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Research Paper

Prediction of highly vulnerable areas to COVID-19 outbreaks using spatial model: Case study of Cairo Governorate, Egypt

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ABSTRACT

COVID-19 has affected over 170 countries around the world. Alarming rate has increased with the increase of infected cases and death rates. Whereas, the World Health Organization (WHO) had declared the COVID-19 virus as a pandemic on 11th March 2020. Preparations were made to face the spread of COVID-19, as predicting the most probable risk areas by using spatial models. Prediction spatial models of COVID-19 risk areas can help the governmental authorities to generate sustainable strategies and set up suitable protocols to control the pandemic. This research presents an attempt of a potential spatial prediction modeling of COVID-19 risk areas in Cairo governorate-Egypt. Four indicator models (demo- graphic, residential, environmental and topographic) were developed using geomatics technology based on the guidelines of the UN-habitat sustainable development goals (SDGs) target (11 & 3). Five predicted scenarios were generated for the most pandemic probability areas by the integration of the four indicator models. The results showed that there are common areas in all scenarios for highly COVID-19 pandemic risk areas. These common risk areas were found in (El Marag, El Salam, Ain Shams, El Mataria, El Gammaleya, Manshiat Nasser, El Mosky, Bolak, Hadaak El Koba, and El Sharbeya) districts. The hotspots zones are characterized by overcrowding, high population density and economic activities, large family size, poor infrastructure service and low rate of education. Moreover, it was noticed that crowding points resulted in traffic density and air pollution, which may affect the pandemic spread. The accuracy assessment results displayed that, the environmental predicted scenario was more consistent with the official data of the Egyptian Ministry of Health and Population) MOHP), while the residential one was less convenient. The result of this study supports the health sector by predicting the hot spots areas. The present study is aimed to develop a proactive plan to confront the pandemic before spreading in the Cairo governorate-Egypt. Also, the proposed prediction model can be an effective aid for decision-makers across the world working on containment strategies to minimize the spread of Coronavirus.

1. Introduction

The COVID-19 first cases were in late 2019 in Wuhan, Hubei Province, China (WHO, 2020). Since then, it has become a global health concern on 11th March 2020 as it affected about 215 countries and territories around the world (WHO, 2020) with a wide variation between and within countries in the spread and severity of cases (Lu et al.,2020). About 83,910,386 cases and 1,839,660 deaths were globally confirmed on 4 January 2021 (WHO, 2020). On the national side, there have been 142,187 confirmed cases of COVID-19 and 7,805 deaths and the numbers are increasing daily (COVID-19 in Egypt, 0000). The COVID-19 has introduced a health challenge as it is a fast rate spreading disease (WHO, 2020). It transmits through the droplets or aerosols of coughs and sneezes, of infected people to the others (www.who.int; www.webmd.-com). Since the person is infected it will take about 2–14 days before the symptoms appear although sometimes there are no serious symptoms exist (Arti and Bhatnagar 2020; Pandey et al., 2020; Koubaa 2020).

Cities are centers of economic, social activities and a large and varied transportation network. Besides, they are characterized by large population density, it is worth to mention that more than 55 % of the world’s population lives in urban cities, and it is
expected to rise to 68% by 2050 (Oliinyk et al., 2020). According to the increasing population growth and the migration searching for work to improve the income level, the slums have appeared in such megacities. Hence, cities are considered hotspots of COVID-19 infections, particularly the global megacities compared to the countryside. Consequently, every country is trying to stop the spread of the virus, especially in megacities.

Geographic information system (GIS) technique has played an important role by providing COVID-19 infections tracking maps and also identifying the factors of virus spread (Thomas 2002; Smith and Mennis 2020; Murugesan et al. 2020; Mollalo et al., 2020). Wherefore, several research studies have developed models to represent the infection patterns of Coronavirus, its' transmission chain and the scale of the virus's spread with respect to different geographical regions (Chinazzi et al., 2020; Qi et al., 2020; Zheng et al., 2020). Other researchers identified the factors that could affect COVID-19 outbreaks separately in urban areas, as (Coskun et al., 2021) focused on the high population density and its correlation to higher virus spread and intensity which is one of the demographic factors. While (Shereen et al. 2020; Copiello and Grillenzoni 2020) studied the effect of social contact points on the dissemination of Coronavirus spread such as the illegal animal markets in Wuhan, China. Slums and poor services including sewage and water sources were the most residential factors that led to more exposure to outbreaks which have been studied by (Franklin and Bevins 2020). Furthermore, there were several studies focused on a correlation between environmental factors as air pollution and meteorological data and the spread of the virus (Wu et al., 2020; Wang et al., 2020; Taghizadeh-Hesary and Akbari 2020).

However, most of the available studies till now in this domain are unable to associate the impact of various factors with each other as they are vital points in preparing decisions for the virus spread containing. The proposed framework in the present study is an attempt to bridge the gap between studying effective factors of COVID-19 outbreaks separately and associate these various factors with each other through a spatial model. Our research study provides a spatial model of prediction of highly vulnerable areas to COVID-19 outbreaks in Cairo governorate-Egypt. This study, in particular, enlists the MCE (multi-criteria evaluation)-AHP (analytic hierarchy process) methodology that can be an effective mechanism for analyzing and minimizing the spread of COVID-19 in the Cairo governorate-Egypt. We have used AHP for prioritizing the various indicators and ranking them as per their weights obtained through literature review and expert knowledge.

![Fig. 1. Location of study area.](image-url)
The defining aspects of the proposed model are as follows:

- A collation of four indicator models that depended on the previous studies and the guidelines of the UN-habitat sustainable development goals (SDGs) target (11 & 3) which include:

  The demographic indicator includes urban population, rate of illiteracy, overcrowding, school enrolment, and quality of society. While, residential indicator refers to the factors of the habitat quality, connection to services, and constructivism density. The environmental indicator contains the crowding points as (bus stops, supermarkets, metro stations, etc.), traffic, road densities, air pollution as (NO$_2$, CO), and land / green spaces ratio. Slope changes and Digital elevation model (DEM) were identified as topographic indicators.

- Mapping the highly vulnerable areas to COVID-19 outbreaks in each indicator model to contain the virus spread.
- Producing five predicted scenarios for the most pandemic probability areas by the integration of the four indicator models.
- Providing a comparison between the most potential risk regions according to the MOHP and the five predicted scenarios to validate it.

Though the present study is aimed to develop a proactive plan to confront the pandemic before spread in the Cairo governorate-Egypt, the proposed prediction model can be an effective aid for decision-makers across the world working on containment strategies to minimize the spread of Coronavirus.

2. Study area

Cairo is the capital of Egypt and one of the largest cities in Africa and the Middle East. It is located in the northeast of the country at the Nile River with an area of 2749.5 km$^2$ and is bordered to the south by Qalyubia and Sharqea governorates and to the west by Giza governorate and to the east by Suez governorate, (Fig. 1). It is divided into 42 districts, with a population of over 9 million (CAPMAS, 2016), representing 10.6 % of the total population of Egypt. Cairo is considered a pole of migrations from all Egypt governorates such as industrial, medical, educational, commercial, governmental authorities, besides the entertainment activities. Furthermore, Cairo’s topography and climate make the pollution even worse. The city lies in a valley surrounded by hills, which hold the poisoned air. In addition, the MOHP statistics showed that Cairo occupied the first rank in the spread of the epidemic in Egypt. Thus, it was given a high priority in terms of studying the factors affecting the spread, then developing a methodology that resulted in a model which predicts the most vulnerable areas to the outbreak of the pandemic.

3. Materials and methods

3.1. Data

The data used in this study were obtained from different sources (Table 1). Remote sensing data included different sources as Sentinel-5 for NO$_2$ and CO pollutant gases, Sentinel-2 to produce the land cover, and the SRTM data was used for the topographic (Slop and DEM) data. The Demographic data was collected from the official reports of the central agency for public mobilization & statistics (CAPMAS). The land use and road layers were obtained from the general organization for physical planning (GOPP). Traffic density layers were created from a web mapping application called the urban observatory.

3.2. Methodology

The urban spatial prediction model of COVID-19 was developed based on the previous studies and the guidelines of the UN-habitat sustainable development goals (SDG 3 &11). Target 3 &11 of sustainable development goals regard good health, safe cities, resilience, and sustainability. Scenarios were created by compiling between 4 different urban indicator models, which are demographic, residential, environmental, and topographic. A variety of 25 factors were used to develop the four main indicator models (Table 2). Previous studies investigated the effect of different factors separately on the pandemic spread. All these factors and some selected UN-habitat’s urban indicators were collected and used as inputs to develop four main indicator models: demographic, residential, environmental, and topographic. These four indicator models were then integrated to provide five scenarios displaying

| Category                  | Date extraction time       | Type      | Source                                                                 |
|---------------------------|----------------------------|-----------|------------------------------------------------------------------------|
| Population density        | 2016                       | Vector    | (CAPMAS)                                                               |
| Overcrowding              |                            |           |                                                                        |
| School enrolment          |                            |           |                                                                        |
| Illiteracy rates          |                            |           |                                                                        |
| Old age ratio             |                            |           |                                                                        |
| Habitat quality           |                            |           |                                                                        |
| Common toilet             |                            |           |                                                                        |
| Connection to services    |                            |           |                                                                        |
| Constructivism density    | 2016                       | Vector    | General Organization for Physical Planning (GOPP)                      |
| Crowding points           |                            |           |                                                                        |
| Road density              |                            |           |                                                                        |
| Pollution                 | Average of month October 2020 | Raster | Sentinel-5 Satellite image with high resolution 7.5 km, Sentinel-5 delivers daily global coverage for climate, air quality, and ozone/surface UV applications.Open Access Hub Extracted from LULC which created from Sentinel-2, with high resolution (10 m$^2$) |
| Land space ratio          | 2020                       | Vector    |                                                                        |
| Green spaces ratio        |                            |           |                                                                        |
| Traffic density           | Up to date 2020            | Vector    | From A web mapping application called the Urban Observatory (https://www.urbanobservatory.org/) Created by Technology/Entertainment/ Design (TED) founder Richard Saul Warman, Radical Media, and Esri. |
| Slope                     | 2013                       | Raster    | Shuttle Radar Topography Mission (SRTM)                                |
Table 2
Selected indicators for prediction of highly vulnerable areas to COVID-19 outbreaks spatial model.

| Demographic Indicator | Sub Factors | (11) Urban population: | (10) Rate of illiteracy | (2) Overcrowding: | (6) School enrolment: | Quality of society: |
|-----------------------|-------------|------------------------|-------------------------|--------------------|----------------------|-------------------|
|                       |             | Population density     |                         | Overcrowding Average size of the family | Primary education ratio | Old age ratio |
| Residential Indicator | Sub Factors | (1) Habitat Quality:   |                         |                    |                      |                   |
|                       |             | Unsuitable habitat     |                         |                    |                      |                   |
|                       |             | Common toilet          |                         |                    |                      |                   |
|                       |             | (6) Connection to services (Poor Services): | |                    |                      |                   |
|                       |             | Sanitation networks    |                         |                    |                      |                   |
|                       |             | Water networks         |                         |                    |                      |                   |
|                       |             | Electricity networks   |                         |                    |                      |                   |
|                       |             | Natural gas network    |                         |                    |                      |                   |
| Environmental Indicator | Sub Factors | Crowding points:     | Roads:                  | Pollution:          | Land space ratio     | Green spaces ratio |
|                       |             | Bus stops              | Traffic density         | NO₂                |                      |                   |
|                       |             | Subway                 | Road density            | CO                 |                      |                   |
|                       |             | Super market           |                          |                    |                      |                   |
|                       |             | Cafes                  |                          |                    |                      |                   |
|                       |             | Theatres               |                          |                    |                      |                   |
|                       |             | Bakeries               |                          |                    |                      |                   |
|                       |             | Factories              |                          |                    |                      |                   |
|                       |             | Hospitals              |                          |                    |                      |                   |
|                       |             | Pharmacies             |                          |                    |                      |                   |
| Topographic Indicator | Sub Factors | DEM                   | Slope                   |                      |                      |                   |

Source: after Urban Indicators Guidelines – 2004 (SAULE JÚNIOR and CARDOSO, 2004).
PS: Indicator number (x) is taken after the UN indicator coding. No numbering indicates that proxy indicator is created by the researchers.
the most predicted pandemic spreading areas. The five predicted potential risk scenarios were then compared to the official data from the MOHP to verify the results. A conceptual flow chart describes the methodology as shown in (Fig. 2).

3.2.1. Air quality

NO$_2$ and CO pollutant gases were studied to investigate the effect of air pollution as an indicator for COVID-19 spreading prediction. NO$_2$ and CO are considered the most dangerous and harmful air pollutants in urban areas (Costa et al., 2014). Power generation, industrial and traffic are the major sources of nitrogen oxides. CO is raised from the burn of fuels (Safar and Labib 2010). The average month of October 2020 was obtained as it is considered one of the most pollutant months during the year. Frequent temperature inversions settle over Cairo in October as a warmer, lighter air mass moves over a colder, denser air mass, trapping a layer of air close to the ground. The inversions still the winds, creating a stagnant soup of unmoving air. Meanwhile, an extremely dry climate means that cleansing rainstorms rarely appear (Leitzell 2011). It was downloaded with spatial resolution 7.5 Km $\times$ 7.5 Km for NO$_2$ and CO gases concentrations from Sentinel-5 satellite data. The data analysis was carried out using the SNAP toolbox for Sentinel applications.

3.2.2. Land cover

A Sentinel-2 satellite image with a spatial resolution of 10 m was used to extract the land cover. The analysis was made by Arc GIS 10.4 software. The image was classified by the Unsupervised-ISO Cluster method into five land-cover classes, which were named: urban areas, space areas, green areas, quarries, and water. A Majority Filter tool was run to clean the output classes. Some pixels have remained, thus other clean-up processes are required. The pixels that remained were cleaned up using the Region Group tool that was applied to collect the pixels that have the same values. And the Set Null operation was used to remove unwanted pixels. Furthermore, a Nibble tool was operated to enhance the used classes by integrating the resulted Majority Filter image with the masked Set Null image. Finally, the output raster classes were converted to vectors for further analysis.

3.2.2.1. Slope and DEM. The topographic data were obtained from the STRM satellite image with a spatial resolution of 30 m. The DEM shows the land heights according to sea level. A Spatial Analyst tool was applied to extract the slope (changes in the Z levels).

3.2.2.2. Demographic & residential data. CAPMAS annual reports were used to obtain demographic data such as population density, overcrowding and average size of the family rates. The ratios of old

![Fig. 2. A conceptual flow chart for the applied methodology.](image-url)
3.2.2.3. Land use. Constructivism density, crowding points, and road density were analyzed by applying equations for the collected vector data from the GOPP.

3.2.2.4. Traffic density. Traffic density layers were digitized from a web mapping application called the Urban Observatory.

3.3. The geography of the COVID-19 pandemic

The importance of geography comes in its ability to link the social sciences and the natural sciences as the main two branches of geography are human and environmental. Human geography is concerned with the spatial aspects of human existence. While, environmental geography studies the patterns of climates, landforms, vegetation, soils, and water. Geographical tools and techniques showed an important role to assess, interpret and respond to any disease pandemic, especially in pandemics like COVID-19 2019 (Murugesan et al., 2020).

3.4. Correlation between urban indicators and COVID-19 risk areas

Studies showed that urban indicators that affect the spread of COVID-19 are demographic, residential, environmental, and topographic indicators (Wang et al., 2020; Shereen et al., 2020; Dehghan Shabani and Shahnazi 2020). The demographic indicators include urban population, rate of illiteracy, overcrowding, school enrolment, and quality of society. While, the residential indicators refer to the factors of habitat quality, connection to services, and constructivism density. Environmental indicators contain the crowding points as (bus stops, supermarkets, metro stations, etc.), traffic, road densities, air pollution as (NO₂, CO), and land / green spaces ratio. Slope changes and DEM were identified as topographic indicators.

3.5. AHP method to computing weights and priorities

The Analytical Hierarchy Process (AHP) is an analyzing method for organizing decisions. AHP provides a rational framework for a needed decision, in which many variables or criteria are considered.
in the prioritization and selection (quantification) of alternatives (Saaty, 1977). The AHP method uses hierarchical structures to represent a problem and then develop priority scales through the numeric scale calibration for measuring the qualitative performances (Saaty, 1977). The first step of the AHP process is defining the problem into smaller constituent parts. In this study, a set of criteria was developed by combining an intensive literature review and expert knowledge and classified into four main groups (Indicators), demographic, residential, environmental, and Topographic Indicators. Each main indicator contains a set of related factors (Sarwar and Imran, 2021; Singh and Avikal, 2020). Five experts from different governmental authorities such as the National Authority for Remote Sensing & Space Sciences (NARSS), General Organization for Physical Planning (GOPP), and Egyptian Environmental Affairs Agency (EEAA) were contributed to derive the sub-factors weights. A pairwise comparison of the criteria was made to estimate the relative weights using Saaty’s scale. Finally, a square matrix a consistency ratio was checked as the required threshold value should be less than 0.1 by the following equations:

\[
CI = \frac{(yy_{\text{max}} - n)}{n - 1} \quad (1)
\]

(CI): Consistency indexn: number of criteria being compared (for a reciprocal matrix, yy max ≥ n).

The consistency ratio (CR) was obtained by dividing the CI by the random consistency number of the same size matrix as follow:

\[
CR = \frac{CI}{CIR} \quad (2)
\]

Where IR is the average value of CIR values for random matrices using the Saaty scale, (Table 3). A Saaty’s scale was utilized in the pairwise comparison matrix for demographic, residential, environmental and topographic indicators respectively, (Table 4). Four indicator models were produced by prioritizing indicators as explained below, (Tables 5–8).

### 3.6. Developing urban spatial prediction model of COVID 19 by geomatics techniques

Studied indicators were grouped according to proper weightings. Each indicator was produced as a map layer for further analysis. A Standardizing process step was generated to transform the attributes of each indicator into a common suitability index, (Tables 9, 10, 11 and 12). These indices reflect a scale number from 1 to 5. The scale 1 refers to the least risk areas for COVID-19 pandemic.

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**Table 9** Standardization of the demographic indicator factors.

| Scale | Demographic Factors |
|-------|---------------------|
|       | Population density (km²) | Overflowing (%) | Average size of the family (%) | Illiterate ratio (%) | Primary education ratio (%) | Higher education ratio (%) | Old age ratio (%) |
| 1     | 465.34–17103.02 | 0.56–0.73 | 2.07–2.44 | 3.49–14.14 | 4.51–7.91 | 64.36–78 | 3.77–8.57 |
| 2     | 17103.02–33740.70 | 0.73–0.91 | 2.45–2.82 | 14.14–24.78 | 7.91–11.30 | 43.86–64.36 | 8.57–13.38 |
| 3     | 33740.70–50378.38 | 0.91–1.08 | 2.82–3.20 | 24.78–35.43 | 11.30–14.70 | 26.67–43.86 | 13.38–18.18 |
| 4     | 50378.38–67016.06 | 1.08–1.25 | 3.20–3.57 | 35.43–46.07 | 14.70–18.09 | 15.98–26.67 | 18.18–22.99 |
| 5     | 67016.06–84653.75 | 1.25–1.43 | 3.57–4.00 | 46.07–57.00 | 18.09–22 | 3.16–15.98 | 22.99–27.89 |

**Table 10** Standardization of the residential indicator factors.

| Scale | Residential Factors |
|-------|---------------------|
|       | Unsuitable habitat (%) | Common toilet (%) | Water unconnected ratio (%) | Sanitation unconnected ratio (%) | Electricity unconnected ratio (%) | Gas unconnected ratio (%) | Constructivism density |
| 1     | 0.47–6.70 | 0.058–6.31 | 0.11–0.74 | 0.16–4.35 | 0.13–1.06 | 1.59–24.03 | 9.66–205.11 |
| 2     | 6.70–12.93 | 6.31–12.56 | 0.74–3.27 | 4.35–8.55 | 1.06–4.09 | 24.03–41.2 | 205.11–400.56 |
| 3     | 12.93–19.16 | 12.56–18.81 | 3.27–8.09 | 8.55–12.75 | 4.09–8.56 | 41.2–58.68 | 400.56–596.01 |
| 4     | 19.16–25.39 | 18.81–25.06 | 8.09–13.03 | 12.75–16.95 | 8.56–12.96 | 58.68–73.46 | 596.01–791.45 |
| 5     | 25.39–31.62 | 25.06–31.31 | 13.03–21 | 16.95–22 | 12.96–22.25 | 73.46–99.46 | 791.45–990 |

**Table 11** Standardization of the environmental indicator factors.

| Scale | Physical Environmental Factors |
|-------|---------------------|
|       | Road density (Km²) | Traffic density (Km²) | Land space ratio (%) | Crowding points (m²) | NO₂ (Mol/m²) | CO*10⁻⁴ (Mol/m²) | Green space ratio (%) |
| 1     | 0.82–1 | 13641.84–17052.30 | 75.51–94.39 | 7339.84–9174.79 | 0.000009–0.000014 | 0.00049–0.00058 | 6.23–32.45 |
| 2     | 1–3.47 | 10231.38–13641.83 | 56.63–75.51 | 5504.88–7339.83 | 0.00014–0.000019 | 0.00058–0.00068 | 4.8–6.23 |
| 3     | 3.47–6.36 | 6820.92–10231.37 | 37.76–56.63 | 3669.92–5504.87 | 0.000019–0.000023 | 0.00068–0.00078 | 1.49–4.8 |
| 4     | 6.36–8.73 | 3410.46–6820.91 | 18.87–37.75 | 1834.95–3604.91 | 0.000023–0.000028 | 0.00078–0.00088 | 1.07–1.49 |
| 5     | 8.73–65 | 0–3410.45 | 0–18.87 | 0–1834.95 | 0.000028–0.000033 | 0.00088–0.00097 | 0–1.07 |

**Table 12** Standardization of the topographic indicator factors.

| Scale | Topographic factors | DEM |
|-------|---------------------|-----|
| 1     | Slope | 0–2.14 | 335.4–417 |
| 2     | 2.14–4.87 | 253.8–335.4 |
| 3     | 4.87–9.72 | 172.2–253.8 |
| 4     | 9.72–18.99 | 906.3–172.2 |
| 5     | 18.99–60 | 9–90.6 |
demographic distribution in Cairo governorate while 5 refers to the most risk areas, (Figs. 3, 4, 5 and 6). Then the weighted overlay process was applied to produce demographic, residential, environmental, and topographic indicators maps. Five scenarios were developed by compilation of the mentioned indicators.

3.7. Accuracy assessment

The overall accuracy and the Kappa Coefficient (KC) were considered in the accuracy assessment of the final output predicated scenarios. The accuracy assessment of the most potential risk

Fig. 3. Standardized factors maps for demographic indicator; (A) Population density; (B) Overcrowding rate; (C) Average size of the family; (D) Illiterate ratio; (E) Primary education ratio; (F) Higher education ratio; (G) Old age ratio.
Fig. 4. Standardized factors maps for residential indicator; (A) Unsuitable habitat ratio; (B) Common toilet; (C) No sanitation; (D) No water network; (E) No electricity network; (F) No natural gas network; (G) Constructivism density.
regions was taken according to the official data from MOHP. The most recorded risk areas obtained by the official data MOHP were presented by 600 random points. The verification step was carried out for each scenario through the “confusion matrix” process using the “ground truth ROI” tool by the ENVI software. The accuracy assessment % and Kappa Coefficient were calculated and obtained for each scenario.
Fig. 6. Standardized factors maps for topographic indicator; (A) DEM; (B) Slope.

Fig. 7. Combined standardized factors maps result for each indicator.
4. Results and discussion

4.1. Relationship between main four indicator models and spread of COVID-19 pandemic

The probability risk areas of each of the four indicator models were presented in (Fig. 7).

The results of demographic indicator model showed that the most probability risk areas were in the north and center parts of Cairo. This is due to the fact that the demographic indicator is

Table 13
Assigned weights for multiple study scenarios.

| Factors     | Demographic | Residential | Physical environmental | Topographic |
|-------------|-------------|-------------|------------------------|-------------|
| Demographic | 55          | 15          | 15                     | 15          |
| Residential | 15          | 55          | 15                     | 15          |
| Environmental | 15        | 15          | 55                     | 15          |
| Topographic | 15          | 15          | 15                     | 55          |
| Equal       | 25          | 25          | 25                     | 25          |

Fig. 8. The most vulnerable areas to COVID-19 outbreaks in each scenario.
related to the population density, and therefore the results showed an increase in the northern areas with a high population increase. Due to the increase in the average family size and old people ratio, the overcrowding resulted in the northern districts: El Marag, El Salam, Ain Shams, and El Mataria. Also, the center districts as El Gammaleya, Manshiat Nasser, El Mosky, Bolak, Hadaak El Koba, El Sharbeya and Tora. The least probability risk areas were located in new cities as New Cairo, 15 May and El-Nozha, where there is a low population with large spaces.

The most risky areas of residential indicator model were El Marag, Bolak, El Azbakeya, Rod El Farg, Shoubra, Bab El Sharia, and El Mosky, that’s because of slums resulting in high constructivism density. While the planned districts showed low risk as El-Nozha, El-Maadi, Awal and Thani Nasr City.

The industrial districts were shown as the most risk areas of the environmental indicator models as El-Sahel, El Zawia El Hamra, El Sharbeya, Hadaak El Koba, El Mataria, El-Zayton, and parts of El Marag and El Salam. These districts considered as crowding points resulted in traffic density and air pollution. Also, the east wind direction affect these areas which are located north and northwest of Cairo. The low risk districts are characterized by high green and land space ratio, as new Cairo, El-Katamea and 15 May.

Finally, the topographic indicator was affected by the slope direction as the most risk areas appeared in the west parts along the Nile River, as El Wayly, Helwan, El Tebeen, El Sayda Zeineb, El Azbakeya, Abdeen and El-Azher. The lower risk districts distinguished by high slopes were Badr, 15 May, El Shrouk and El Katameya.

4.2. Representation of COVID-19 probability areas scenarios

Scenarios were developed by the integration of the previous 4 main indicator models. Each scenario was produced by prioritizing one selected indicator over the others, resulting in 4 scenarios. Furthermore, there was an equal scenario, which gives all the indicators equal weights, (Table 13).

The highly vulnerable areas to COVID-19 outbreaks in each scenario were illustrated in (Fig. 8) & (Table 14), as following:

These results expose some significant findings as follows:

- The environmental scenario ranked first in highly vulnerable areas to COVID-19 outbreaks with a total area (171.582 km²) percent (13.98%). Due to humans and economic activities which lead to increased air pollution. The most risk zones resulted in 21 districts (El Marag, El Salam, Ain Shams, El Zaytoon, El Mataria, El Gammaleya, Manshiat Nasser, El Mosky, Bolak, Hadaak El Koba, El Sharbeya, El Zawia El Hamra, Rod El Farg, El Zaher, Shoubra, El Azbakeya, Bab El Sharia, Abdeen, El Darb El Ahmar, Manshiat Nasser, El Sayda Zeineb, Misr El Qidima, El Khalifa and El Wayly). While the less risky areas resulted in the new districts as New Cairo and the 15 may city because of the large green areas.

- The flatness of slope - unlike the areas located on the high slopes - crowded streets, and slums were considered as the main reasons for taken the topographic scenario second rank. The most vulnerable areas to COVID-19 outbreaks in this scenario were found in 7 districts El Wayly, Helwan, El Tebeen, El Sayda Zeineb, El Azbakeya, Abdeen and El-Azher with a total area (168.3 km²) percent (13.7%).

Table 14
The most vulnerable areas to COVID-19 outbreaks.

| Scenario   | Area Km² | %    |
|------------|----------|------|
| Demographic| 86.078   | 7.014|
| Residential| 4.838    | 0.394|
| Environmental| 171.582 | 13.98|
| Topographic| 168.374  | 13.72|
| Equal      | 100.778  | 8.30 |

Fig. 9. Relationship between the urban pattern and COVID-19 Outbreaks in equal scenarios.

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The high population density, illiteracy rate, and slums have made the demographic scenario occupy the third rank with an area of (86.078 km²) and a percent (7.014%) of the total Cairo governorate area. Ten districts represented the highly vulnerable areas to COVID-19 outbreaks (El Marag, El Salam, Ain Shams, El Mataria, El Gammalya, Manshiat Nasser, El Mosky, Bolak, Hadaak El Koba, and El Sharbeya) in this scenario.

Finally, the residential scenario was ranked last in highly vulnerable areas to COVID-19 outbreaks with a total area (4.838 km²) percent (0.394%). Moreover, this scenario can give more effective results in any other region in Egypt due to the nature of the capital, Cairo of unsuitable habitat, high constructivism density, and poor service area.

The equal scenario is the best scenario for highly vulnerable areas to COVID-19 outbreaks because it takes into consideration all the indicators of sustainable development, whether demographic, residential, topographic, or environmental without focusing on one indicator. The urban environment had a clear effect in highly vulnerable areas to COVID-19 outbreaks in the equal scenario. Slums are more vulnerable to COVID-19 outbreaks than well-planned areas. Fig. 9 showed that the planned areas take into account the availability of the spaces between buildings and green spaces, which provide airflow, such as New Cairo. While the most vulnerable risk areas to the spread of the epidemic are characterized by dense buildings and random construction, such as El Marag and El Sharbeya. (Fig. 9).

### 4.3. Accuracy assessment of potential COVID 19 pandemic risk areas scenarios

The environmental scenario was more consistent with the MOHP official data for the most potential risk regions with an overall accuracy of 96.32 %, (Table 15). Whereas, the environmental scenario included the crowding points which are considered as infection points: bus stops, subways, cafes, and markets. Also, air pollution, traffic density, and land space ratio played an important role in the pandemic. The least overall accuracy was obtained for the residential scenario by 76.62%. The residential scenario did not achieve the hoped result in our study area. Perhaps the capital differs from other cities in increasing the load on residential indicators as a result of its occupation of the highest population density. Hence, it has a high rate of unsuitable habitat, common toilet, constructivism density and poor infrastructure (water, sanitation, electricity, gas).

Although many previous studies have dwelt upon the infection dynamics factors worldwide, there is still no common or standardized mechanism that collecting the different factors and indicators together for tracing the COVID-19 outbreak. Thus, our paper is an initiative to propose a standardized approach that can help in containing COVID-19 by devising more effective countermeasures.

### 5. Conclusion

Spatial modeling is an effective tool which helps to provide the strategists with the necessary data required to formulate contain-ment policies for controlling the virus in the severely affected regions in Cairo governorate - Egypt. The model includes MCE-AHP for prioritizing the available indicators to control the spread of COVID-19. The approach developed by us is based on the previous studies and the guidelines of the UN-habitat sustainable development goals (SDG 3 & 11) which regard good health and making cities safe, resilient, and sustainable. The proposed model provides a systematic framework for predicting of highly vulnerable areas to COVID-19 outbreaks through four urban indicator models (demographic, residential, environmental, and topographic). These indicator models were integrated together to produce five predicted scenarios. That can provide more focus to healthcare services and methods that would efficiently and quickly reduce the spread of COVID-19.

The results show that the environmental scenario ranked first in highly vulnerable areas to COVID-19 outbreaks with a total area (171.582 km²) percent (13.98%), due to humans and economic activities which lead to increased air pollution such as El Marag, El Salam and Ain Shams. While the Less vulnerable areas are characterized by well-planned in the new districts as New Cairo and the 15 may city. The results display that the residential scenario was ranked last in highly vulnerable areas to COVID-19 outbreaks with a total area (4.838 km²) percent (0.394%). Moreover, this scenario can give more effective results in any other region in Egypt due to the nature of the capital, Cairo of unsuitable habitat, high constructivism density, and poor service. Furthermore, the results illustrate that the environmental scenario was more consistent with the MOHP official data of the highly vulnerable areas to COVID-19 outbreaks. While the residential scenario was less consistent with it. An effective modeling study would provide the decision-makers with the necessary approach to develop containment policies for controlling the virus spread in the various affected regions of Egypt not only in Cairo. On the other hand, the proposed model can also be a template for predicting the spread of other pandemics in Egypt. An appropriate methodology would further enhance the war against the virus by studying the correct infection dynamics. The study concluded that urban planners should take into consideration the environmental and health aspects in the sustainable urban planning of cities and districts.

Future work includes model improvement by adding more health data so that the results of the possible scenarios will be more accurate. Besides, the model will be developed to be applied to different pandemics according to the way the pandemic spreads.

### Conflict of Interest

The authors declare no conflict of interest

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