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Coronavirus disease vulnerability map using a geographic information system (GIS) from 16 April to 16 May 2020

Seyed Vahid Razavi-Termeh a,1, Abolghasem Sadeghi-Niaraki a,b,1, Soo-Mi Choi b,*

a Geoinformation Tech. Center of Excellence, Faculty of Geomatics, K.N. Toosi University of Technology, Tehran, Iran
b Dept. of Computer Science and Engineering, and Convergence Engineering for Intelligent Drone, Sejong University, Seoul, Republic of Korea

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Abstract

In recent months, the world has been affected by the infectious coronavirus disease and Iran is one of the most affected countries. The Iranian government’s health facilities for an urgent investigation of all provinces do not exist simultaneously. There is no management tool to identify the vulnerabilities of Iranian provinces in prioritizing health services. The aim of this study was to prepare a coronavirus vulnerability map of Iranian provinces using geographic information system (GIS) to monitor the disease. For this purpose, four criteria affecting coronavirus, including population density, percentage of older people, temperature, and humidity, were prepared in the GIS. A multiscale geographically weighted regression (MGWR) model was used to determine the vulnerability of coronavirus in Iran. An adaptive neuro-fuzzy inference system (ANFIS) model was used to predict vulnerability in the next two months. Results indicated that, population density and older people have a more significant impact on coronavirus in Iran. Based on MGWR models, Tehran, Mazandaran, Gilan, and Alborz provinces were more vulnerable to coronavirus in February and March. The ANFIS model findings showed that West Azerbaijan, Zanjan, Fars, Yazd, Semnan, Sistan and Baluchistan, and Tehran provinces were more vulnerable in April and May.

1. Introduction

The outbreak of the new coronavirus, also known as COVID-19, began in Wuhan, China, in January 2020, becoming a sudden public health crisis and a severe threat to lives in most parts of the world (Zhu et al., 2020; Jiang et al., 2020). Previous outbreaks of coronaviruses include acute respiratory syndrome (SARS-CoV) and Middle Eastern respiratory syndrome (MERS-CoV), previously known as risk factors for public health (Rothen and Byrareddy, 2020; Yang et al., 2020). Coronavirus primarily targets the human respiratory system, and in some cases, results in fatal lung injury and death. The interval between a person’s exposure to an infectious virus and the onset of symptoms is approximately 5–7 days (range, 2–14 days) (Cowling et al., 2015). The primary symptom is fever, and approximately after five days, signs of acute respiratory infection appear. Healthcare staff and those with chronic illnesses are at a high risk of the disease (Kim et al., 2015). According to the World Health Organization’s (WHO) reports, on March 16, 2020, 164837 people suffered from coronavirus in 146 countries, of whom 6470 have died. China, Italy, Iran, and South Korea have been countries with the highest rates of coronavirus infection worldwide. The coronavirus outbreak in Iran began on February 19, 2020, and according to the WHO, on March 16, 2020, about 14,000 people were infected in Iran, of whom 724 died.

Due to the increasing prevalence and growth of this disease, it is necessary to find ways to manage and cope with it. Because the disease depends on many parameters, including spatial information, it is essential to analyze this information to predict and control it (Svendsen et al., 2012). One useful tool is the geographic information system (GIS), which reduces costs by analyzing spatial and non-spatial data, significantly helping managers and decision-makers control the disease. The GIS has been used to process health data, analyze geographic distribution, disease prediction mapping, surveillance, and epidemic disease management (Johnson and Johnson, 2001; Mesgari and Masoomi, 2008; Palaniyandi et al., 2016). Location-based analysis can help prevent and manage the disease, including disease risk mapping, identification of areas sensitive to coronavirus, and disease clustering (Gwitira et al., 2018). A sufficient understanding of the current situation in the region can be achieved by defining the vulnerable areas of the disease and

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updating the risk maps. Health managers and planners will provide better and more practical solutions for disease control and management. So far, much research has been conducted on the spatial modeling of coronaviruses. Mollalo et al. (2020) modeled coronavirus outbreaks in the United States using artificial neural network modeling. Gao et al. (2020) visualized the spread of coronavirus in 2019 using cartograms. Rosenkrantz et al. (2020) investigated the necessity of using GIS science for COVID-19 mapping. Arab-Mazar et al. (2020) prepared a hot spot map of COVID-19 outbreaks in Iran. Xiong et al. (2020) examined the spatial statistics and factors affecting COVID-19 at both, prefecture and county levels in Hubei Province, China. Franch-Pardo et al. (2020) studied spatial analysis and GIS in COVID-19. Guliyev (2020) determined the spatial effects of COVID-19 using a spatial panel data model. Almeida et al. (2020) examined Brazil’s vulnerability to COVID-19 using a spatial metric. Ramírez and Lee (2020) examined the emergence, social, and health determinants of COVID-19 in Colorado using spatial analysis. Studies have examined meteorological parameters, such as temperature and humidity, and their coronavirus effect. Pirouz et al. (2020) investigated the effects of relative humidity and mean temperature on coronavirus. Meteorological data (30 years) on temperature and humidity and their effect on the coronavirus were analyzed by Liu et al. (2020). Lin et al. (2020) investigated the outbreak of coronavirus based on meteorological and social data. Using the adaptive neuro-fuzzy inference system (ANFIS) model and comparing it with the multiscale geographically weighted regression (MGWR) model, a coronavirus vulnerability map has not yet been prepared using ineffectual factors. Therefore, the objective of this study was to use spatial data and predictive algorithms such as MGWR and ANFIS to forecast maps of the vulnerability of coronaviruses in April and May in Iran. Given the recent prevalence of this disease, there are some limitations regarding its parameters. In this study, based on available and influential data on coronavirus such as population density, percentage of older people, temperature, and humidity, we predicted coronavirus vulnerability mapping in Iranian provinces.

2. Materials and methods

This study was conducted in four steps. In the first step, data on the number of patients with coronavirus were collected from Iranian provinces. In the second step, four coronavirus factor parameters, including temperature, humidity, percentage of older people, and population density were prepared based on previous studies and WHO reports. In the third step, GIS analysis and the MGWR model were used to model the current state of coronavirus in Iran. In the fourth step, time series analysis using the ANFIS model was used to predict the vulnerability of the disease in the next two months. A summary of the research steps is shown in Fig. 1.
2.1. Study area

Iran is a country in southwest Asia and the Middle East with an area of 1.65 million and 79.9 million Km$^2$. In terms of width, Iran ranks second in the Middle East, 18th globally, and is ranked 17th in terms of population. Iran is bordered by Armenia, Azerbaijan, Turkmenistan, and the Caspian Sea to the north, Afghanistan and Pakistan to the east, Turkey and Iraq to the west, and the Persian Gulf and the Sea of Oman to the south. Iran is located in the Northern Hemisphere between latitudes 25$^\circ$–40$^\circ$ N and longitude 44$^\circ$–63.5$^\circ$ E of the Greenwich Mean Time, indicating that Iran is in a temperate zone. Iran has 31 provinces, as shown in Fig. 2.

2.2. Coronavirus statistic in Iran

According to the WHO reports, from February 19, 2020 to March 16, 2020, approximately 14,000 people were infected with the coronavirus in Iran, of whom 724 died. Most statistics were related to Tehran (3744 patients), Mazandaran (1374 patients), Isfahan (1301 patients), and Markazi (713 patients), respectively. Fig. 3 shows the number of patients in Iranian provinces.

2.3. Factors affecting coronavirus disease

The prevalence and transmission of coronavirus depends on several factors. Given the recent coronavirus outbreak, no research has been conducted to identify all influencing factors. Because this study addresses the vulnerability of coronavirus, according to previous research and reports by the WHO, four criteria, including temperature, humidity, percentage of older people, and population density, were identified as factors affecting coronavirus (Jin et al., 2020). Humidity and temperature criteria generally affect the prevalence of influenza diseases, and since coronavirus is a type of influenza, these two criteria can influence the incidence of the disease (Memarzadeh, 2012; Zhang et al., 2015).
Temperature and humidity criteria were prepared based on Iranian meteorological data from February 1, 2020, to March 16, 2020, to assess the current vulnerability of coronavirus. These two criteria were collected based on the average data for 2010–2019 for the two months of April and May to determine the vulnerability for the next two months of coronavirus infection in Iran. According to the WHO reports, most patients and deaths occur in the elderly. Thus, using Iran’s 2018 census reports, the percentage of older people in each province was collected. Because of the rapid transmission of coronavirus, areas with a high population density are at greater risk of developing it. The population density criterion was prepared based on reports from the Iranian Census Bureau in 2018. The criteria for the four factors affecting coronavirus were created in the GIS for modeling (Fig. 4).

2.4. MGWR model

A GWR model is a method for achieving higher accuracy in analyzing location-based relationships. The GWR model is based on the idea that model parameters or coefficients can be estimated at any point in a location (Paez, 2006). The GWR model assigns more relative weights to closer observations and less to those that are more distant. In other words, the GWR model to estimate the local coefficients uses only geographically close observations. This weighting method is based on the idea that geographically close observations are the best way to estimate local coefficients (Lloyd and Shuttleworth, 2005). The constant consideration of the scale of all relations in the analysis is one of the GWR problems. The MGWR is a GWR extension that allows relationships to be analyzed on various spatial scales (Fotheringham et al., 2017). The MGWR model has one dependent variable and one or more independent variables, as shown in Equation (1).

$$y_i(u) = \beta_0(u) + \sum_{j=1}^{n} \beta_{bj}(u)x_{ij}$$

where $y$ is the dependent variable at point $u$, $x$ is the independent variable at point $u$, $bwj$ represents the bandwidth used for the calibration of

Fig. 3. Number of people with coronavirus in the Iranian provinces.
the conditional relationship of \( j \) in \( \beta_{bwj} \), and \( \hat{\beta} \) is the model estimator calculated by equation (2):

\[
\hat{\beta}(u) = (X^T W(u) X)^{-1} X^T W(u) y
\]

(2)

\( W(u) \) is the square matrix of weights, where the weight assigned values depend on the \( u \) point position in the studied region, \( X^T W(u) X \) is the spatially weighted covariance matrix, and \( y \) is the value of the dependent variable at point \( u \).

Independent and dependent data samples were used to implement the MGWR model. The MGWR model was implemented in MGWR 2.2 (https://sgsup.asu.edu/sparc/mgwr). In this study, the number of coronavirus patients in each province was used as dependent data, and the values of the four criteria of humidity, temperature, population density, and older people were used as independent variables. Sensitivity analysis was used to investigate the importance of the effective criteria in modeling and to eliminate the uncertainty. The relative decrease (RD) index was used to calculate the sensitivity of the MGWR model (Equation (3)) (Rahmati et al., 2020; Razavi-Termeh et al., 2021).

\[
RD = \frac{R^2_{all} - R^2_i}{R^2_{all}} \times 100
\]

(3)

\( R^2_{all} \) is the coefficient of determination of all factors, \( R^2_i \) is the coefficient of the conclusion of factor (i) removed from the model, and RD is the index of relative decrease.

2.5. ANFIS model

By modeling the performance of the human brain, artificial neural networks extract the latent rules behind this information by processing experimental data without considering the physics of the problem (Jang,
Compared to conventional models, these models require fewer inputs and less computational time. A fuzzy system is a logical "if-then" rule using the concept of linguistic variables and fuzzy decision-making processes to visualize the input variables’ space over the output variables. The combination of logic-based fuzzy systems and artificial neural network methods that can extract knowledge from numerical information has resulted in an adaptive neural fuzzy inference system (Raza-Termeh et al., 2020a). The structure of the ANFIS model consists of five layers, as shown in Fig. 5.

The layers in the ANFIS model are defined as follows (Ranjgar et al., 2021). For layer one, each node contains adaptive variable nodes (Equations (4) and (5)):

\[ O_{1,i} = \mu A_i(x) \]  
\[ O_{1,i} = \mu B_i(y) \]  

where \( x \) and \( y \) are the input nodes, \( A \) and \( B \) are the linguistic variables, and \( \mu A_i(x) \) and \( \mu B_i(y) \) are membership functions for that node.

Every node has the role of a “fuzzy AND” operation used for firing strength calculation of the rules as the output layer. The output of each node is the product of all the input signals to that node (Equation (6)):

\[ O_{2,i} = W_i = \mu A_i(x) \mu B_i(y), \quad i = 1, 2 \]  

where \( W_i \) is the output for each node.

The third layer includes a set of fixed nodes. The nodes in this layer are, in fact, the normalized outputs of layer two, which are referred to as the normal firepower (Equation (7)):

\[ O_{3,i} = \pi f_i = \frac{W_i}{w_1 + w_2}, \quad i = 1, 2 \]  

Each node in layer four is associated with a node function (equation (8)):

\[ O_{4,i} = \pi f_i = \pi_l(p_i x + q_i y + r_i) \]  

where \( \pi f_i \) is the normalized firepower of layer three, and \( p_i, q_i \), and \( r_i \) are the node parameters. The parameters of this layer can be interpreted as the resulting parameters.

The fifth layer contains a single node denoted as \( \sum \), which is the sum of the fourth layer output values and shows the final result of the ANFIS model, which is shown in equation (9):

\[ O_5 = \sum \pi f_i = \sum w_i f_i, \quad i = 1, 2 \]  

In implementing the ANFIS model, the values of four variables of temperature, humidity, older people, and population density for each province were used as input variables (independent variables) and the number of coronavirus disease patients in each province as the target variable (dependent variable).

### 3. Result and discussion

The disease statistics in each province and four parameters for temperature, humidity, older people, and population density were used to map vulnerability to coronavirus in Iran’s provinces using the MGWR model. The RD index results are presented in Table 1.

Table 1

| Excluded factor         | \( R^2 \) (%) | Relative decrease (RD) of \( R^2 \) (%) |
|-------------------------|---------------|----------------------------------------|
| Population density      | 22.7          | 70.3                                   |
| Older people            | 66.87         | 12.12                                  |
| Humidity                | 70            | 8.015                                  |
| Temperature             | 73.3          | 3.67                                   |
| All factors             | 76.1          | –                                      |

![Fig. 5. ANFIS layers structure (Razavi-Termeh et al., 2020b).](image)

![Fig. 6. Importance of the factors affecting coronavirus using the MGWR model.](image)

In implementing the ANFIS model, the values of four variables of temperature, humidity, older people, and population density for each province were used as input variables (independent variables) and the number of coronavirus disease patients in each province as the target variable (dependent variable).
The population density criterion had a significant effect on the spread of coronavirus in the study area. The findings of temperature and humidity indicate that the occurrence of coronavirus in the study area is not influenced by these two criteria. Based on the MGWR model, the parameters of population density, older people, humidity, and temperature in Iran had a significant influence on coronavirus (Fig. 6).

The population density criterion influences the incidence and transmission of coronavirus. According to various studies, population density affects the prevalence of coronavirus. The results of this study are consistent with those of previous studies (Ahmed et al., 2020; Rocklov and Sjödin, 2020; Babbitt et al., 2020). The use of socio-economic services, such as banks, pharmacies, and gas stations, increases population density. In areas with a high population density, the distribution of these services is not scattered. Therefore, the coronavirus is more likely to spread due to the close proximity of people in these locations (Babbitt et al., 2020). Aging is associated with several psychological, social, and environmental diseases. Fragility in the elderly increases the risk of various infections and reduces the body’s immunity (Babbitt et al., 2020). Liu et al. (2020) found that coronavirus infection was three times more common in the elderly. Because the elderly have a weakened immune system, the prevalence of the disease among them is high. Underlying diseases, such as diabetes and pulmonary disease, make people more susceptible to the disease. In addition to having weak immune systems, older people have underlying diseases such as diabetes and pulmonary diseases that make them more susceptible than young people to coronavirus (Banerjee, 2020).

Researchers have confirmed that respiratory infections improved under unusually cold conditions and low humidity, and that low humidity may also be necessary for respiratory illnesses (Ma et al., 2020). However, humidity had little effect on the prevalence and vulnerability of coronavirus in the study area. According to the results, the temperature criterion did not have a significant effect on coronavirus in Iran. While temperature criterion can affect the coronavirus’s durability on surfaces, in this study, there was no strong relationship between temperature and the prevalence of coronavirus. The results of this study concerning the temperature criterion are consistent with the results of
A vulnerability map of the coronavirus in Iran’s provinces is shown in Fig. 7. According to the MGWR model results, Tehran, Qom, Mazandaran, and Gilan provinces are more vulnerable than other parts of Iran. High population density and higher percentages of the elderly are the biggest causes of vulnerability in these four provinces.

To predict and prepare the vulnerability maps for April and May, we used time series using the ANFIS model. Five-fold cross-validation was used to select the best training and data ratio in the ANFIS model. The results of the $R^2$ coefficients are summarized in Table 2. The highest value of $R^2$ is related to the 5-fold cross-validation with a value of 0.9533, and the lowest value of this coefficient is associated with 1-fold cross-validation with a value of 0.6295. The $R^2$ coefficient results indicated a high correlation between coronavirus disease and the four population density, elderly, temperature, and humidity criteria. Therefore, the 5-fold results were used to map the vulnerability of the coronavirus. A graph of the values fitted by the observed values is shown in Fig. 8.

The graph of the target and output data of the ANFIS model is shown in Fig. 9. The results show the appropriate fit of the output and target data for Iranian provinces.

ANFIS modeling was performed in MATLAB 2018 software, and the results were transferred to ArcGIS 10.3, to create a coronavirus vulnerability map (Fig. 10).

According to the ANFIS model results, West Azerbaijan, Zanjan, Fars, Yazd, Semnan, Sistan and Baluchistan, and Tehran provinces were more vulnerable than other provinces in April and May. According to the MGWR model results, in February and March, the provinces of Tehran, Gilan, Mazandaran, and Alborz were more vulnerable. Tehran province has a population of 16 million, with a higher population density leading to higher transmission of coronavirus in this province. On the other hand, Tehran province is known as the economic center of Iran, allowing the rest of Iran’s provinces more access to Tehran; this increases the prevalence of coronavirus, making the province more vulnerable. One way to reduce Tehran province vulnerability is to prevent people from attending social gatherings and enforcing household quarantine. Gilan and Mazandaran provinces are highly vulnerable due to their high population density and a higher percentage of older people. The provinces of Gilan and Mazandaran have many tourist attractions, with many tourists traveling to these three provinces each year. The presence of travelers from different regions increases the population of these three provinces and spreads the coronavirus. Therefore, to reduce the disease incidence, we proposed that travelers should be prevented from accessing these three provinces. Because of its proximity to Tehran and its industrialization, Alborz province has many industrial factories, with a large number of workers from neighboring provinces. The workers can spread the coronavirus to the central due to their business trips. Therefore, it is recommended that provincial industrial centers be temporarily closed to avoid the spread of the disease.

| K-fold cross validation | $R^2$    |
|-------------------------|---------|
| 1-fold                  | 0.6295  |
| 2-fold                  | 0.9458  |
| 3-fold                  | 0.7308  |
| 4-fold                  | 0.8864  |
| 5-fold                  | 0.9533  |

Table 2: Result of 5-fold cross-validation.
4. Conclusions

The spread of coronavirus in many parts of the world, including Iran, has caused significant public health problems. Therefore, management and planning to address and reduce diseases are needed. The purpose of this study was to investigate the vulnerability of Iranian provinces to coronavirus using four parameters: temperature, humidity, percentage of older people, and population density using GIS. According to the MGWR model results, population density and older people affected coronavirus in Iran greatly. Based on the results of the MGWR model in February and March, Tehran, Mazandaran, Gilan, and Alborz provinces were more vulnerable to coronavirus than other Iranian provinces. According to the results of the ANFIS model for April and May, West Azerbaijan, Zanjan, Fars, Yazd, Semnan, Sistan and Baluchestan, and Tehran provinces were more vulnerable to coronavirus than other Iranian provinces. According to the results of the ANFIS model for April and May, West Azerbaijan, Zanjan, Fars, Yazd, Semnan, Sistan and Baluchestan, and Tehran provinces were more vulnerable to coronavirus than other Iranian provinces. Therefore, avoiding travel and overcrowding in these provinces is suggested, owing to the provinces’ high population, tourist attractions, and industrial centers. Managers and decision-makers can identify high-risk provinces and provide them with more health facilities using coronavirus vulnerability maps.

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CRediT authorship contribution statement

Seyed Vahid Razavi-Termeh: Conceptualization, Formal analysis, Investigation, Software, Validation, Visualization, Writing – original draft, Data creation and. Abolghasem Sadeghi-Niaraki: Conceptualization, Methodology, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. Soo-Mi Choi: Project administration, Writing – review & editing, Funding acquisition.
Declaration of competing interest

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

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