Scholarly Publisher
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JOURNAL	International Journal of Innovative Technologies in Social Science
p-ISSN	2544-9338
e-ISSN	2544-9435
PUBLISHER	RS Global Sp. z O.O., Poland

ARTICLE TITLE	IDENTIFYING COVIDOGENIC ENVIRONMENTS IN URBAN SECTORS OF KHROUB CITY (ALGERIA): A GIS-BASED APPROACH TO ASSESSING PANDEMIC RISK AND VULNERABILITY
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ARTICLE INFO	Mouna Mazri, Saif Eddine Chettah, Manal Yahiouche. (2024) Identifying Covidogenic Environments in Urban Sectors of Khroub City (Algeria): a GIS-Based Approach to Assessing Pandemic Risk and Vulnerability. *International Journal of Innovative Technologies in Social Science*. 2(42). doi: 10.31435/rsglobal_ijitss/30062024/8155
DOI	https://doi.org/10.31435/rsglobal_ijitss/30062024/8155
RECEIVED	14 April 2024
ACCEPTED	19 May 2024
PUBLISHED	23 May 2024
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IDENTIFYING COVIDOGENIC ENVIRONMENTS IN URBAN SECTORS OF KHROUB CITY (ALGERIA): A GIS-BASED APPROACH TO ASSESSING PANDEMIC RISK AND VULNERABILITY

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DOI: https://doi.org/10.31435/rsglobal_ijitss/30062024/8155

ARTICLE INFO

Received 14 April 2024
Accepted 19 May 2024
Published 23 May 2024

KEYWORDS

Covidogenic Environment, GIS, Vulnerability Indicators, Exposure, Sensitivity, Adaptive Capacity.

ABSTRACT

This study aims to assess the pandemic risk in the Algerian city of Khroub and develop a monitoring and health management tool to combat Covid-19 and other respiratory infections. To address the lack of statistical data at the micro-urban level, the authors conducted a household survey in Khroub between July and September 2022. The primary objective of this survey was to collect comprehensive data on vulnerability indicators at the scale of Khroub's urban sectors. The study utilized 13 indicators of vulnerability to Covid-19, selected from previous studies and research published by public health organizations and agencies. GIS technology was used to locate covidogenic environments (milieu) in Khroub, resulting in the creation of a GIS database called "Covidogenic Milieu." This study provides valuable insights for identifying vulnerable urban sectors and implementing adaptive measures to mitigate the effects of Covid-19. In the case of Khroub, the research also made relevant suggestions on how to address the identified vulnerability for the benefit of local authorities who commissioned this study.

Citation: Mouna Mazri, Saif Eddine Chettah, Manal Yahiouche. (2024) Identifying Covidogenic Environments in Urban Sectors of Khroub City (Algeria): a GIS-Based Approach to Assessing Pandemic Risk and Vulnerability. *International Journal of Innovative Technologies in Social Science*. 2(42). doi: 10.31435/rsglobal_ijitss/30062024/8155

Introduction.

On March 11, 2020, Covid-19 was declared a pandemic by the WHO, causing the most serious health crisis of the century. The impact of this pandemic has been uneven. The prevalence and lethality of the disease worldwide showed that some populations were more exposed to infection and mortality than others. As a result, some regions have proven more resilient or vulnerable than others. This finding challenges the importance of location in epidemiology, where studies have focused on the pathogen and the host without making progress in understanding the location of the epidemic. However, the Centers for Disease Control and Prevention (CDCP) has noted that in infectious diseases, the "who" and "when" often depend on the "where" (1). Geographers have been interested in mapping pandemic locations, particularly the spatial modeling of Covid-19 via geographic information systems (GIS). Through the geospatial identification of potential transmission sites, which we refer to here as “covidogenic environments”[1], the use of GIS allows the visualization of ongoing endemic dynamics and their prediction. After processing and cross-analyzing data on vulnerability indicators (VIs), GIS has the advantage of spatializing these environments and segmenting them according to their degree of risk. GIS thus opens up new perspectives on health issues when operationally integrated into a Spatial Reference Decision Support System (SRDSS) (6). Despite the growing number of geographic approaches using GIS to study pandemic risk around the world (2, 3), this type of research remains very modest in North Africa. Most other published work examines national or continental scales except for pandemic modeling in the city of Cairo (4) and the Algerian city of Batna (5), which remain highly relevant at suburban scales. Nevertheless, the finer scales of pandemic modeling are most effective in guiding prevention and decision-making (7). Following on from the two aforementioned papers, this paper will examine pandemic risk in the City of Khroub. It should be noted that the research was commissioned by the city's local authorities. The aim is to provide a monitoring and health management tool to cope with the pandemic Covid-19 and demonstrate greater resilience to other endemic respiratory diseases.

1. Methods and materials.

1.1. Study area.

Located in northeastern Algeria (Figure 1), with a latitude of 36° 16′ 00″ North and a longitude of 6° 41′ 00″ East, the city of Khroub is located in the Northern Hemisphere region that has been declared at high risk of high pandemic transmission (Bannister et al , 2020). With an estimated population of 115,000, Khroub is one of Algeria's largest cities according to the national nomenclature. Administratively, it is part of the Wilayal territory of Constantine, one of the five largest pandemic areas in the country with the highest incidence and mortality rates during Covid-19 (8). Despite the fact that Algerian health services only publish data at the wilayal level, without reporting the exact epidemiologic situation of each city, we assume that because Khroub is one of the main urban centers in the Wilaya of Constantine, it is duly involved in the criticality of the incidence and case-fatality rates in this Wilaya.

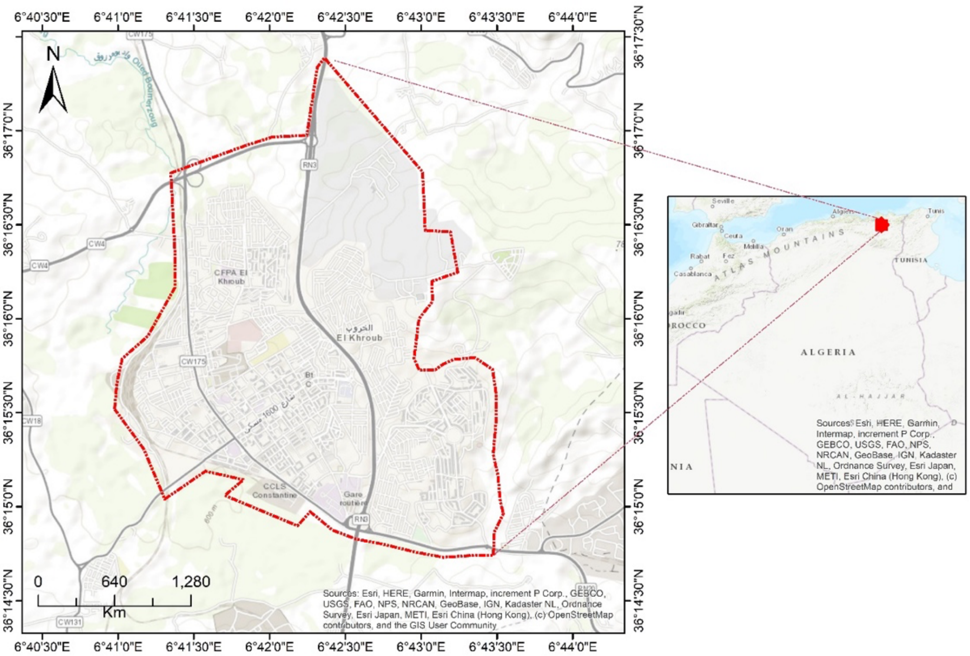

Figure 1. Study area location (authors).

[1] If any crisis scenario stimulates vocabulary and terminological innovation, we recommend using the term covidogen as a lexical borrowing of the terms carcinogen and epidemiogen to refer to these at-risk contexts.

1.2. Approach.

To implement a thematic GIS on covidogenic environments, we have adopted an approach divided into three phases:

- **Setting up vulnerability indicators (VIs).**

Based on previous studies that summarize the progress of research on the risk factors of a pandemic, we were able to identify 13 VIs to Covid-19 as detailed in table 1. These have been selected for their ability to be measured at a micro-urban scale and, of course, at a neighborhood scale. Climatic, macroeconomic (GDP), or managerial indicators (beds, nurses, etc.) were excluded. The 13 VIs were selected from two types of literature. These include studies and research published by public health organizations and agencies (9-12) and those published in high-impact factor journals. Consequently, the classification of our selected VIs corresponds to the conceptual framework (figure 2) related to "vulnerability" (V), which is manifested by three fundamental dimensions: exposure (E), sensitivity (S), and adaptive capacity to risk (AC) (13), measured by White et al (14) using the following equation:

$$V = (E*S)/AC$$

Table 1. Classification and description of the selected VIs.

Type of vulnerability	Variables/Indicators	Calculation method	Relevance of the indicator according to the literature
1	2	3	4
EXPOSURE Refers to the potential risk of contamination resulting from the presence of people in environments with a high probability of virus transmission. Thus, the socio-spatial proximity in the residential space becomes the main factor of exposure.	Demographic Density	By dividing the number of inhabitants of a neighborhood by its total area	It measures the concentration of population in urban space. Density affects social distancing within neighborhoods (17-20).
	Occupancy per unit (TOL)	Enumeration of the number of individuals living in the same house	It measures the interpersonal closeness between family members within the home (21,22)
	Occupancy per room (TOP)	Enumeration of the number of individuals living in the same dwelling and sharing the same room	It measures the interpersonal proximity between family members in a room (21,22)
	Ventilation and sunlight in the dwellings Total	Counting the number of dwelling with poorly ventilated spaces facing north or northwest	Indoor ventilation and UV light help reduce SARS-CoV-2 infectivity (10, 23, 24).

Table 2. Continuation.

1	2	3	4
SENSITIVITY Refers to the probability of succumbing to a hazard (15). In our study, we consider the health and demographic characteristics of the population that may predispose to disease.	Chronic diseases	Number of inhabitants with at least one chronic disease: diabetes, hypertension, cardiovascular, respiratory, renal.	Both chronic disease, age, and masculinity increase the risk of complications and lethality (10, 25-27)
	Age	Number of inhabitants over 60 years old.	
	Masculinity	Number of males inhabitants over 18 years old.	
	Vaccination Total	Number of people who have not been vaccinated against Covid19	Anti-Covid19 vaccine coverage is negatively correlated with Covid-19 reproduction rate and intensive care hospitalization rates (28)
ADAPTIVE CAPACITY Refers to social resilience and the ability of a community potentially exposed to hazards to adapt to them by resisting or transforming to maintain an acceptable level of functioning [16]. It is associated with socioeconomic and prevention-related indicators.	Revenues	Number of inhabitants with a monthly income < 30 000 DA	Economic fragility hinders access to health care and social security (17, 20, 29-33)
	Unemployment	Number of unemployed residents.	
	Education	Number of illiterate inhabitants.	Education level reduces access to health risk information and reduces the likelihood of accessing higher-income employment (17, 20, 29-33)
	Prevention Total	Number of residents not complying with prevention measures	Handwashing, wearing masks, respect for distancing and eviction from frequented places are the barriers to the virus transmission (9,10)

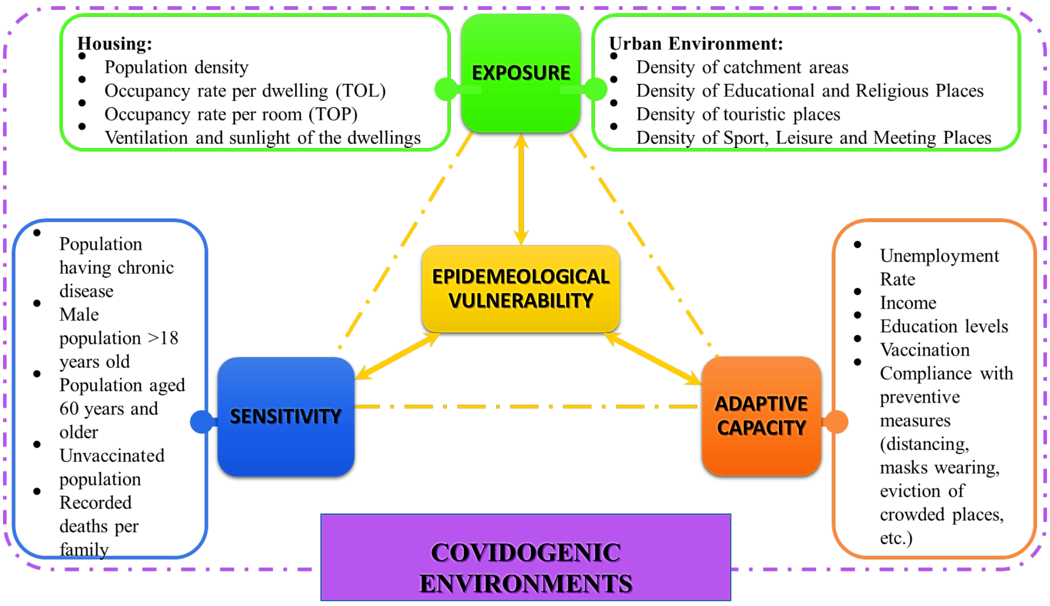

Figure 2. Conceptual framework of the study (authors).

- **Statistical data collection.**

As previously stated, the lack of statistical data connected to the variables targeted by this research at the micro-urban level in Khroub has prompted us to approach the living environments by conducting a household survey between July and September 2022. This marks the end of the first three epidemic outbreaks in Algeria. The survey methodology was technically assisted by the regional health observatory (ORSEst), while the fieldwork was backed by the city of Khroub's municipal authorities. Based on Krejci and Morgan's (33) sampling approach, our survey sample included 1050 houses with a total of 5536 persons inhabiting the residential sectors. However, this study excluded urban sectors that are being occupied or with a low population density (figure 3).

The survey is areal in design, with three levels of geographic units (primary, secondary, and tertiary sample units) spanning from macro to micro. In other words, we progressed from the district level through the housing unit to the dwelling occupied by the household. The plan is built on digital cartographic support, which enables a probabilistic sample selection based on more exact estimations of the variables of interest (35). The city's territory has been operationally divided into eight urban sectors (figure 3) based on the physical boundaries provided by the National Statistics Office (ONS).

The goal is to supplement current information on these sectors with epidemiological data that can help to improve urban resilience. The face-to-face interview is the primary mode of data collection, with interviewers mobilizing to ensure both the door-to-door survey and the daily entry of replies obtained on Google Forms[2] to avoid the risks of tablet surveys (cost, connection speed, etc.). SPSS software was used to process the data that was entered. The primary goal of this household survey is to collect enough comprehensive data to inform the VIs at the scale of Khroub's urban sectors. These data were extensively utilized to create our GIS database "Covidogenic Milieu."

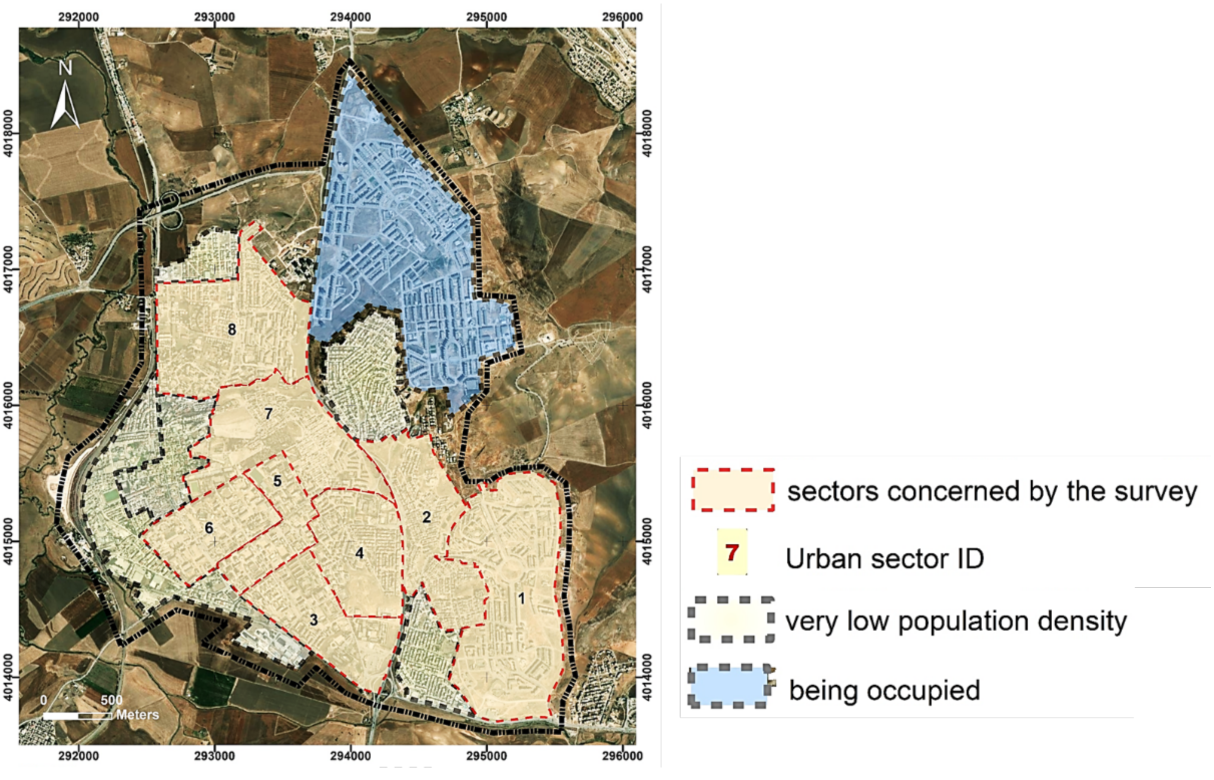

Figure 3. Urban sectors concerned by the household survey in khroub city (authors).

[2] Accessible via the link https://forms.gle/UuNWvecoVqtZq2hb7

- **Data geo-processing and weightings.**

Because the input criteria layers will be in different numbering systems with varying ranges, all indicators in ArcGIS Desktop 10.8 are required to be reclassified on the same measurement scale. In other words, using the Weighted Overlay tool, which offers features enabling geospatial aggregation of VIs based on multi-criteria analysis, we reclassified the VIs values in the input rasters into a risk rating scale ranging from 1 to 8 based on two models. The first involves crossing variables related to the same vulnerability typology to model three vulnerability situations (Exposure, Sensitivity, and Adaptive Capacity). The second approach involves superimposing all of the variables to illustrate epidemiological vulnerability. The weight of importance (influence rate) required for the weightings shown in Table 2 reflect the strength of the dependency relationship between each vulnerability indicator and the risk of contamination or lethality, provided that the sum of the rates of influence relating to one or both of the vulnerability dimensions equals 100%. These rates were calculated in collaboration with ORSEst epidemiologists. The fact that variables measuring density, housing quality, vaccination, comorbidity, age, education levels, and application of barrier measures are the most frequently mentioned in institutional reports (9-12) and experimental studies that have measured their degrees of correlation with disease (17-33), justifies their highest rates.

Table 2. Weightings of the selected VIs.

Type of vulnerability	Variables/Indicators	Estimated influence rate
EXPOSURE	Demographic Density	25%
	Occupancy per unit	20%
	Occupancy per room (TOP)	20%
	Ventilation and sunlight in the dwellings	35%
	Total	100%
SENSITIVITY	Chronic diseases	27%
	Age	27%
	Masculinity	16%
	Vaccination	30 %|
	Total	100%
ADAPTIVE CAPACITY	Revenues	20%
	Unemployment	15%
	Education	30%
	Prevention	35%
	Total	100%

2. Results:

Table 3 shows the degree of vulnerability of each sector, considering the sectors with a high level of vulnerability, those that have recorded the highest rates according to the variable under consideration, and those that have concurrently verified the most indicators (denoted by an X). The eight sectors can be enumerated in decreasing order of vulnerability as follows: S7, S6, S3, S8, S1, S5, S2, and S4.

Table 3. Identification of vulnerable sectors by indicator.

INDICATORS		Areas of high to very high vulnerability							
		S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**
EXPOSURE	TOL		×					×	
	TOP	×	×	×	×		×	×	
	Density					×	×	×	×
	Ventilation /Sunshine		×	×	×			×	
	Highly frequented workplaces			×				×	×
SENSITIVITY	High rates of Comorbidity				×		×	×	
	High rates of Masculinity greater than or equal to 18 years	×		×		×		×	×
	High rates of Age ≥60 years					×	×		×
	High rates of Unvaccinated	×	×	×	×	×	×		×
	High death rates					×		×	
ADAPTIVE CAPACITY	High rates of unemployment	×	×		×		×		
	High rates of Low income	×		×			×		×
	High rates of No Education	×		×			×	×	
	High rates of Low Education							×	
	High rates of Non-compliance with distancing (2m)					×			×
	High rates of Not washing hands	×		×			×		×
	High rates of frequenting gathering places		×		×		×	×	
	High rates of not wearing a mask			×			×		×
Number of confirmed indicators		7	6	9	6	6	11	11	9

The mapping of the several potential scenarios provides a clear perception of the distribution of pandemic risk throughout the examined region. First, the vulnerability by exposure, as represented primarily by residential indicators, suggests an average degree for six urban sectors (Figure 4). By exposure, Sector S5 is the most covidogenic. Sector S3 is expected to have a decreased covidogenic risk since the density is reduced to 107 homes/Ha and only 2% of the houses have inadequate ventilation and sunshine. Sector S6 has therefore achieved catastrophic densities and housing shortages.

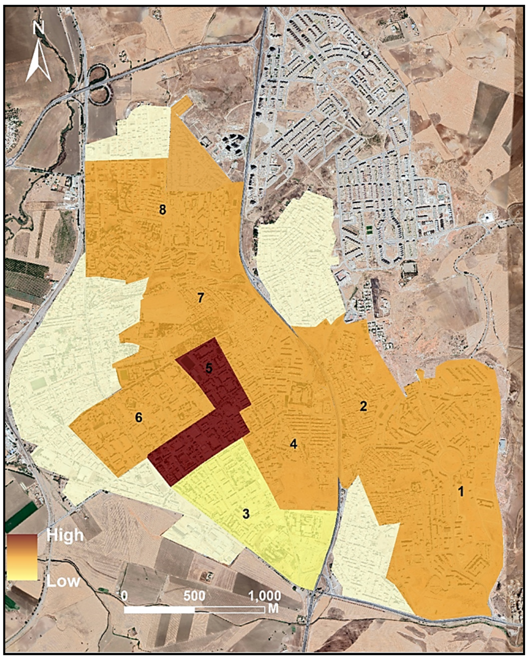

Figure 4. Disease Exposure Scenario in urban sectors of Khroub (authors).

In terms of health vulnerability, four covidogenic sectors have been identified: S1, S2, S5, and S7, which contain male populations that surpass 28% and senior populations that exceed 20% of the overall population, respectively. Furthermore, vaccinated people account for no more than 20% of the overall population. Sector S6 has higher health resistance than the others since it has a smaller senior population and a vaccination rate equivalent to 30% of the total population. Although there are no high values in the health indicators, their intersection is essential in sector S2, which is the most vulnerable to the pandemic (Figure 5).

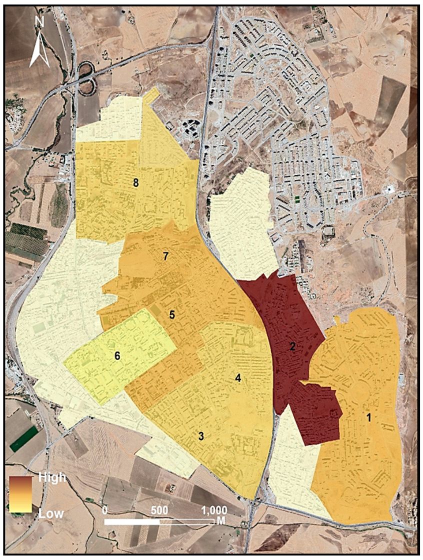

Figure 5. Disease Vulnerability Scenario in urban sectors of Khroub (authors).

Five of the eight assessed sectors had just average adaptive capacity, exposing the city to rapid pandemic spread. Adaptive capacity is lower in S4 and S5 than elsewhere, and this appears to be connected to socioeconomic and cultural factors (Figure 6). Indeed, the unemployment rate in these two sectors is 20%, while the low-income rate in S5 is the greatest (40% of the entire population). During the pandemic crisis, the proportion of inhabitants who do not wear bibs or wash their hands is greatest between S3 and S8. S8 has a crucial part of the population that does not respect distance.

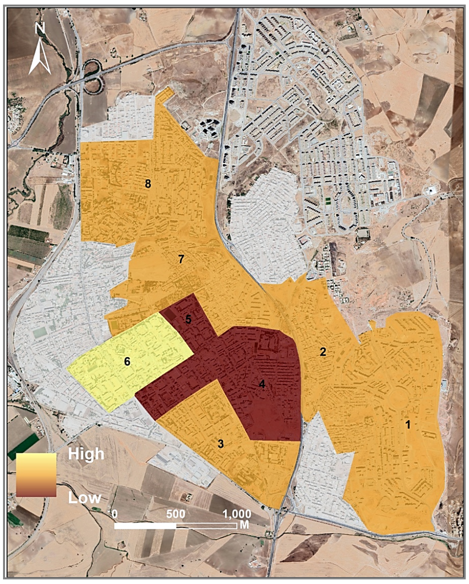

Figure 6. Pandemic resilience scenario in urban sectors of Khroub (authors).

3. Discussion.

The city-level indications suggest a large pandemic risk, which might be lethal for the 75% of the population who are not vaccinated, and especially for the 34% of the population who are susceptible to it (due to a chronic disease or being over 60 years old). When confronted with this risk, the ability to adjust is restricted in particular by the economically and culturally vulnerable level of the 46% of inhabitants with few means and the 17% who are illiterate. At the housing district scale, the results show variability in the spatial representation of risk variables and, as a result, a more clear picture of the modeling of covidogenic settings based on the three vulnerability scenarios. The epidemiological scenario by degree of vulnerability (Figure 7) reveals a very discrete distribution of pandemic risk, as only two categories of environments are distinguished: the most covidogenic (S3, S5, and S7) and the least covidogenic (S1, S2, S4, S6, and S8). This visualization is less effective if we want to create a tool for preventive and decision support, therefore depicting the risks present in urban sectors according to their degree and kind of vulnerability appears less beneficial.

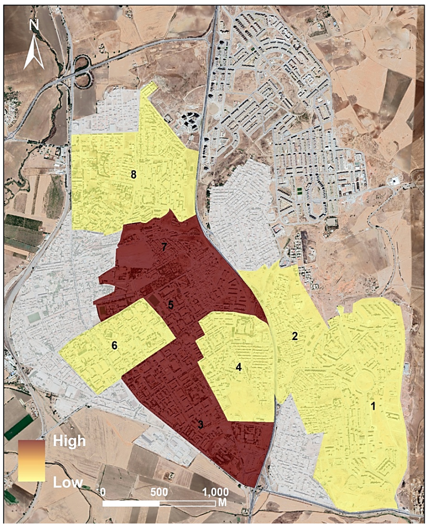

Figure 7. Epidemiological scenario according to the degree of vulnerability in urban sectors of Khroub (authors).

As a result, Figure 8, which highlights the sectors with high risk based on the three scenarios, appears to be more significant in terms of the more targeted preventative action it allows for. The comparison of Figures 7 and 8, as well as the observation of Tables 1 and 4, allow us to: (i) rule more comprehensively on the parameters of health insecurity in the eight sectors studied, and (ii) draw some correspondences between the various VIs.

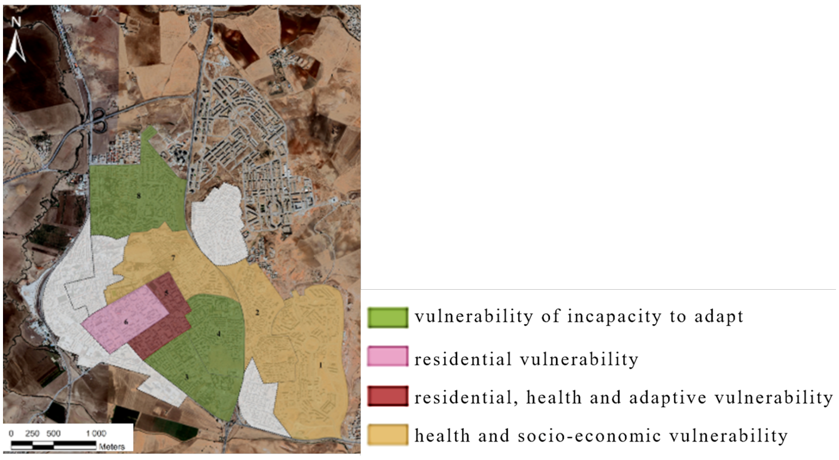

Figure 8. Epidemiological scenario according to degree and type of vulnerability in urban sectors of Khroub (authors).

The S5 sector, which was shown to be the most covidogenic (according to Figure 7), is also the most exposed and vulnerable to the illness, despite its poor adaptability. The covidogenic nature is associated with a unique type of collective housing with a very high density (234 inhabitants/Ha), an occupancy rate per dwelling (TOL) that surpasses five individuals per dwelling (that is, an average ratio of 10m^2 of living space per person). Poor ventilation and sunshine conditions heighten the danger of exposure, which affects 5% of the entire dwelling stock. Unemployment, poor income, illiteracy, and chronic sickness are all at an all-time high. In addition to the crucial cultural indicators, the S5 population appears careless about barrier gestures and everyday preventative behaviors (particularly mask-wearing and avoidance of meeting locations). The fragility of S5 is therefore evocative of the discourse on socioeconomic determinants of health (36) and shows the problematic link between housing quality and health with sharpness.

Furthermore, the illness's mortality appears to be more likely in sectors S1, S2, and S7, which are already more sensitive to the sickness than the others. Sector S7, which is also one of the most covidogenic (figure 6), has a high proportion of low-income earners as well as the greatest proportions of chronically unwell (20%) and illiterate (23%). Surprisingly, the vaccination rate (14.11%) is at its greatest level, indicating that the population with a low level of education is less skeptical of vaccination. Unemployment is highest in S1 and S2 (20%), hurting the lives of the city's younger residents. In sectors S4, S3, and S8, the incapacity to adapt is connected to economic fragility and non-compliance with preventative measures, with some connections identified between low income and the frequentation of meeting places. S3's highly covidogenic nature is substantiated by a greater percentage of the low-income population (45%) and a quarter of the population's failure to use preventive measures.

4. Conclusions and recommendations.

This study investigates an area-based method for calculating pandemic risk related to Covid-19 or other potentially dangerous respiratory infectious risk viruses. Using GIS, it was demonstrated that the scenarization of pandemic risk, based on numerous spatial modeling linked to the kind and degree of vulnerability, is more important for predicting pandemic dynamics and implementing an appropriate preventive and response strategy. Thus, the scenarios and hierarchies derived from this research demonstrate the GIS's operability as a Spatial Reference Decision Support System (SADRS), since it becomes feasible to estimate the most exposed people to the pandemic while being informed about the sort of risk incurred. Access to such information is likely to direct and measure action, particularly in terms of allocating material, financial, and human resources less arbitrarily.

In the specific case of Khroub, it is recommended that action be directed against the discovered vulnerability. Because of their high health sensitivity and lethality risk, sectors S5, S2, S1, and S7 are expected to gain improved access to testing and immunization. The most economically vulnerable populations in sectors S1, S2, and S3 are more likely to be eligible for material and financial assistance and free medical treatments. For the most illiterate population in S7, awareness and outreach initiatives would be more beneficial to organize. On the other hand, vulnerability owing to exposure primarily due to residential characteristics raises the discussion on the ratios to be accepted for living space in future housing schemes, as well as new proposals for more efficient construction.

Acknowledgments: the authors would like to thank and express their gratitude to the Agence Universitaire de la Francophonie (AUF) who funded this research project under Grant Agreement DRM-6863.

Declaration of Interest Statement.

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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