0.68	-0.85	-2.58	4.49	2.78	4.88	-3.0	0.22	4.60	-1.81	0.034
Lorestan	0.01	1.71	0.12	-0.75	-2.27	3.58	0.24	5.04	-1.35	0.40	4.62	-0.51	0.044
Markazi	0.72	0.73	1.11	-0.68	-0.07	2.95	0.44	4.37	-1.71	-1.28	4.74	-1.21	0.033
Mazandaran	0.91	1.71	-0.68	0.17	-2.04	3.27	-1.80	2.63	-0.46	-1.55	4.34	-3.75	0.072
North Khorasan	1.46	1.71	2.54	0	1.25	2.87	0.01	3.28	-0.93	0.57	4.27	-3.56	0.023
Qazvin	0.28	0.73	0.29	-0.25	-0.30	2.12	1.01	2.11	-1.59	-2.74	4.97	-2.91	0.038
Qom	0.58	0.73	1.64	-0.75	0.15	3.05	-0.03	4.45	-3.10	-3.09	4.82	-3.07	N/A
Razavi Khorasan	1.70	1.22	3.86	0.02	2.80	1.76	-0.03	3.44	-1.81	1.17	3.81	-2.18	N/A
Semnan	2.07	0.73	2.77	-0.28	1.21	3.70	-0.40	3.62	-3.45	-3.15	4.64	-2.89	N/A
Sistan & Baluch***	2.27	0.73	4.07	-2.02	1.13	3.94	0.84	1.87	-0.68	1.89	2.05	0.94	0.015
South Khorasan	2.30	0.73	4.85	-0.25	2.87	0.98	0.03	4.05	-0.61	5.39	2.79	0.50	0.011
Tehran	1.49	0.73	0.85	-0.16	-0.22	4.85	-1.29	0.08	-3.22	-3.82	4.36	-2.94	N/A
West Khorasan	-1.81	1.71	0.16	-1.04	0.07	6.27	2.41	3.68	-0.99	1.26	3.98	-2.47	0.061
Yazd	2.59	0.24	3.16	-1.08	3.21	3.83	-0.23	3.24	-1.86	2.58	3.87	-0.92	0.077
Zanjan	-1.43	1.22	-0.23	-0.69	-2.04	3.79	1.39	3.67	-0.89	0.089	4.86	-2.71	0.020

* Chaharmahal and Bakhtiari
** Kohgiluyeh and Boyer-Ahmad
*** Sistan and Baluchestan

TABLE 22.3

Correlation and P value obtained from Pearson, Kendall, and Spearman, Pearson P-Value: P-P value; Kendall P-value: K-P value; Spearman P-value: S-P value.

Indicators	Pearson	P-P value	Kendall	K-P value	Spearman	S-P value
Cloud Cover	-0.16	0.43	-0.18	0.20	-0.29	0.15
ET	0.13	0.53	0.19	0.24	0.24	0.25
P	-0.35	0.08	-0.28	0.05	-0.39	0.05
SP	0.14	0.49	0.11	0.44	0.19	0.36
SM	0.06	0.74	-0.05	0.70	-0.06	0.77
T	0.10	0.62	0.03	0.80	0.06	0.77
Wind	0.15	0.47	0.12	0.41	0.16	0.43
CO	0.04	0.82	0.06	0.69	0.09	0.65
HCHO	-0.03	0.88	-0.10	0.50	-0.12	0.54
NO2	-0.25	0.22	-0.24	0.09	-0.33	0.10
O3	0.24	0.24	0.02	0.86	0.04	0.84
SO2	-0.22	0.27	-0.19	0.19	-0.31	0.13

22.4 Conclusion

In this study, we examined the association between 12 spatial indicators obtained from satellite observations and COVID-19 cases in Iran using time-series analysis. Our findings indicated that changes of SO₂, NO₂, and precipitation were highly correlated with the number of COVID-19 cases. At least two correlation analysis methods including Pearson, Kendall, and Spearman and their P-values confirm that there was a relation between the three mentioned indicators and the number of COVID-19 cases. Changes of the effective indicators can be measured in other periods, so results may be useful for public health decision makers to mitigate the disease effects. As a future work, it is recommended to apply the methodology based on the number of COVID-19 deaths. Moreover, spatial modeling disease using these indicators is recommended as another topic for future studies.

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