Graphical Abstract

Urban Vulnerability Assessment for Pandemic surveillance
Jeisson Prieto, Rafael Malagón, Jonatan Gomez, Elizabeth León

Schematic diagram of the Urban Vulnerability Assessment in Pandemics

(a) Literature review  (b) Find distribution  (c) Group by similar

Vulnerable factors \( \mathcal{V} = \{V_1, \ldots, V_M\} \)
Probability distribution of \( \mathcal{V} \)
\( f_{\mathcal{V}}(x) = (f_{V_1}(x), \ldots, f_{V_M}(x)) \)

Similar groups \( \mathcal{C} = \{C_1, \ldots, C_L\} \)

(e) Vulnerability index

Cluster Rank
\( C_1 \) 4
\( C_2 \) 3
\( C_3 \) 2
\( C_4 \) 1

Cluster Rank
\( C_1 \) 4
\( C_2 \) 3
\( C_3 \) 2
\( C_4 \) 1

R1
R2
RM

NOTE: This preprint reports new research that has not been certified by peer review and should not be used to guide clinical practice.
Highlights

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- Conceptual framework for Urban Vulnerability Assessment (UVA) in Pandemics is proposed.
- UVA helps decision-makers to review how the strengthening of surveillance and control measures would mitigate Pandemics.
- UVA is tested in the current COVID-19 Pandemic in Bogotá, Colombia using publicly available data.
- UVA creates not only one, but a set of vulnerability indices (i.e., low-high, lowest-highest, and 1-10) to Pandemic surveillance in Bogotá, Colombia.
Urban Vulnerability Assessment for Pandemic surveillance

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\begin{abstract}
A Pandemic devastates the life of global citizens and causes significant economic, social, and political disruption. Evidence suggests that Pandemic’s likelihood has increased over the past century because of increased global travel and integration, urbanization, and changes in land use. Further, evidence concerning the urban character of the Pandemic has underlined the role of cities in disease transmission. An early assessment of the severity of infection and transmissibility can help quantify the Pandemic potential and prioritize surveillance to control of urban areas in Pandemics. In this paper, an Urban Vulnerability Assessment (UVA) methodology is proposed. UVA investigates the possible vulnerable factors related to Pandemics to assess the vulnerability in urban areas. A vulnerability index is constructed by the aggregation of multiple vulnerability factors computed on each urban area (i.e., urban density, poverty index, informal labor, transmission routes). UVA provides insights into early vulnerability assessment using publicly available data. The applicability of UVA is shown by the identification of high-vulnerable areas where surveillance should be prioritized in the COVID-19 Pandemic in Bogotá, Colombia.
\end{abstract}

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\begin{articleinfo}
\textbf{Keywords:} Urban vulnerability, Vulnerability assessment, Infectious diseases, Pandemic, COVID-19 vulnerability index, Spatial analysis
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\begin{declarations}
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\begin{1int}
1. Introduction

Pandemics are large-scale outbreaks of infectious diseases that increase morbidity and mortality over a big geographic area and cause significant social, political, and economical disruption (Madhav et al., 2017; PAHO, 2009). Previous Pandemics (Madhav et al., 2017), have exposed gaps related to the timely detection of disease, tracing of contacts, availability of basic care, quarantine and isolation procedures, and health sector preparedness (i.e., global coordination and response mobilization) (Moon et al., 2015; Panmanathan et al., 2014). Suddenly, significant policy attention has focused on the need to identify and limit emerging outbreaks that might lead to Pandemics and to expand and sustain investment to build preparedness and health capacity (Lederberg et al., 2003). Nonetheless, the timeliness of implementing these measures is paramount to control a highly contagious disease. Efficient prioritization of investigation of high-vulnerable areas would optimize the use of resources and potentially limit the size of the Pandemic (Ethelberg et al., 2009ab; Whittaker et al., 2009).

Vulnerability assessment describes the degree to which socioeconomic systems and physical assets in geographic areas are either susceptible or resilient to the impact of disaster (i.e., Pandemic). Besides, it helps to determine what types of preparedness and response activities might help lower the vulnerability classification most quickly. Once priority vulnerable areas are identified, it will be possible to understand the definition of why certain locations may need to be prioritized for preventative action and response efforts (de Mattos Almeida et al., 2007; Moore et al., 2017; PAHO, 2009; Madhav et al., 2017). Several models have been proposed to quantify vulnerable geographic areas over the infectious disease domain, i.e., vector-borne diseases (Hagenlocher et al., 2014), Dengue (de Mattos Almeida et al., 2007), malaria (Kienberger and Hagenlocher, 2014; Hagenlocher and Castro, 2015), and Ebola (Moore et al., 2017). More recently, a COVID-19 vulnerability index for urban areas in India was proposed (Mishra et al., 2020). This study proposes a vulnerability Index by aggregating weighted scores of a set of variables related to COVID-19 precaution of social distance and lockdown in geographic areas of four metro cities in India.

On the other hand, the recently published response plan for the current COVID-19 Pandemic, UN-Habitat has underlined the urban-centric character of the infectious disease (UN Habitat, 2020). It says, more than 1430 cities are affected by the Pandemic in 210 countries and well above 95% of the total cases are located in urban areas. Further, the World Health Organization (WHO) emphasized that the first transmission in the COVID-19 Pandemic did happen in the internationally connected megacities(WHO, 2020). Even though there is urban universality of the disease, the cities of the global south are more susceptible given their population densities, low income, risky occupations, and lack of affordable health services (Mitlin, 2020).

In this paper, a conceptual framework for Urban Vulnerability Assessment (UVA) in Pandemics is proposed. UVA conducted a comprehensive review of relevant literature to identify vulnerable factors influencing Pandemics. These factors are used to generate an index that allows us to identify and rank potentially vulnerable urban areas. UVA helps decision-makers to review how the strengthening of surveillance and control measures would mitigate the vulnerability of Pandemic. UVA is tested in the current COVID-19 Pandemic in Bogotá, the crowdest city of Colombia. Us-

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consider both factors related to past Pandemics (i.e., 1881 Fifth cholera, 1918 Spanish flu influenza, 1957 Asian flu influenza, 2003 SARS, 2009 h1n1, 2013 West Africa Ebola) and factors found in the current COVID-19 Pandemic. The search retrieved studies for which the study’s title, abstract, or keywords indicated the study examined a type of vulnerability in Pandemics. Then, a manual assessment is made for every study against eligibility criteria:

- The study provided a quantitative or conceptual analysis of a type(s) of vulnerability factors related to infectious diseases (or Pandemics).
- The actual analysis or argument of the study earnestly included vulnerability.
- The study focuses on urban areas.
- To be eligible the study focuses more on the vulnerability analysis at geographic area than on the individual vulnerability of infectious diseases.

Then, the vulnerability factor the study focused on, the geographic focus of the study and the methods used to assess the vulnerability is recorded. This involved examining the title, abstract, or keywords, or full-text version if required. We listed the country or region(s) where the study focused. For theoretical studies, studies that presented examples without a geographic focus, or studies with an unclear geographic focus, the geographic location is listed as Not Applicable (NA). Table 1 summarizes the 10 studies that considered for the analysis of vulnerability factors related to Pandemics.

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1 Unicode emojis (book) are generated with Latex.
Table 1
Summary of studies considered to vulnerability factors related with Pandemics.

| Reference          | Vulnerable factor(s)                      | Geographic focus | Methods                                      | Main findings                                      |
|-------------------|-------------------------------------------|------------------|----------------------------------------------|---------------------------------------------------|
| (Chen et al., 2010) | Essential worker, Household size, Age, Gender | Singapur         | Demographic, clinical, treatment, and laboratory data | Describe incidence and vulnerable factors for Pandemic in healthcare personnel |
| (Madhav et al., 2017) | Geographic spark, Geographic spread, Burden quantification, Disease importation, Essential worker, Healthcare access | NA              | Epidemiology evidence of previous infectious diseases | Covers the concerning of vulnerability, impacts, mitigation and Pandemic knowledge gaps |
| (Jordan et al., 2020)  | Medical preconditions, Age, Gender, Essential worker | United Kingdom   | Epidemiology evidence of COVID-19            | How the vulnerability might vary in different population groups or settings |
| (Jung et al., 2020)   | Time delay illness, Insufficient follow-up, Age, Gender | China            | Demographic, clinical, treatment, and laboratory data | Provides insights in early vulnerability assessment using publicly available data |
| (Oppenheim et al., 2019) | Medical workforce, Hospital capacity, Water and sanitation, Logistics, Per capita income, Public education | NA              | Conceptual framework for epidemic preparedness and response | Epidemic Preparedness Index (EPI) for assessing resilience to epidemic and Pandemic outbreaks |
| (Moore et al., 2017) | Health infrastructure, Demographics, Disease dynamics, Governance, International support, Economic growth | NA              | Literature review and expert elicitation | Identify the most vulnerable countries to infectious disease outbreaks |
| (Morse, 2001)        | Population growth, High-density facilities, Worldwide movement, Inadequate sanitation | NA              | Epidemiology evidence of previous infectious diseases | Identification of specific factors responsible for disease emergence |
| (Summers et al., 2010) | Socioeconomic status, Age, First Aid knowledge, Rural or urban living | New Zealand     | Epidemiology evidence of previous infectious diseases | Description of vulnerable factors for death in an outbreak of Pandemic |
| (PAHO, 2009)         | Public transportation, Nearby food market, Overall poverty rate, Healthcare access, Public services access | NA              | Vulnerable indicators for area classification | Identify geographic areas to be prioritized for preventative action and response efforts |
| (Xu et al., 2020)    | Geographic spread, Transmission routes, Infectious period | NA              | Demographic, clinical, treatment, and laboratory data | Epidemiological modeling to reduce the disease burden |

Note: Studies retrieved from the literature search. NA means not applicable.

2.2. Statistical data analysis

Let $\mathcal{S}$ be a geographical space under investigation (i.e. state, county, or city) defined in terms of a finite set of $N$ smaller spatial units (i.e. counties, census tracts, or zip codes); that is $\mathcal{S} = \{1, 2, \ldots, N\}$. Let $V$ be a set of $M$ vulnerable factors, and $V_k$ the values of the $N$ spatial units in the $k$-th vulnerable factor $V_k = \{v_{k,1}, \ldots, v_{k,N}\}$. The raw data for each factor are normed across all countries over the range 0 (best) to 1 (worst), see Fig. 1(b), by estimating the probability density $f_{V_k}$ at specific spatial unit $x$ using the Kernel Density Estimation (KDE) method.

$$f_{V_k}(x) = \frac{1}{N \lambda} \sum_{i=1}^{N} K_{\lambda}(x, v_{k,i})$$

(Prieto et al. 2020: Preprint submitted to IJDRR)
where $\mathcal{K}$ is the kernel (a non-negative function) and $\lambda$ is the smoothing parameter called the bandwidth.

As a proposal to identify spatial units with possible high levels of vulnerability, a cluster analysis is made to group spatial areas with similar characteristics. Then, using a clustering algorithm (i.e., K-means), the spatial areas are grouped according to their probability distribution for the $M$ vulnerable factors, see Fig. 1(c).

### 2.3. Create vulnerability index

In order to assign a vulnerability level (rank) to each cluster, a Borda’s count aggregation method is proposed (Emerson, 2013). The Borda’s method takes as input a set of ranks $R = \{R_1, \ldots, R_M\}$ (where $R_k$ is an order of the Clusters $C = \{C_1, \ldots, C_L\}$ in the $k$-th vulnerability factor), and produce single rank by mixing the orders of all the input ranks. For this, let $t_{R_k}^C$ the position of the Cluster $C_i$ in the rank $R_k$. A new aggregated value of ranking or the $i$-th Cluster is defined as:

$$ R(C_i) = \sum_{k=1}^{M} |C| - t_{R_k}^C $$

For the vulnerability level assignment problem, a set of ordered lists or ranks is calculated using the centroid of each cluster. Therefore, Borda’s count aggregation method is used, that is, vulnerability factor ranks $R_k$ were made sorted the values of each centroid for the $M$ vulnerability factors. Next, these $M$ ranks were combined using Borda’s method to construct the aggregated vulnerability rank, see Fig. 1(d). Finally, these vulnerability rank is associated with a vulnerability index, i.e., higher rank indicates higher vulnerability, see Fig. 1(e).

### 3. Vulnerability index for the COVID-19 in Bogotá, Colombia

#### 3.1. Study area and data sources

UVA is tested by the creation of a vulnerability index for the current COVID-19 Pandemic in Bogotá city, the largest and crowded city in Colombia. Bogotá is a metropolitan city with 7,412,566 inhabitants living in an area of 1775km$^2$ (995km urban and 718km rural), at an altitude 2640m, with an annual temperature ranging from 6 to 20$^\circ$C, and annual precipitation of over 840mm. Bogotá is composed of 621 Urban Sectors$^2$. Each Urban sector belongs to one of the 112 Zonal Planning Units (UPZ), see Fig. 2.

Information was obtained from the National Department of Statistics (DANE), from District Planning Secretary of Bogotá (SDP), and District Mobility Secretary of Bogotá (SDM). Data comprised public information about demographic, transportation, socio-economic, and health conditions reported from 2011 to 2020. A summary of the dataset is presented as follows:

- **MON_2017 (SDP , 2011, 2017):** Dataset provided by SDP and it contains set monographs to provide a physical, demographic and socioeconomic vision of Bogotá and its districts.
- **SDM_2017 (SDM, 2018):** Dataset provided by SDM and it presents detailed official information of the characterization of mobility in Bogotá.
- **CNPV_2018 (DANE, 2018a):** Dataset provided by DANE and it is the national census made in 2018 and provides statistics about socio-demographic information Colombia.
- **DANE_2018 (DANE, 2018b):** Dataset provided by DANE and it contains the results of the Multidimensional Poverty Index that analyze educational conditions, health, work, access home public services, and housing conditions.
- **DANE_2020 (DANE, 2020):** Dataset provided by DANE and it presents a vulnerability index based on demographic and health conditions relevant for COVID-19 Pandemic.

Since the datasets’ information are in different spatial units (i.e., Urban sectors, UPZ), the spatial unit using in this study is the Urban sector (more atomic), and the information at UPZ level is then transformed into Urban sectors by spatial transformation (i.e., an Urban sector belongs to one and only one UPZ, then the UPZ values are assigned to the Urban sector).

#### 3.2. Vulnerability categories

Given the public data available for Bogotá, and the vulnerable factors find in the literature review (see Section 2.1)
Table 2
Vulnerability domains for the COVID-19 case in Bogotá, Colombia.

| Vulnerability domains            | Vulnerability factor(s)                  | Definition                                                                 | Dataset        |
|----------------------------------|------------------------------------------|---------------------------------------------------------------------------|----------------|
| Where and how he/she lives       | Urban density                            | Number of people inhabiting a given urbanized area                        | CNPV_2018      |
|                                  | Age                                      | Number of people aged 15–34 years (SARS-CoV-2 incidence increased (Goldstein and Lipsitch, 2020)) | CNPV_2018      |
| Comorbidities                    |                                          | Groups areas according to their demographics and comorbidities             | DANE_2020      |
| Poverty index                    |                                          | Multiple deficiencies in health, education and standard of living          | DANE_2018      |
| Socio-spatial segregation        |                                          | Absence of interaction between individuals of different social groups     | (Alfonso R, 2016) * |
| Where and how he/she works       | Educational                              | Number of educational buildings (i.e., preschool, primary and high-school, research centers, technical training centers, Universities) | MON_2017      |
|                                  | Cultural                                 | Number of cultural buildings (i.e., theaters, concert halls, libraries, museums, civic centers, community halls) | MON_2017      |
|                                  | Sports                                   | Number of sports buildings (i.e., stadiums, coliseums, sports clubs, country, racetracks, swimming pools) | MON_2017      |
|                                  | Food markets                             | Number of food market buildings (i.e., Central market, market square)     | MON_2017      |
|                                  | Formal Labor                             | Number of commercial buildings with license                               | MON_2017      |
|                                  | Informal Labor                           | Percentage structure of the informal employed according to the workplace  | (SDP, 2018) *  |
| Where and how he/she gets around | Public Transportation Dependency         | Number of Trips generated throughout the day (trips longer than 15 min)  | SDM_2017      |
|                                  | Transmission routes                      | Number of asymptomatic people at the peak of the Pandemic                | (Gomez et al., 2020) * |
|                                  | Geographic impact                        | Number of dead people after 100 simulation days                           | (Gomez et al., 2020) * |

* Values calculated in the cited paper.

A set of domains is proposed to analyze the vulnerability in Bogotá. Throughout the course of the study, we found that the most-relevant concepts and associated measures fell into three common domains: (i) Where and how he/she lives, (ii) Where and how he/she works, and (iii) Where and how he/she gets around. Factors and associated measures within these three domains provide vulnerable factors for the quantitative analysis. Table 2 shows the domains proposed and its corresponding vulnerable factors associated with it.

3.2.1. Where and how he/she lives

Several demographic factors influence the degree of vulnerability of the Urban sector to Pandemics. The relevant literature emphasizes the role of such factors as urban density, age, and the degree of urbanization (i.e., socio-spatial segregation). The level of education or literacy and the quality of the health care system (i.e., included in the poverty index) can also play a helpful role in mitigating the spread and effects of infectious diseases (Moore et al., 2017). Further, most data on COVID-19 Pandemic suggest that people with underlying health conditions such as respiratory and cardiovascular disease, and cancer (i.e., comorbidities) are more vulnerable than people without them.

3.2.2. Where and how he/she works

Urban sectors with high-density facilities (i.e., educational buildings, cultural buildings, sport buildings, food markets, all formal labor) are more vulnerable to the spread of contagious diseases due to space limitations within and between households, growth and mobility, and limited water, sanita-
Where and how he/she gets around

3.2.3. Where and how he/she gets around

Understand transmissibility, risk of geographic spread, transmission routes, and vulnerable factors for infection (i.e., geographic impact) provides the baseline for epidemiological modeling that can inform the planning of response and containment efforts to reduce the burden of disease (Xu et al., 2020). As well, there have been claims that the use of public transport (i.e., public transportation dependency) has also led to the spread of infectious diseases (PAHO, 2009)

3.3. Vulnerability analysis

To understand the distribution of the vulnerability factors over the Urban sectors, the raw data for each factor are normed across all Urban sectors over the 0 (less vulnerable) to 1 (most vulnerable). The normalization was made estimating the probability density using the Kernel Density
Estimation (KDE)\(^4\)

Fig 3 shows the normalization for the three domains. For each vulnerable factor the KDE estimation is shown and the vulnerability value is then associated with the found distribution. Further, the vulnerability value is plotted over all Urban sectors in Bogotá, where red color means higher vulnerability (higher probability) and green color means lower vulnerability (lower probability). The results show the spatial correlation that exists for some vulnerable factors, especially for the *Where and how she/he works* domain. In contrast to the *Where and how she/he lives* domain, where the spatial correlation is not clear, the vulnerability is distributed across the geography area under study (Bogotá).

### 3.4. Vulnerability index

To provide better response for vulnerability assessment, UVA generates three different models to assess vulnerability in different ways. The first model has three different clusters to get a vulnerability index from low to high (i.e., low, medium, high). The second model has five different clusters to get a vulnerability index from lowest to highest (i.e., lowest, low, medium, high, highest). The third model has then clusters to get a vulnerability index from 1 to 10. Fig 4 shows the different models (i.e., 3 clusters, 5 clusters, and 10 clusters). For each model, the clusters generated are shown over Bogotá’s map and the centroids are presented for all generated clusters. The centroids are ranked (from lower to lower) getting 14 ranks (one for each vulnerable factor). Then, Borda’s count method is used to get a unique ranking for each cluster.

Finally, a vulnerability label is assigned for each cluster based on the ranking (i.e., higher rank indicates higher vulnerability). Fig 5 shows the final vulnerability index for the three different vulnerability index constructed with UVA. For Vulnerability index I, the results show high vulnerable urban sectors in the south and west part of the city. On the other hand, the Vulnerability index II shows how some Urban sectors change from medium-vulnerability (in comparison with the Vulnerability index I) to low or high-vulnerability. The Vulnerability index III presents an interesting scenario, where the spatial correlation between urban sectors (showed in Vulnerability index I and II) is not remarkable getting an unbiased vulnerability index for COVID-19 in Bogotá, Colombia.

### 4. Conclusions and Future Work

An Urban Vulnerability Assessment (UVA) for Pandemic surveillance is proposed. UVA highlights the vulnerability based on a set of 14 vulnerable factors found in the literature. The vulnerable factors are ranked for each spatial unit under study using some statistical methods like Kernel Density Estimation (KDE) and Clustering Analysis. To generate a unique vulnerability index, Borda’s count method is used.

The proposed UVA is tested in the current COVID-19 Pandemic in Bogotá city, the largest and crowded city in Colombia. UVA creates not only one, but a set of vulner-

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\(^4\)KDE uses the Gaussian kernel for its estimations and Scott’s Rule for the bandwidth selection (Scott, 2015).
ability indices (i.e., low-high, lowest-highest, and 1-10) to Pandemic surveillance. Surveillance is of primary importance to monitor the burden of disease and will give both local authorities and the global community a chance for a quick response to public health threats.

UVA could be used to build evidence for planning, modeling, and epidemiological studies to better inform the public, policymakers, and international organizations and funders as to where and how to improve surveillance, response efforts, and delivery of resources, which are crucial factors in containing the COVID-19 Pandemic. It must concern the spatial inequality problems in multiple deprivations and other deprecating characteristics. Thus enabling equity-based urban planning that vows to restrict the transmission of COVID-19 now or any similar Pandemic in the future.

**Fig. 5:** Vulnerability indices generated using UVA for the current COVID-19 Pandemic in Bogotá, Colombia. Vulnerability index I has 3 levels from low to high (left); Vulnerability index II has 5 levels from lowest to highest (middle); and Vulnerability index III has 10 levels from 1 to 10 (right).

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