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Study on the spatial relationships in the number of Covid-19 patients based on ordinary least squares regression and Moran's spatial autocorrelation test (Case study: Iran, Lorestan province)

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A B S T R A C T

In order to examine the spatial relationships of the number of patients, effective factors in increasing the number of patients should be determined. The information layers of dependent variables and independent variables were plotted in the GIS system. In the next stage, ordinary least squares regression and the Moran spatial correlation test were used to investigate the significant relationship between the dependent variable and each of the explanatory variables. The results show that the most influential variables in increasing the number of patients are in the first place the urban working population variable and in the second and third place the total population and total working population. The average variable of ambient temperature along with the mentioned variables is an important factor in the release of Covid-19. Because in the study of the average ambient temperature in three periods, it was found that the number of patients increased with decreasing temperature. Hence, to vaccinate the target groups, it is recommended to vaccinate the urban working population in the first stage, and also the observance of health protocols is strongly recommended in areas where the average ambient temperature is lower.

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1. Introduction

The new coronavirus was identified in December 2019 in Wuhan, Hubei, China, and consequently renamed SARSCoV-2 (Boulos and Geraghty, 2020). This virus creates severe respiratory failure and as a result, the patients are more hospitalized in intensive care units (ICUs), and have a higher mortality rate (Su et al., 2021). The World Health Organization (WHO) introduced these conditions as an international public health emergency on January 30, 2020 (Sohrabi et al., 2020), and on March 12, 2020 (Analytica, 2020) declared it as a pandemic. Age over 60, male gender, severe obesity, and chronic kidney disease have been associated with hospitalization in intensive care units and above-average mortality rates (Suleyman et al, 2020). Old age, and another disease, was associated with significantly higher mortality rates (Mohammad Ebrahimi et al., 2021). Research on its transmission has been continued since its beginning. It has been claimed that the main transmission route is indirect contact, i.e., contact with contaminated surfaces and then transmission of Covid-19 infection through the mouth, nose, or eyes (Qu et al., 2020).

Another way of transmission is through respiratory droplets from one person to another (Li et al., 2020) when a certain amount of pathogens is inhaled by others while talking, coughing, and sneezing (Yang et al., 2020). It is actively expanding around the world and has become a unique challenge for the health, economic, and lifestyle care of the community. Countries are struggling with a number of tactics to minimize the spread of Covid-19: banning parties, closing schools, halting traffic, locking cities, enforcing curfews, and sealing places (Kumar, 2020). On-site risk assessment and rapid preventive measures need more time (Bhunia et al., 2021). This comprehensive global social, environmental, and economic crisis is severely affecting people's daily lives and changing people's common behaviors (Ahmar and Boj, 2020). The study of epidemiological features and spatial and temporal trends of Covid-19 in the Mashhad region, with classical statistical approaches and GIS showed that the use of temporal spatialization methods to identify transmission trends and high-risk areas could be documented and help policymakers in the design and implementation of appropriate interventions to control and prevent Covid-19 and other pandemics with rapidly spread (Mohammad Ebrahimi, et al, 2021). To develop the best response strategies, epidemiologists and health policymakers need to analyze and demonstrate the spatial and temporal prevalence of the virus (Estimated, 2009). Today, pandemic surveillance is based on and focused on the potential of Geographic Information Systems (GIS) (Esri, 2020). Space tools for mapping Sars Covid-2 events globally demonstrate how space methods can be useful in identifying new health facility locations for affected groups (Parvin et al., 2021). The high mortality rate of Covid-19 highlights the need to better understand the causes and spatial spread of disease, which in turn can shed light on the prediction of disease worldwide and thus improve public health policies (Adegboye et al., 2017). Many studies have used spatial techniques to evaluate the spatial and temporal characteristics of Covid-19 (for example, center, density of hot and cold clusters, direction, etc.) (Biswas and Sen, 2020). Some of the main spatial techniques are spatial autocorrelation, spatial-temporal interactions, hotspots, and clusters which are used in emerging infectious disease research (Robertson and Nelson, 2014). The Geographic Information System (GIS) has revolutionized today and allowed us to view spatial or geographic information in a meaningful way. There are many uncertainties about the Covid-19 pandemic, many of which have spatial components that allow the disease to be geographically interpreted and technically mapped (Subramanian et al., 2020). Health organizations, especially the World Health Organization (WHO), are increasingly using spatial analysis to show and control the spread of disease. Geographic Information Systems (GIS) have shown successful results in infectious diseases and their applications are very useful in mapping the geographical distribution of disease outbreaks as well as visualizing transmission processes and modeling the spatial environmental aspects of disease occurrence (Hashtarkhaniet al., 2020). Geographic mapping can help public health decision-makers, travelers, and local populations at risk to monitor trends and patterns that are hidden in the data and often change over time (Shariati et al., 2020). The regional and local effects of the Covid-19 crisis are highly heterogeneous (Amdaoud et al., 2021). Governments are responsible for the important issues of health care control measures, social services, economic development, and public investment that are at the forefront of crisis management (Allain-Dupre et al., 2020). Because of the geographical spread of the virus, city officials, epidemiologists, and experts must respond quickly and plan to deal with the virus (Esri, 2011). The Moran s I test and the Getis-ord index is widely used to represent the distribution of a wide range of infectious diseases (Wang et al., 2015; Tran et al., 2004). As the global Covid-19 pandemic continues, modeling and analysis of the Covid-19 expansion trend has attracted widespread attention. Various emission simulation models have been proposed to predict the spread of the pandemic and the effectiveness of related control measures (Wu et al., 2021). Because the expansion of Covid-19 reflects geographic dependence, GIS can combine different spatial datasets based on reference land and enhance the integration of health data with underlying characteristics (Wu and Zhang, 2021). At the same time, descriptive modeling research that depends on the strength of GIS has examined the Covid-19 spatial relationships with socioeconomic and environmental characteristics (Smith and Mennis, 2020). Researchers reported spatio-temporal heterogeneity in Texas and provided scientific evidence for an effective Covid-19 disease monitoring system (Wu and Zhang, 2021). A study in India examined the spatial distribution of Covid-19, and spatial clustering patterns using spatial autocorrelation techniques revealed that most disease clusters were concentrated in the central and western states of India and that this cloning technique would help public health professionals to identify risk areas and make real-time decisions to control viral disease (Bhunia et al., 2021). In China, spatial analyses of Covid-19 outbreaks have been performed and important points of virus origin as well as the daily flow of new cases have been identified (Tang et al., 2020). Inverse Distance Weight (IDW), Hot Spot, and Geography Weighted Regression (GWR) methods for analyzing Covid-19 data in Tehran showed that most of the deaths were men, but the mortality rate was higher in women than men, and also there was a direct relationship between the area of houses and Covid-19 contamination. The results also show the disproportionate distribution of the disease in Tehran, in the eastern regions the number of infected people is higher than in other regions and there is a relationship between population density in residential and office-commercial areas and the number of Covid-19 cases in all areas, especially for people in densely populated areas (Nasiri et al., 2021). Keikhosravi and Fadavi in the metropolis of Tehran showed that according to the height of peaks and the number of patients with Covid-19, the time between infection with the virus and the onset of symptoms is between 2 to 5 days (Keikhosravi and Fadavi, 2021). As the world's second most populous country, India is facing a health crisis, so spatial vulnerabilities must be identified to identify the region at risk. In spatial analysis to identify hot spots, four factors of total population, population density, and the arrival of foreign tourists to India have been considered responsible for identifying the focal point of the new corona virus (Parvin et al., 2021). The results of spatial autocorrelation and regression to explain the pattern of Covid-19 transmission in Bangladesh showed that population density is an important factor in Covid-19 release and densely populated areas such as Dhaka and Narayanganj are among the worst affected areas (Sarkar et al., 2021). In examining the spatio-temporal heterogeneity of Covid-19 expansion in Texas, USA, GWR models provided higher fit and more information based on geographic data than OLS models. Population, hospitalization, and age structure have been proposed as positive effects on cumulative cases of Covid-19 and suggest that rigorous strategies should be adopted to inhibit Covid-19 (Wu and Zhang, 2021). In this research, it is tried to investigate the relationship between the number of infected with Covid-19 in Lorestan province and the variables of temperature, population, city area, topography of the region, urban and rural population. the results of these studies can help to understand the dynamics and processes of controlling the spread of Covid-19 in space and time, which can help policymakers adopt more appropriate measures and strategies to reduce the prevalence of this pandemic.

2. Material and Methods

Lorestan province with an area of 29308 square kilometers is one of the mountainous provinces in the west of Iran. This province has 11 cities, 29 districts, and 85 villages. According to the census of 2019, with more than 1850000 people, it is the thirteenth province of the country in terms of population. 64.4% of the province's population lives in urban areas and 35.6% in rural areas. Among the cities, Khorram Abad has the highest population density and Haft Cheshmeh has the lowest population density (www.amar.org.ir). In this research, first, the statistical data of the number of Covid-19 patients by city in the period of 20/4/2020 to 6/9/2021 were received from the Ministry of Health. The incidence of Covid-19 virus can be related to different factors. Because of this, in order to investigate the spatial relationships of the number of patients, and the factors that affect the rate of increase in the number of patients, the dependent variable (number of Covid-19 patients) and independent variables (city area, population density, city population, urban working population, total working population (rural and urban), topography, average annual temperature) were plotted for modeling in GIS environment as vector maps. In the next step, ordinary least squares regression (OLS) was used to investigate the significant relationship between the dependent variable and each of the explanatory variables. Among the various linear methods for estimating model parameters, the OLS method is known as the most widely used and dominant method. This method tries to fit the best regression line to the data by minimizing the sum of squares. The typical regression model is a global pattern that is based on the assumption of constant communication in space and the variables are estimated as in other areas of study. The general relation of the OLS pattern is as described in relation (1).

$$y = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \in \quad (1)$$

Where y is the dependent variable, $\beta_0$is the intercept, $\beta_i$is the estimated coefficients for the independent variablex_i, p is the number of independent variables and ∈ is the error component (Pohlmann and Leitner, 2003). In OLS analysis, statistics from 1 to 5 were used to fit the points and determine the most important factor in increasing the number of patients with Covid-19.

1. Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent viable)=

2. Probability and Robust Probability: Asterisk (*) indicates a coefficient is statistically significant ($p < 0.01$); if the Koenker (BP) Statistic is statistically significant, use the Robust Probability column (Robust_Pr) to determine coefficient significance.

3. Koenker (BP) Statistic: When this test is statistically significant ($p < 0.01$), the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). You should rely on the Robust Probabilities (Robust_Pr) to determine coefficient significance and on the Wald Statistic to determine overall model significance.

4. Jarque-Bera Statistic: When this test is statistically significant ($p < 0.01$) model predictions are biased (the residuals are not normally distributed).

5. R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance. Finally, Moran spatial auto-correlation analysis was used to distribute the residues. In this analysis, the residual distribution must be normal for the OLS analysis to be valid, otherwise the residuals are not acceptable.

The range of Moran index values can vary from -1 to +1. A value equal to +1 indicates the highest degree of positive spatial correlation, a value equal to -1 indicates the highest degree of negative spatial correlation, and a value equal to zero indicates the maximum degree of randomness of the value distribution (Tu and Xia, 2008). The Moran index can be calculated using Equation (2).

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} wij} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij(z_i-\bar{z})(z_j-\bar{z})}{\sum_{i=1}^{n}(z_i-\bar{z})^2} \quad (2)$$

Where:

N is the number of samples, $\bar{z}$ is the mean value of the variable z, z_i is the value of the variable in location i, z_j is the value of the variable in other places ($j \neq i$) and wij is the weight function which is the inverse of distance between two points i and j (Huo et al., 2012; Zhang et al., 2008).

3. Results and discussion

3.1. Evaluation of the Number of Patients with Covid-19

Statistics related to Covid-19 in Lorestan province, by cities, were collected from 20/4/2020 to 9/6/2021 from the hospitals of this province. During the considered period in the province, 116704 people were positive cases of Covid-19, of which 40078 people have been hospitalized. Of the hospitalized cases, 1781 were died. According to Fig. 1 at the county level, the highest number of Covid-19 cases belongs to the center of the province, in Khorramabad County. This city alone has 28.7% of the number of patients. After that, Barjroud and Doroud counties with 16.9% and 10.7% have recorded the highest cases. The least positive cases of Covid-19 belong to Chegeni City with a frequency of 2622 people (2.2%). Fig. 2 shows the number of patients and hospitalizations in the province. Based on this figure, two main peaks of Covid-19 are observed during the statistical period. The first peak continues from 3/8/2020 to 13/12/2020. In this peak, the number of patients in the province reaches 38,618 and the number of hospitalizations reaches 12,715. The second peak of Covid-19 starts from 28/2/2021 and continues until 8/6/2021. In this peak, the number of patients reaches 50,627 and the number of hospitalized cases reaches 15,293. In general, the number of deaths in two corona peaks is more than 70%.

3.2. Investigating the Relationship between Dependent Variable and Independent Variables using OLS and Moran s Index Analysis

3.2.1. Temperature Variable

To investigate the relationship between the dependent variable (number of patients) and the independent variable (average temperature), first, the average temperature of the province was prepared by MODIS sensor product in the period of 20/4/2020 to 20/6/2021. Then the average temperature was determined for different cities (Figure 3). Based on Fig. 3, the lowest average temperature belongs to Aligudarz city with a temperature of 10.3 °C and the highest average temperature belongs to Khorramabad city with a value of 44.6 °C. To analyze the OLS test between the number of patients and the mean temperature, its statistical statistics were calculated in GIS software. Based on Table 1, the relationship between patients and mean temperature has a negative relationship. This means that with decreasing temperature, the number of patients with Covid-19 has increased. The robust column is significant with a value (* 0.022). Therefore, based on the P_value, the temperature variable is an effective variable in predicting the number of patients with Covid-19. In order to check that the temperature variable is the main factor in the number of patients, the Jarque-Bera-Statistic column should not be significant either. If in this case, this column is significant (* 10/07). Therefore, it can be concluded that the temperature factor is a variable affecting the number of patients, but this variable alone is not enough to predict the number of patients with Covid-19, other variables should be considered.

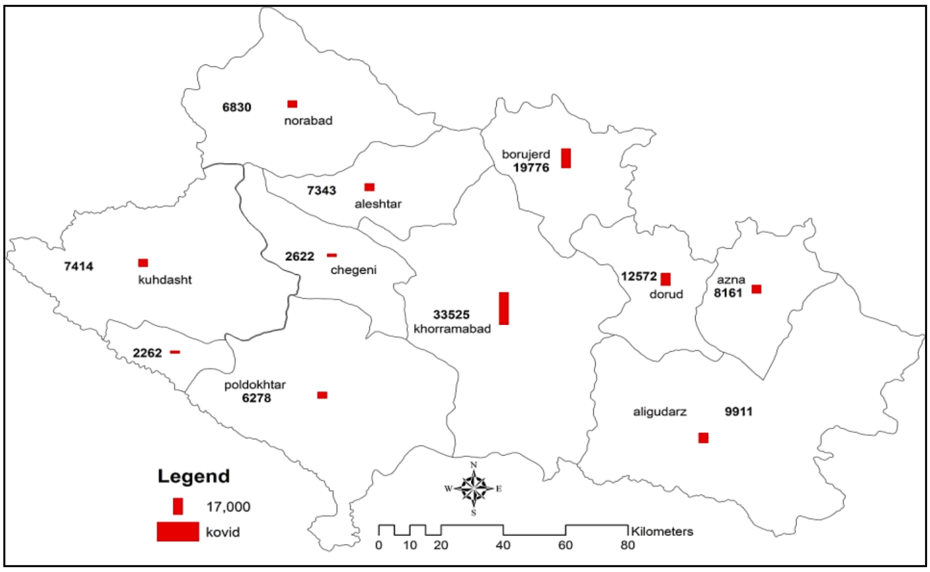


Fig. 1. Number of Covid-19 patients in different cities (20/4/2020 - 9/6/2021).

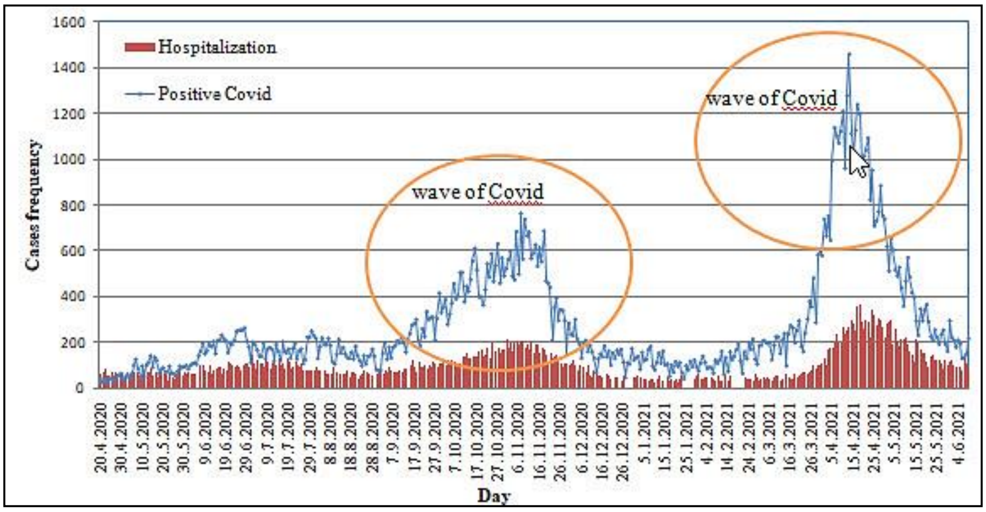


Fig .2. Number of patients and cases of hospitalization with Covid-19 in Lorestan province.

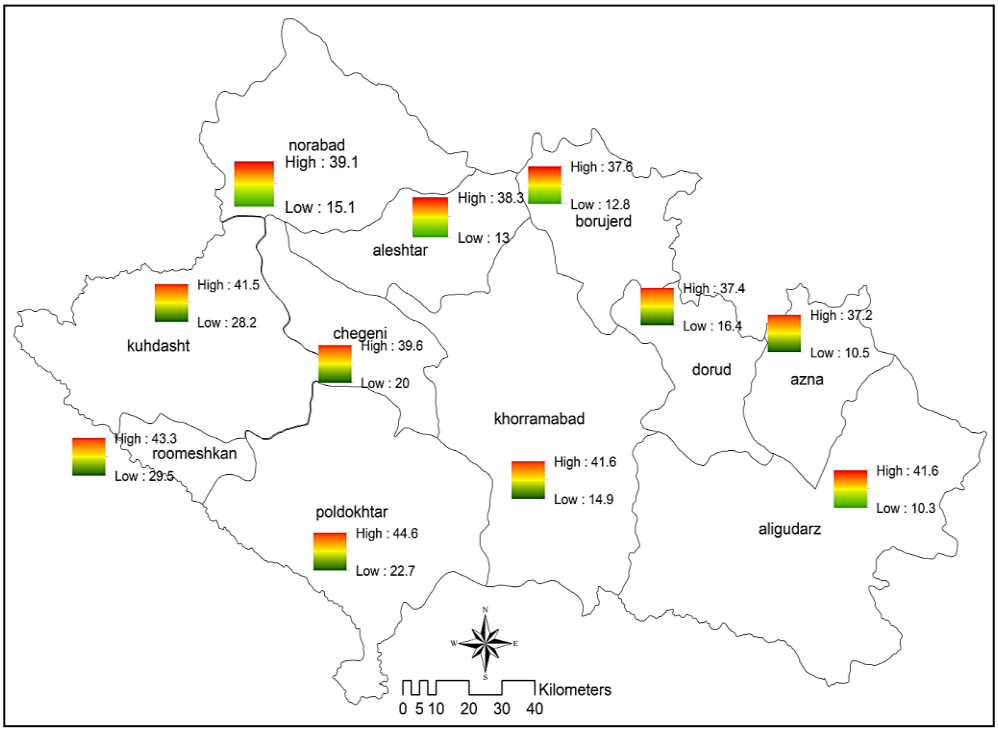


Fig. 3. Average temperature of Lorestan province by city during the statistical period.

For a more accurate study of the temperature variable, the mean temperature of the two peak periods of Covid learning was also examined and statistical relationships with OLS analysis are shown in Table 1. In both corona peaks, the number of patients increases with decreasing temperature and decreases with increasing temperature. In the first peak (cold period) the amount of P-value is significant and in the second peak (warm period) the relationship is not significant. Therefore, due to the effect of temperature, the observance of health protocols is doubled when the temperature decreases. For a valid OLS analysis, the data distribution must be random, otherwise residuals in OLS analysis are not acceptable. Therefore, for this work, the Moran spatial autocorrelation analysis method was used between dependent variable and a dependent variable. For the residuals to be acceptable, the Moran index must be zero or close to zero, in other words, it must be a random distribution. If the Moran distribution is scattered or clustered, we must look for other variables to model. As shown in Table 1, the average temperature variable of the whole statistical period, the average temperature of the first peak (cold period), has a random distribution, and the average temperature of the second peak (warm period), has a cluster distribution. Hence, the temperature factor, especially in the cold seasons of the year, is a variable affecting the increase in the number of patients with Covid-19.

3.2.2. Population Variable

Population variables were calculated for all age groups. According to Table (1), the coefficient of population variability is positive and with increasing population, the number of patients with Covid-19 also increases. The results of the statistical components of OLS analysis confirm the same. The amount of P_value in both Probability and Robust columns with a value of 0000 is significant. On the other hand, due to the insignificance of the Koenker column, for the significance of the population variable, the implementation of the population variable is valid as a factor influencing the statistical results of both the Probability and Robust columns. Also, the significance of R-Squared columns at 95 and 94% and the analysis of Moran spatial correlation, which estimated the index at (0.046), show the pattern of random distribution of data distribution. As a result, all of the above indicate the impact of population variables on the number of coronavirus patients.

3.2.3. Urban and Total Employed Population Variables (Urban and Rural)

Other influential variables are urban and total employed population variables. The urban working population includes all those who work in urban environments and the total working population includes all people who work in both rural and urban environments. It seems that these two variables are more susceptible to Covid virus, because people are active outside their residential areas, due to more contact with people in the community. Therefore, they were investigated as two separate variables. Based on the results of Table 1, the OLS analysis coefficient is significant in both positive variables and the P_value in both Probability and Robust columns with a value of 0000. This means that the number of people infected with the virus will increase as the working population grows. In order to compare the two variables with each other, which variable has the greatest impact on the number of patients, the Akaike index should be examined. In the Akaike index, the variable that has the lowest numerical value among the variables has more executability. Therefore, the urban working population variable is the most effective variable affecting the number of patients with Covid-19 with a numerical index of 201.9 compared to the total public population variable.

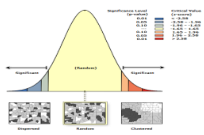
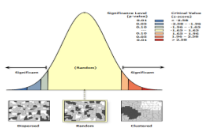
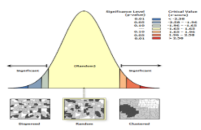
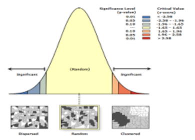
3.2.4. Variables of Area and Population Density

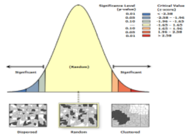
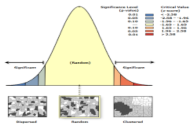
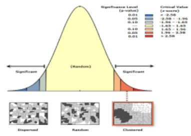
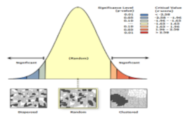
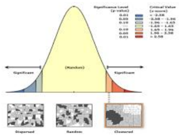
To study the area of cities, first, the polygon map of cities of Lorestan province in GIS software was converted to a UTM coordinate system, and then the area of each city was calculated in terms of square kilometers. The area variable has the least effect on the dependent variable (number of patients) among the studied variables. According to Table 1, the coefficient of the population variable is positive. This means that as the area increases, the number of patients increases. As the area increases, the number of residential areas increases, which will increase the number of people infected with the coronavirus. The rest of the statistical components performed by OLS analysis and Moran index are not significant, so the area factor cannot be introduced as an effective variable. But when the rate of population density (people per square kilometer) is calculated, the population density variable is statistically significant in terms of P_value components of the Moran index. The significance of the Jarque-Bera-Statistical index indicates that the population density variable alone cannot be an influential factor. Other variables should also be considered in this regard.

3.2.5. Topographic Variable

In order to investigate the topography of the region, first the DEM map of Lorestan province was obtained from the site (https://earthexplorer.usgs.gov) and then the average height of each city was calculated in GIS software. As noted in the Jarque-Bera-Statistics column, the altitude factor, like the area variable, alone cannot be a factor in increasing the number of people infected with the virus.

Table 1. Statistical results of OLS model and Moran index between dependent variable (number of patients) and independent variables.

Variable	Coefficient	Probability	Robust	Koenker	Jarque-Bera	Akaike's Information Criterion	Multiple R-Squared	Adjusted R-Squared	Moran s Index	Distribution pattern
population	0.062	0000*	0000*	0.039	0.675	206.76	0.95	0.94	0.046	
Population density	103.77	0.048*	0.00938*	0.615	11.51*	234.8	0.36	0.29	-0.120	
Urban working population	0.30	0000*	0000*	0.178	0.797	201.90	0.968	0.964	0.064	
Total employed population	0.23	0000*	0000*	0.00068	0.88	208.57	0.94	0.93	0.024	

Average temperature ((statistical period	-1347.7	0.2000	0.0220*	0.34	10.07*	237.74	0.17	0.08	0.148	
Average temperature in the first wave (cold (period	-345.06	0.413	0.1009	0.254	13.25*	218.32	0.075	-0.027	-0.070	
Average temperature in the second wave ((warm period	-801.48	0.0712	0.0108*	1.15	1.84	214.65	0.317	0.241	0.513	
topography	5.37	0.408	0.120	0.00001	11.102*	238.98	0.077	-0.025	0.169	
Area	2.53	0.168	0.219	3.26	2.1	237.4	0.19	0.19	0.11	

4. Conclusion

On December 31, 2019, China informed the World Health Organization of various cases of unusual pneumonia in Wuhan, a city in the capital of Hubei Province. On January 30, the World Health Organization declared a public health emergency around the world. In February, it began to spread in Iran, Italy, and other countries. Subsequently, the disease became a pandemic, and by the end of March, half of the world's population had been quarantined. The outbreak of coronavirus, called COVID-19, has raised global concerns in many countries. Human health is affected by various environmental and social factors such as habitat, temperature, population, etc. Health issues will almost always have a spatial dimension. Investigation of the characteristics of these places, including demographic and environmental characteristics, is very important for epidemiological studies. In the field of health, GIS is a useful tool for planning, health education, monitoring, and evaluation of health programs. The use of statistical techniques and analyses such as ordinary least squares regression and Moran index in GIS helps to study the spatial and temporal distribution and environmental causes of patients. In this study to investigate the spatial relationships between the number of patients, dependent variable (number of Covid patients), and independent variables (city area, population density, city population, urban working population, total working population (rural and urban), topography, average annual temperature) were tested in GIS software using ordinary least squares regression analysis (OLS) and Moran index. In Lorestan province, in a total of 416 days (20/4/2020 to 9/6/2021), about 116704 people were infected with Covid-19 virus, of which about 40078 people were hospitalized in the province and about 1781 people died. Khorramabad city with a frequency of 28.7% is among the cities in first place, followed by Barjroud (16.9%) and Dorud with a frequency (10.7%). A total of two outbreaks of coronavirus have occurred in the province, accounting for more than 70% of all deaths. The results of the analysis of the OLS index and Moran index indicate that the temperature variable along with other variables can be introduced as an effective variable to increase the number of patients. In all three periods (average temperature of statistical period, average temperature of hot period, average temperature of cold period), with decreasing temperature, the number of patients has increased. Due to the significance of the Jarque-Bera-Statistical index for the average temperature of the statistical period and the average temperature of the cold period, in addition to this variable, other variables should be introduced to affect the number of patients.

The main and influential variables on the number of patients with Covid-19 are population-related variables (population, urban working population, total working population, population density). The P-value of population-related variables is significant. The coefficients of all variables related to the population are positive and with increasing population, the number of coronavirus patients increases. Also, in terms of the Moran correlation index, these variables have a random distribution pattern of data distribution. Despite the significance and high correlation coefficient, the effect of each of the population variables for increasing the number of infected people according to Akaike's Information Criterion index is different. The most effective variables on increasing the number of patients with Covid-19 are the urban working population variable with Akaike index (201.9) and then the population variables (206.76 index) and the total working population variable (208.57 index). Therefore, in order to vaccinate the target groups, it is recommended that the urban working population be vaccinated in the first stage. Also, in the cold seasons of the year and areas of the cities of the province where the average temperature decreases, the observance of health protocols is strongly recommended in order to reduce the number of patients with Covid-19.

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