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A methodology for managing public spaces to increase access to essential goods and services by vulnerable populations during the COVID-19 pandemic

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Abstract

Purpose – The purpose of this paper is to present a spatial decision support system (SDSS) to be used by the local authorities of a city in the planning and response phase of a disaster. The SDSS focuses on the management of public spaces as a resource to increase a vulnerable population's accessibility to essential goods and services. Using a web-based platform, the SDSS would support data-driven decisions, especially for cases such as the COVID-19 pandemic which requires special care in quarantine situations (which imply walking access instead of by other means of transport).

Design/methodology/approach – This paper proposes a methodology to create a web-SDSS to manage public spaces in the planning and response phase of a disaster to increase the access to essential goods and services. Using a regular polygon grid, a city is partitioned into spatial units that aggregate spatial data from open and proprietary sources. The polygon grid is then used to compute accessibility, vulnerability and population density indicators using spatial analysis. Finally, a facility location problem is formulated and solved to provide decision-makers with an adaptive selection of public spaces given their indicators of choice.

Findings – The design and implementation of the methodology resulted in a granular representation of the city of Lima, Peru, in terms of population density, accessibility and vulnerability. Using these indicators, the SDSS was deployed as a web application that allowed decision-makers to explore different solutions to a facility location model within their districts, as well as visualizing the indicators computed for the hexagons that covered the district's area. By performing tests with different local authorities, improvements were suggested to support a more general set of decisions and the key indicators to use in the SDSS were determined.

Originality/value – This paper, following the literature gap, is the first of its kind that presents an SDSS focused on increasing access to essential goods and services using public spaces and has had a successful response from local authorities with different backgrounds regarding the integration into their decision-making process.

Keywords COVID-19, Resilience, Vulnerability, Decision support

Paper type Research paper

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1. Introduction

In the planning and response phase that follows a disaster, such as an earthquake or a pandemic, cities face several challenges. Whether these challenges involve broken supply chains, material convergence or isolated populations with increasing deprivation costs (Shao *et al.*, 2020), the authorities and response teams must allocate resources efficiently to minimize damage and reduce the magnitude of the humanitarian crisis. In emerging markets, cities operate with highly dense commercial areas, which, given their population density and road network characteristics, become critical logistic zones (Winkenbach *et al.*, 2018).

These zones provide essential products and services to the nearby population as well as to a demographic that travels to the supply points in these zones or uses delivery services to consume from them. But during a disaster or pandemic, when the population must access these products and services, these logistic zones can be subject to disruptions that prevent distant populations from travelling to them, either because of transportation system restrictions or because the public system is insecure. The effects of these disruptions are compounded in areas with high urbanization rates; according to the United Nations (2014), in Latin America approximately 75% of the population lives in urban areas.

Within this paradigm, cities like Lima (Peru), Bogota (Colombia) and Santiago (Chile) have had an accelerated, informal urban planning (Inostroza, 2017), which led to accessibility issues (focused on access to essential services and food supply), as well as an unequal access to quality infrastructure and services. This, coupled with the population density present in Latin-American cities, may enhance the humanitarian crisis and the unequal access to resources. As such, these factors represent a latent food, job and monetary vulnerability to disasters (PNUD, 2020) as well as negative externalities from urban sprawl toward the fringe of the city (Duranton and Puga, 2013; Glaeser, 1997), highlighting the essential role of accessibility to supply these areas with goods and services when handling a pandemic which requires strong quarantines.

During a pandemic, such as COVID-19, cities have an array of available response options. In Latin-America, the extended quarantines with curfews and social distancing regulations were still a challenge to manage in and of itself, as the total number of positive cases was above the world average (Atalan, 2020), with Brazil, Colombia and Argentina leading the region (World Health Organization, 2020). This, coupled with the high occupancy rates of ICU infrastructure, brought a near-collapse of the health-care system in the region (MINSA, 2020; Minsalud, 2020). These policies directly translated into several businesses closing due to the inability to maintain social distancing within their workplace, which escalated the sanitary crisis into an economic one. To counterbalance this effect, public spaces show great potential. Since they are available to local authorities for their administration, they can be used as a tactical response tool to increase the accessibility to basic services. As such, critical goods and services may be accessed by vulnerable populations using these public spaces, increasing the resilience of supply chains, businesses and health-care infrastructure, which was tested in an uncertain reality. Consequently, the need for tools that allows communities, organizations and people to navigate this uncertainty into a restoration of order in society has great potential to be fulfilled by information systems (Sakurai and Chughtai, 2020).

Previous research has shown the potential of information systems in crisis management. Specifically, during the COVID-19 pandemic, researchers have approached how urban features (such as population density) affected the spread of the virus during a lockdown, where an increase in accessibility to essential services was proposed as a component to strengthen resilience after a lockdown (Kang *et al.*, 2020). Another approach is to harness microblogging platforms to understand how an outbreak behaves and to disseminate useful information. Rudra *et al.* (2018) studied this phenomenon by using Twitter as the digital platform from which data collection, classification and summarization were performed, concluding that the role of information systems in outbreak management is paramount.

The current approaches to understanding COVID-19 suggest that the effective management of such pandemics relies heavily on digital and data-driven solutions and resilient systems (Chen *et al.*, 2020; Djalante *et al.*, 2020; Victor Herrera *et al.*, 2020; Ting *et al.*, 2020). Chen *et al.* (2020) studied how Chinese central government agencies used social media to promote citizen engagement during the COVID-19 crisis. By scraping data from "Healthy China" (an official Sina Weibo account of the National Health Commission of China), the authors examined how citizen engagement relates to media richness, dialogic loop, content type and emotional balance. Victor Herrera *et al.* (2020) studied how the different branches of clinical management (i.e. ethics, analytics and resilience) face innovation and digitization during pandemics such as COVID-19, emphasizing on the role of clinical analytics and their data reports to the public and decision-makers in an actionable format.

Djalante *et al.* (2020) designed a framework for health-emergency disaster risk management by gathering data from different responses to COVID-19 (at global, regional and tactical levels), where the need for better data collection, either for risk assessment or tracking contagion outbreaks, was advocated as a core concept for future allocation of resources. Ting *et al.* (2020) present different ways in which digital technologies can support the public health strategies (virtual clinics, live tracking of at-risk communities and public information dissemination) and their effect on the mitigation of COVID-19's impact. Even so, literature focusing on how a data-driven, spatial decision support systems (SDSS) to manage public spaces with a focus on increasing the accessibility to a set of goods and services is very shallow (Sharifi and Khavarian-Garmsir, 2020). Within their research, Sharifi and Khavarian-Garmsir (2020) identified different governance trends (quarantines and public space sanitization), smart city initiatives (social media patterns and modelling the spread of the virus) and transportation and mobility patterns (most cases in Italy were strongly correlated to the number of trips 21 days before) during the COVID-19 pandemic which point to the possible synergies between public space management and digital solutions.

The objective of this paper is to propose a methodology to manage public spaces to increase the accessibility to essential goods and services by vulnerable populations using open data sources. The methodology is implemented into a web-based SDSS, which identifies areas of low accessibility to essential goods and services and public spaces to be used as a resource to increase the accessibility. By combining web-based platforms, accessibility indicators and algorithms for optimization, the final SDSS will look to increase the resilience of the community and their supply chain infrastructure by supporting the planning and response by local authorities during a humanitarian crisis.

The remainder of this paper is structured as follows. Section 2 presents the relevant literature related to facility location problems (FLPs), accessibility, spatial analysis and decision support systems (DSS). Section 3 describes the data collection and spatial aggregation procedures, the algorithm for candidate selection and the specific model formulation for the allocation of public space-based facilities to increase access to essential goods and services. Section 4 outlines the main results and discusses them. Section 5 addresses the implications of our results for policymakers and stakeholders of the public space management and disaster response within a city. Finally, Section 6 presents the conclusions and recommendations for future research.

2. Related work

DSS, accessibility and location analysis are broad and rich research areas. Within this section, a review of related work in each of these areas will be presented, focusing on the fundamental papers in each research field and the applications and intersections between them that have a similar objectives to those in this paper. FLPs were first introduced by the seminal papers of Hakimi (1964) and Hakimi (1965). Through the formulation of medians and centers in a graph, the foundation of methods to solve for the optimal location of a number of means is presented through case studies with the common objective of maximizing coverage or minimizing the distance from the median to a set of points.

These papers sparked the research field in location science. From the initial formulation, Laporte (2015) presents a collection of common problems, formulations and algorithms within location science analysis. Applications of facility location models range from supply chain (Melo *et al.*, 2017) to the public sector (Shariff *et al.*, 2012; Zhang *et al.*, 2016) and to healthcare and disasters (Church *et al.*, 2004). Further applications of different types of location models are available in Daskin (2011), Zanjirani Farahani and Hekmatfar (2009). Among these, the most relevant to these paper are the p-median and covering location problems.

Within the field of humanitarian logistics, several authors have highlighted the need for decision support tools to manage pandemics and disasters. Fang *et al.* (2020) details the implementation of the Fangcang shelter hospitals in Wuhan, China, to increase the accessibility to health-care infrastructure. The authors list several characteristics for the design of said facilities and the problems in construction, where one of the main issues was the lack of planning regarding the location of temporary medical facilities and their sanitary needs (ventilation and sewage). Shavarani (2019) uses a multi-level facility location-allocation model to find the best topology for both relief centers and recharge stations to cover a large-scale area with minimum and feasible incurred costs and waiting times using drones. Using Tehran as a case study, the authors find increase coverage for drone delivery of relief packages (by allocating charging stations) while reducing waiting times and total cost. Maharjan *et al.* (2020) develop a methodology for the allocation of mobile logistics hubs as part of the Augmentation of National and Local-Level Emergency Logistics Preparedness project in Nepal. Using by formulating the location of these hubs as maximal covering location problem, the authors balanced the solution of the model (number and location of facilities) with qualitative knowledge from experts to arrive at five first-priority locations from 59 candidate locations.

Timperio *et al.* (2013) propose a decision support framework for disaster relief network design. By studying Indonesia, the authors use geographical information systems (GIS) and fuzzy analytic hierarchy process (AHP) to select a set of facilities for the disaster relief supply chain. By combining mathematical modelling and qualitative methods, the authors concluded that six distribution centers should be allocated within Indonesia, with the practical limitation that the facilities were considered uncapacitated. To solve large FLP instances, recent work centered on providing heuristics for large instances of the capacitated (Avella *et al.*, 2009; Jena *et al.*, 2017) and uncapacitated (De Armas *et al.*, 2017) FLP have provided efficient algorithms to solve large instances within the FLPs of location analysis. Even though the value of public spaces for disaster relief is acknowledged in the literature, to the best of the authors' knowledge, there is a lack of research on the use of public spaces to increase the accessibility to essential goods and services during disasters. By using a p-median formulation, this paper seeks to allocate a set of facilities that, by offering said goods and services, increase the accessibility of vulnerable populations to them.

Having computationally efficient algorithms leads to the development of DSS, which look to create a simple interaction between decision-makers and analytical approaches to a problem. Examples of these DSS are Erdoğan *et al.* (2019), Burdziej (2012) and Pick *et al.* (2017). Erdoğan *et al.* (2019) presents a spreadsheet-based decision support system for medium-sized FLPs (up to 600 nodes and 200 customers). Using tabu search, a heuristic solution is presented within an Excel spreadsheet. Within its case study, the allocation of maternity health-care services is analyzed within England. The application of p-median led to the assessment of the current infrastructure and possible increases in infrastructure, where excluding the Paulton facility provided improvements to the system.

On the other hand, to produce an open-source, web-based, SDSS, Burdziej (2012) presents the foundations, implementation and case study of a spatial DSS to analyze accessibility in Torun, Poland. Similar developments were accounted for in the literature review from Pick *et al.* (2017), where other concepts and case studies were explored within the DSS literature. The visualization of a DSS can focus only on indicators (i.e. accessibility, urban mean speed and CO_2 levels) or it can be complimented with territorial indicators (see González-Feliu (2018) for a review of territorial analytics indicators) which present the spatial distribution of data and indicators by using maps, raster images or contours. Within this review, the need for tools to visually manage the results from analytical models to make decisions regarding the location is of special importance. Even so, an SDSS that allows decision-makers to interact with a model that informs their decision regarding public spaces and their use to increase accessibility is lacking within the literature.

The main attributes of DSS mesh seamlessly with spatial analysis techniques. Regarding COVID-19, Franch-Pardo *et al.* (2020) present a thorough review of papers within the literature that have used spatial analysis and GIS to study the virus outbreak. Within this review, several papers relate strongly to the objective of this paper. By analyzing spatio-temporal patterns in China, Gross *et al.* (2020) identified that the virus propagation adopted the flight of Levy, a tendency of fractal movement found in human mobility. Furthermore, spatial analysis was also used from a spatio-temporal perspective to assess the impact of lax containment efforts (Desjardins *et al.*, 2020) or mandatory confinements (Orea and Alvarez, 2020; Giuliani *et al.*, 2020). The latter concluded that those provinces that were closest to epicenters of COVID-19 in Spain were benefited from the confinements since the contagion rates were reduced. Sarwar *et al.* (2020) presented an open GIS that closely relates to the DSS developed in this paper. By providing a friendly interface that allows users to collect and analyze outbreak data in Pakistan, accurate spatial segmentation of epidemic risk areas and appropriate levels of prevention can be made given the population flow and density. This led to the authors' engagement with public authorities to assess vulnerable regions and work to mitigate concerns about the adequacy of health-care services with constant information flows. Another perspective for the use of spatial analysis to study COVID-19 is to focus on health geography issues. Such issues may include the challenges of establishing measures to control virus outbreaks in developing countries (de Kadt *et al.*, 2020; Gibson and Rush, 2020) or the accessibility to health-care infrastructure by elderly people in need of medical assistance (Lakhani, 2020), both of which are strongly complemented by the use of GIS.

A third axis for related research is the field of accessibility. As initially defined by Hansen (1959), accessibility is the ease with which activities at one place may be reached from another via a particular travel mode or any available modes (such as walking, driving or cycling). From the literature review of Shi *et al.* (2020), the most related work to this paper is centered on accessibility metrics to measure vulnerability. The study of accessibility with relation to vulnerability has different approaches. Mostly focused on indicators based on road networks, papers such as Taylor *et al.* (2006) evaluate vulnerability based on the impacts of network degradation on socio-economic indicators within Australia, where main accessibility indicators computed are the Hansen integral accessibility index and the ARIA index.

Similarly, Chen *et al.* (2007) studies explained network-based accessibility measures for assessing vulnerability of degradable transportation networks. The indicators developed in this paper aim to consider the consequence of one or more failures within the road network in terms of travel time or generalized travel cost increase, as well as the behavioral responses of users due to the failure in the network. From an application perspective, Chang and Nojima (2001) and Sohn (2006) applied different sets of accessibility indicators to measure vulnerability to disasters, where Chang and Nojima (2001) analyzed the 1995 Hyogoken-Nabu earthquake and Sohn (2006) analyzed the Maryland flood. Finally, Reggiani *et al.* (2015) studied the relationship between vulnerability, accessibility, reliability and resilience of a transportation system, emphasizing the role of connectivity. The authors then concluded that when studying the relationship between accessibility and vulnerability, the relationship was not strictly linear.

From the review of related work, it is evident that operations research, DSS, spatial analysis and accessibility are closely related. Even so, as evidenced in Sharifi and Khavarian-Garmsir (2020), literature focusing on the data-driven governance of public space to increase the accessibility to essential goods and services is very shallow if not non-existent. As such, this paper aims to fill this literature gap by presenting an SDSS for data-driven governance of public spaces to increase the accessibility of vulnerable populations to essential goods and services in a pandemic or disaster context.

3. Methodology

The methodology of this paper is split into three phases: (1) data collection, spatial aggregation and indicator computation; (2) modelling and sensitivity analysis; and (3) SDSS development. The first phase focuses on gathering the necessary sources of data to describe a city. Using spatial aggregation into regular polygons, a set of indicators regarding accessibility, vulnerability and population density are computed. The output of this phase is a regular polygon surface that contains each indicator as an attribute of a polygon.

Taking as input the regular polygon surface, the second phase (modelling and sensitivity analysis) uses the indicators to identify potential target areas and then runs an FLP model to select specific public spaces as recommendations to decision-makers. With the output of this stage – the filtered areas and the selected public spaces – the third stage constructs an interactive interface between the data, models and the end user. By presenting the spatial distribution of data and allowing the user to select indicators and visualize how their decisions affect the selections of polygons and public spaces, an SDSS is constructed to aid decision-makers to plan and react to a pandemic when using these spaces to increase the accessibility to essential goods and services.

3.1 Data collection, spatial aggregation and indicator computation

The first stage of this methodology focuses on collecting the necessary sources of data to construct relevant accessibility and vulnerability indicators, the optimization model and the SDSS. These data sources may be collected primarily from open-source repositories, such as LandScan, Humanitarian Data Exchange (HDX) and OpenStreetMaps (OSM) or private sources of data that provide a more complete spatial data set to enable this methodology (such as Guía de Calles [NAVI Systems EIRL, 2020]) These data sources, however, come in different spatial resolutions. For example, to represent population density, LandScan provides a raster image with pixels roughly equal to a squared-kilometer. In contrast, Facebook's High-Resolution Settlement Layer (available from HDX) provides a 30-m resolution dataset for their population density maps. Aside from this, the road networks provided by OSM are in graph or LineString resolution.

These differences in format and resolution call for a spatial aggregation procedure to take place to enable comparisons between urban and peri-urban areas. First, a spatial unit needs to be selected. The choice can range from 100×100 m grids to hexagons of different resolutions to census zones. In this paper, we chose Uber's H3 hexagonal grid system (Uber, 2020). Splitting the world in a hexagonal system has several advantages. First, every polygon can be split into a set of regular hexagons, which allows for a better coverage of an urban area via spatial units. Second, and most importantly, the aggregation and disintegration of H3 hexagons into finer or coarser resolutions does not represent significant computational costs. Finally, H3 allows for compressed representations of hexagon clusters. This compression provides computational performance benefits since a large number of hexagons which provide little to no information are reduced into a single group for distance matrix calculations.

Once the spatial units are set, the next process is divided into two: aggregation and down-sampling. For data sources with finer resolution than the hexagon set, different aggregation strategies can be followed. Population density maps require simple aggregations (summing the total population within a hexagon), while road network coefficients may require different weights when aggregating. For data sources that are of coarser resolutions than the hexagon set (a census zone or district), different strategies for down-sampling are available: *k*-ring smoothing, Gaussian smoothing or simple proportional assignments. With all the data sources aggregated, the accessibility indicators can be computed either at hexagon resolution or at city block resolution.

To compute the accessibility indicators, three main approaches from the literature were selected. First, the basic isochronic definition from Koenig (1980) was implemented to generate the isochrone contours for 5-, 10- and 15-min travel times from every block within the city. With a finer hexagon resolution, these contours can also be created for the hexagon centroids. The second approach, focused on estimating a pressure map for each block, is based on the formulations presented in Ritsema Van Eck and De Jong (1999). The authors define pressure as "*the expected number of customers for a new shop based on a 'fair share' allocation*." Mathematically, the concept of pressure for a spatial unit is defined as follows:

$$N_j = \text{Number of stores } i \text{ for which } C_{ij} < \text{Range} \tag{1}$$

$$DS_j = \frac{D_j}{(N_j + 1)} \tag{2}$$

$$\text{Pressure}_k = \sum_j DS_j \quad \forall j \text{ such that } C_{kj} < \text{Range} \tag{3}$$

where D_j is the demand at store j and C_{ij} represents the cost of travelling from location j to store i. In Equation (2), DS_j represents a ratio between the demand of each store j and the number of stores within the range (1 is added to avoid zero division issues). This definition depends on a range or acceptable distance parameter (Range), which is tunable for applications in which the acceptable distance follows an isochronic definition (15-min travel time, 1 km distance, etc.). The third and final approach follows the formulations in Hu *et al.* (2020). Within this paper, the authors provide an accessibility to healthy foods indicator that contemplates both the catchment area of a store and the access from a city block/district/county (denoted as E2SFCA).

This indicator is computed in two stages. First, for each store at location j, all blocks m within a distance buffer d_0 from j are used to formulate a catchment area for store j. Next, the population at block m is weighed using the friction function from Equation (4) (which uses a Gaussian function with the distance d_{mj} between block m and store j) when calculating the final ratio (R_j) of stores to population demand in Equation (5) (where S_j is a weight assigned for different store types and D_m is the population at block m).

$$G(d_{mj}, d_0) = \begin{cases} \dfrac{e^{-1/2(d_{mj}/d_0)}}{1 - e^{-(1/2)}}, & d_{mj} \leq d_0 \\ 0, & d_{mj} > d_0 \end{cases} \tag{4}$$

$$R_j = \frac{S_j}{\sum_{m \in \{d_{mj} \le d_0\}} G(d_{mj}, d_0) D_m} \tag{5}$$

With the results of this initial procedure, the final accessibility A_i is computed by searching all stores within a buffer d_0 from a block i. Once again, the friction function is used to weight the distances between block centroids and stores, given the following expression:

$$A_i = \sum_{n \in \{d_{ni} \le d_0\}} G(d_{n_i}, d_0) R_n \tag{6}$$

With the accessibility indicators computed, aggregating them spatially does not require a specialized procedure. The pressure map was designed to sum DS_j within a spatial unit, while E2FSCA can be aggregated using sums or averages. These indicators are stored as attributes of each hexagon (or polygon).

The final set of indicators to compute are those related to vulnerability. As detailed in PNUD (2020), the three most relevant indicators for computation are the labor, monetary and water access vulnerabilities. Monetary vulnerability is defined as whether or not a household has an income level greater than or equal to the market basket. Labor vulnerability is also a categorical variable, which evaluates whether or not a household has an income level above the minimum wage. Finally, the water access vulnerability computes the percentage of households within an area that have access to the public water network. As with the accessibility indicators, these indicators are added as attributes to each polygon, completing the output for this stage.

3.2 Modelling and sensitivity analysis

Using the hexagon surface generated in the previous phase, the next step is to use the computed indicators to (1) identify prospect public spaces to use as facilities; (2) filter the search space for the optimization model; and (3) use a *p*-median model to select the public spaces to use. To achieve the first and second goals, Algorithm 1 presents the procedure used to filter the available hexagons into the candidate set for the optimization model.

The algorithm uses four main parameters: a hexagon set, a number of candidates to select, a threshold for accessibility or other relevant indicator and a buffer size. Using the output from the previous phase, this algorithm starts by sorting the hexagons using accessibility (a continuous vulnerability indicator or a composite accessibility-population measure like the one presented in Banick *et al.* (2021) may also be used) and population density. Both metrics are continuous, so the sorting procedure should not encounter ties. This sort looks to identify those hexagons with the lowest accessibility and highest population. Since the main goal is to identify hexagons with low accessibility and high-population density, a sense of priority is needed when sorting. This helps to avoid situations in which marginal differences in accessibility cause a low-population density hexagon to be selected over a high-population density hexagon. Using this "priority" in which the algorithm first sorts by population density and then by accessibility, the goal of selecting high-population density hexagons with low accessibility is achieved.

After the sort, the algorithm iterations begin. First, the id of the top hexagon (H[0, id]) is added to the candidate output. Next, those hexagons that lie within the buffer with size b from this top hexagon are removed to avoid selecting adjoining hexagons. After removing the top hexagon from the set, the algorithm continues its iterations until either the number of candidates is reached or the top hexagon has a higher accessibility value than the threshold.

Algorithm 1 Hexagon selection

```
1: Parameters: hexagon set (H), maximum candidates (max_candidates), accessibility threshold (at), buffer size (b)
2: Outputs: candidate set (c)
3: Set c = {}
4: Sort H by population density and accessibility (descending, ascending)
5: while length(c) < max_candidates and H[0, A_i] < at do
6:     Append H[0, id] to c
7:     Filter out all hexagons in H within b of H[0]
8:     Remove H[0] from H
9: end while
10: Return c
```

The zones within set c, or their centroids, conform the candidate set for the p-median model. As per Daskin (2011), this model aims to solve the p-median FLP, which can be summarized as selecting p facilities from a candidate set such that the total cost is minimized (the objective function minimizes the total demand-weighted distance between each demand node and the nearest facility, see Equation (7)). For further insight into the formulation and applications, we refer the readers to Marianov and Serra (2011), Drezner and Hamacher (2001) and Daskin (2011). From these zones, the available public spaces can be extracted to refine the candidate set, which, in turn, provides a more refined analysis of the decisions to be made by local authorities. Following the formulations in Laporte (2015), a p-median problem can be expressed mathematically as follows:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} dem_j k_{ij} x_{ij} \tag{7}$$

s.t.

$$\sum_{i=1}^{n} x_{ij} = 1 \quad \forall j \in \text{Customers} \tag{8}$$

$$\sum_{i=1}^{n} y_i = p \tag{9}$$

$$x_{ij} \leq y_i \quad \forall i \in \text{Facilities} \quad \forall j \in \text{Customers} \tag{10}$$

$$y_i \in \{0, 1\} \quad \forall i \in \text{Facilities} \quad \forall j \in \text{Customers} \tag{11}$$

$$0 \leq x_{ij} \leq 1 \quad \forall i \in \text{Facilities} \quad \forall j \in \text{Customers} \tag{12}$$

where dem_j is the demand of customer j, k_{ij} represents the travel cost from customer j to facility i and p is the total number of facilities to activate. The decision variables x_{ij} and y_i represent the demand percentage for customer j to be served by facility i and whether facility i is active or not, respectively. Constraints (8) enforce that the total demand for each customer is served by an active facility. Constraints (9) ensure that only p facilities are active, while Constraints (10) relate both variables. Finally, Constraints (11) and Constraints (12) provide binary and non-negativity constraints.

The output of this phase, as discussed previously, is the id of each active facility. The application of this model is subject to the p-median assumptions. As such, both assumptions are fulfilled, since the operating cost of the facilities within a zone is constant (they are administered by local authorities) and, even though the commercial activities within the public spaces selected may vary, the general structure of the facility remains the same with the objective of increasing availability to the goods and services that each specific zone within a city may need.

3.3 Spatial decision support system development

For the final phase of this methodology, the development of the SDSS, the outputs from all the previous phases are required. The objective of the SDSS is to support decisions regarding the use of public spaces to increase accessibility, so it is evident that the hexagon layer must be included to visualize the spatial distribution of accessibility. To interact with the model, a set of sliders, dropdowns and other components were used to set the parameters for the hexagon selection procedure, indicators to show and the sorting (ascending descending). Figure 1 presents the different building blocks for the SDSS and how they interact.

As shown in Figure 1, the three interactive indicators are the accessibility, vulnerability and population density indicators. The hexagon map takes them as input, and with the number of hexagons to select (also interactive) filters the map to show the areas which require special attention to increase accessibility. With these filters, and using a public space database collected with OSM, the FLP optimization can be accessed using an application programming interface (API). This API would take as input the parameters for the model (p, dem, k) and return the indices for each selected facility, barring large instances that take

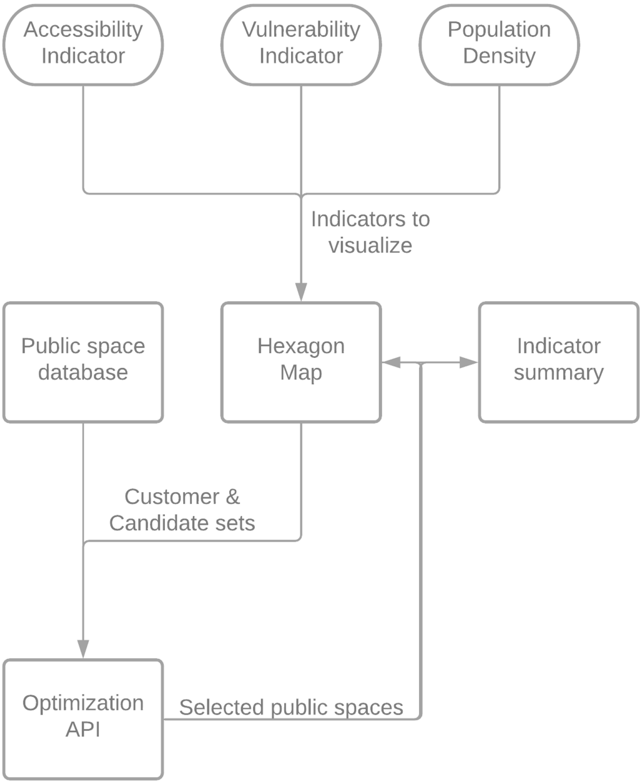

Figure 1.
Spatial decision support system components and interactions

significant CPU times. These ids would later be used in both the hexagon map to display the facilities within their hexagons and in an indicator summary.

This indicator summary would visualize how the selected indicators vary between the solution of the FLP model, a top 10 ranking using the hexagon selection and a random selection. The goal is for the end user to visualize the potential decisions to take. By showing the indicators they select as most relevant, the two solutions (FLP and top 10) can be compared to take the final decision either in their preparation for a disaster or during their response.

4. Implementation and results

In this section, the main set of results following the aforementioned methodology will be presented. The three sets of results will be comprised of the following: results from the data collection, spatial aggregation and candidate selection procedure, results from the formulation and solution of different FLPs (varying the hyperparameters present in the candidate selection) and the development of the SDSS.

4.1 Characterization of the city

The following sections are the result of implementing the methodology from this paper in Lima, Peru. As a city with approximately 10 million inhabitants, Lima concentrates roughly 30% of Peru's population (Instituto Nacional de Estadistica e Informatica [INEI], 2014). Administratively, Lima is divided into 43 districts, each with complete independence regarding public policy (i.e. delivery hours and public space use). As such, Lima's road network, which has a total of 793,557 nodes and 280,567 edges, does not present a homogeneous structure or planning. This is the result of the independence of each district, as well as the informal growth of the city. Furthermore, since Lima is located near the equator (−77 and −12), its location within the fire belt, as well as being exposed to the El Niño phenomenon (the most recent case in 2017) highlights the possible natural disasters Lima can face.

To implement the methodology, all experiments will be run using Python 3.7. For indicator computation GeoPandas, NumPy, UrbanPy will be used. To build, solve and deploy the optimization engine for the SDSS, FastAPI and PuLP will be used, hosting the API endpoints and the experiments on a Ubuntu 18 LTS server using a 32-core (3.9 GHz) CPU, 256 GB of RAM, 16TB for result storage and a Tesla T4 GPU (16GB RAM, compute capability of 7.5).

4.2 Data collection, spatial aggregation and indicator computation

The first set of results is focused on the collection of the primary sources of data, their spatial aggregation and the results from the candidate selection algorithm. To download the said data sources (HDX, OSM and Point of Interests (POIs)) UrbanPy was used to tap into the open-source repositories and convert them into a table structure, assigning a geometry to each record. An example of the result of these download procedures is present in Figure 2, where three population density maps were downloaded: young adults, children and elderly population. As mentioned in the previous section, since these maps are provided as point geometries, they need to be aggregated into hexagonal spatial units.

Figure 2 shows the result of such aggregation into H3's resolution 8 hexagons, which have an average area of 0.71 km^2. When selecting a resolution, it is important to consider the number of unique hexagons to be created, their average area and the level of spatial granularity. The full detail of each resolution's area can be found in H3's documentation [1], where it is clear that a coarser resolution (closer to 0) provides a smaller number of hexagons

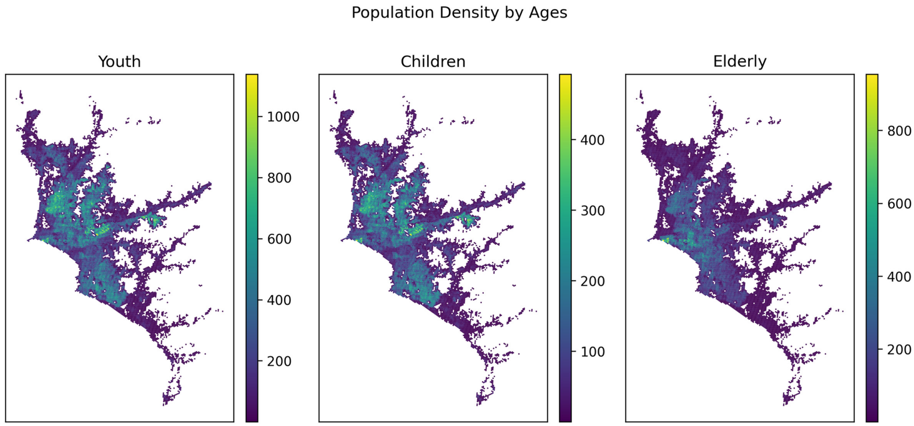

Figure 2.
Population density + demographics aggregated by resolution 9 H3 hexagons

with drastic increases in the average area. On the other hand, a more granular representation (closer to 15) refines the detail up to a "coffee table" resolution but results in a larger number of hexagons. Using the more granular resolutions comes with a second setback: by creating smaller and smaller hexagons, the resulting spatial units do not cover a single block within a city, hence none of the indicators described in this paper can be computed. The benefit of choosing a resolution between 7 and 9 is that they provide good spatial granularity (close to 1 km^2 in area) without compromising the complexity of the hexagon selection procedure by generating large candidate sets. Our methodology does not constraint the user to a set resolution, since city-wide applications benefit from coarser resolutions (7 or 8) and local applications benefit from granular resolutions (9 or 10). This base layer of hexagons will be the basis of all further spatial aggregations. Since the population density maps are of point geometry, a simple point-in-polygon spatial operation that aggregates the total population within a hexagon by summing the values from each point is implemented. Conversely, data sources of polygon geometry, such as income levels or accessibility indicators calculated based on city blocks, require a different approach.

Since the hexagon layer resolution does not guarantee that each spatial unit will contain a city block (Figure 3), a more suitable approach is an overlay of both layers. As shown in the right figure of Figure 3, several hexagons may contain portions of blocks within the same neighborhood. To provide a suitable, yet computationally efficient, approximation, the overlay operation that was implemented consists of assigning the value from the block resolution layer that is proportional to the area of the block covered by the hexagon. The results of applying this kind of overlay are presented in Figure 4, where the resulting overlay maintains the spatial distribution of the original data source without adding too much noise to the aggregated hexagon layer.

A further evaluation of the effects of this procedure on the spatial distribution of the original data set is presented in Figure A1, where across different resolutions, aggregation methods and input data sources, the spatial distribution of the original data source is maintained. This overlay procedure results in five new features being added to the hexagon layer. As shown in Figure 5, the income levels are separated into high, medium-high, medium, medium-low and low. The scale of these values is based on the percentage of blocks of an income level present within (or overlayed in this case) a hexagon. A similar procedure to that of the population density maps is used to aggregate the number of commercial establishments (segmented into services, manufacturing, retail and beverage, food and

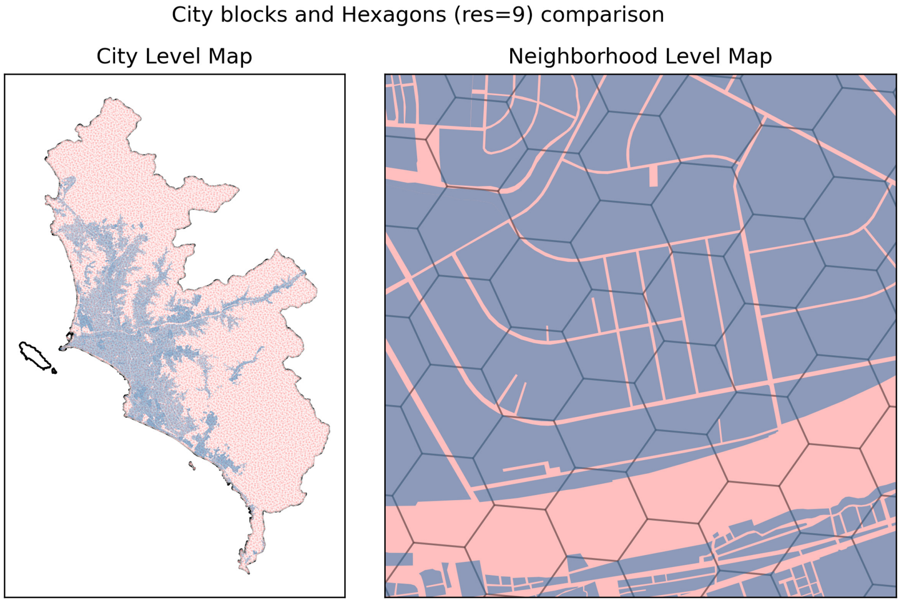

Figure 3.
Size comparison of City Blocks and resolution 9 H3 hexagons in different levels

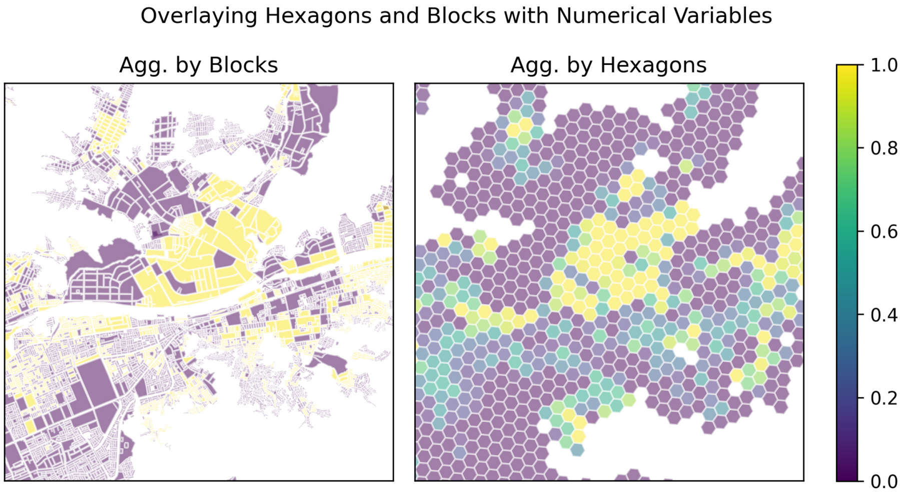

Figure 4.
Overlaying percentage of mid-level income from blocks to hexagons

accommodation), where the values of the new features are based on the POI count within each hexagon.

From these initial data sources, several indicators of interest to decision-makers may be computed. First, using routing engines based on the road network of Lima, a duration and distance matrix can be computed for the city in terms of access from each hexagon to health-care facilities and food supply facilities. For this paper, the OpenSource Routing Machine (OSRM) (Luxen and Vetter, 2011) was used to compute the distance and duration matrices using the walking profile (this methodology and implementation support any of the mobility

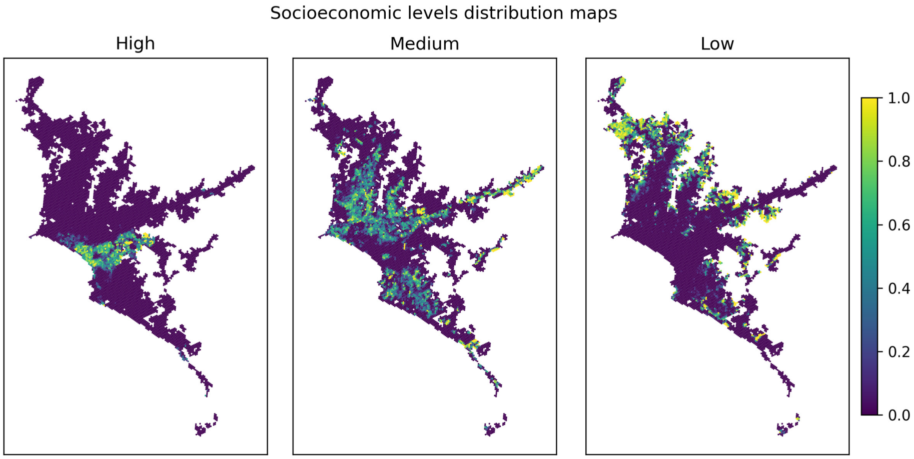

Figure 5.
Block percentage by socioeconomic level aggregated by resolution 9 H3 hexagons

profiles supported by OSRM). Using OSRM [2], the shortest path – in terms of travel time or distance – from a hexagon centroid to a healthcare or food supply facility based on a mobility profile (e.g. walking, driving and cycling) can be computed using the network topology downloaded from OSM. These results of the said computations, as shown in Figure A2, present the already mentioned phenomenon that the fringe of the city is the most vulnerable in terms of distance traveled and the duration of a trip to the nearest facility. To complement these indicators, and to have a more holistic perspective over accessibility within Lima, the pressure map from Ritsema Van Eck and De Jong (1999) and the accessibility surface from Hu *et al.* (2020) were computed based on the hexagon layer.

Both surfaces in Figure 6 present a similar issue with different interpretations. The accessibility indicator, which considers how many POIs are within a buffer from a hexagon and how many hexagons intersect the buffer from a POI, shows that the financial and commercial centers of Lima present the highest accessibility. To a lesser extent, the figure also shows that the residential areas surrounding these centers have high levels of

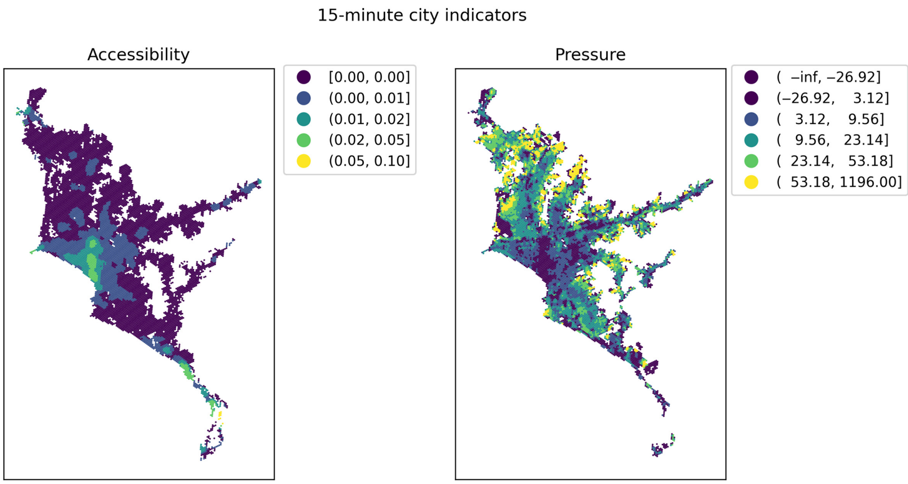

Figure 6.
Accessibility surface from Hu *et al.* (2020) (left) and pressure map from Ritsema Van Eck and De Jong (1999) (right)

accessibility. The pressure surface, computed based on the population and number of POIs within a buffer of each city block, emphasizes the accessibility issues to essential services in the fringe of the city. Comparing both indicators, it is evident that the accessibility map presents a smoother spatial distribution, where accessibility follows the Gaussian friction adjustment in the original formulation. Since accessibility is computed using hexagons, it is also worth noting that the southern outliers correspond to coastal populations within large districts that concentrate their goods and services near the Panamericana Sur highway. The effects of computing this indicator at a hexagon level are that these zones with low-population density and high commercial density near the urbanized zones present the highest accessibility values (0.1 for accessibility and 1196 for pressure), alluding to zones where the walking distance between city blocks and commercial establishments are low and the population density is spatially overlapped with the commercial density.

The final set of indicators that were computed for candidate selection were socio-economic vulnerability indicators. Such indicators may include monetary, labor and water access vulnerability (Figure 7). Since these indicators may be categorical (i.e. monetary and labor vulnerabilities), they may not necessarily be the most suitable for the hexagon selection procedure. Even so, these indicators are valuable for decision-makers, hence their inclusion into the SDSS. With these indicators computed, the output of this initial set of results is a set of candidate hexagons based on a number of candidates (setting p for the FLP) and a buffer size from which to filter nearby hexagons.

Table 1 presents a sample from San Juan de Lurigancho, Lima's most populated district. Within the values in this table, the inverse interpretation of accessibility and pressure that was discussed previously is shown (high accessibility, low pressure and vice-versa). Also, the monetary, labor and water access vulnerabilities are shown in this sample, where this district contains households with high access to the public water network (9% and 8%) and close to no access to the water network (97%). Even though this sample does not show it, there are households (and by extension, hexagons) that are subjects of monetary and labor vulnerability. From the 734 hexagons that allow the computation of these indicators, only 8% are subjects to labor and monetary vulnerability. This comes in contrast with the analysis of a commercial district such as Miraflores (Table 2). Even though Miraflores is a much smaller district (48 hexagons vs 1,032 in San Juan de Lurigancho), it presents no monetary, labor or water vulnerabilities. Given that this district is the commercial district within Lima, it is logical that there is close to no pressure and high accessibility, as shown in the table.

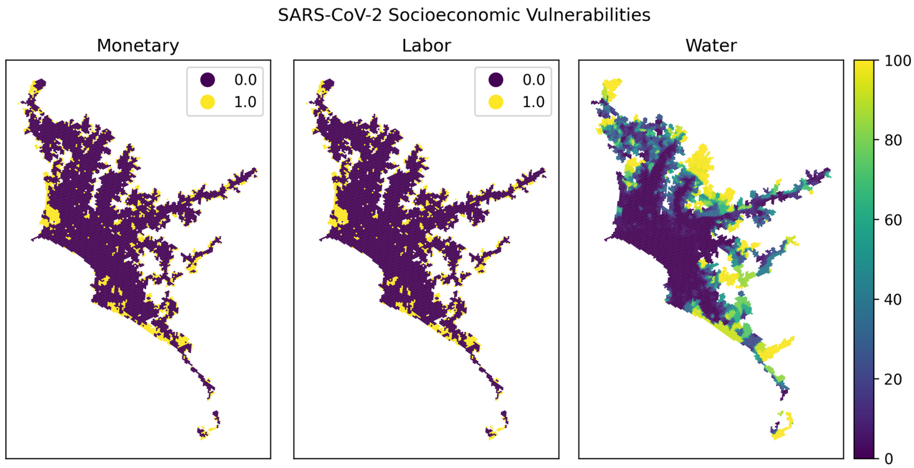

Figure 7. Socioeconomic vulnerabilities related to the SARS-CoV-2 pandemic

4.3 Modelling and sensitivity analysis

The second set of results corresponds to running a set of FLP instances. Said instances follow a grid search pattern, where the hexagon selection hyperparameters (number of candidates and buffer size) are permuted to analyze computational costs such as model build and solve times and the effect of these permutations on the objective value. The selection of the specific values to permute relies on the size of the candidate set (based on p) and analyzing the allocation of the facilities by changing the walking travel time threshold (15-, 30- and 60-min). As mentioned previously, these experiments were ran using the PuLP library in conjunction with the Cbc optimizer. The choice of using the Cbc optimizer over other alternative open-source solvers (such as GLPK) is first based on its flexibility. As a branch and cut solver, Cbc is designed to easily integrate with user-designed cut generators and heuristics. Second, it is supported by default in PuLP so no extra configuration is needed. And finally, within the open-source alternatives, it is the fastest in single thread instances [3] while supporting multi-threading. Even so, this methodology does not constraint the user to the use of a specific solver. Within other use cases in the humanitarian logistics literature, other solvers and optimization software have been used such as CPLEX (Rodríguez-Espíndola *et al.*, 2018), Lingo (Maharjan *et al.*, 2020) or search algorithms (Jia *et al.*, 2007). All of these alternatives can be taken into consideration, especially for large instances.

The results of this grid search procedure are summarized in Table 3. From this table, several insights can be gathered. First of all, solutions within the same p value cannot be compared directly. Since the selection procedure output from Algorithm 1 is likely to vary given the buffer size, assuming that a solution with a larger buffer size is better based on the objective value is not accurate. What can be gathered in terms of the objective function value is that instances with a smaller buffer size (1,250 m) present the highest cost. This is natural given that there is less flexibility to choose from, and the selected facilities are likely to have less coverage than those selected using higher buffer sizes.

A second important insight is the effect of buffer size on the build and solve time of the instances. Across all experiments, except for those with $p > 50$, increasing the buffer size increases both build and solve times. This, once again, is due to the increased number of candidate hexagons from the selection procedure and possible facilities to choose from by filtering those within the buffer. This effect can be explained by the hexagon selection procedure. When selecting a large number of hexagons, the number of hexagons within a

Table 1. Accessibility, pressure and vulnerability summary within San Juan de Lurigancho

Hex ID	Population	Accessibility	Pressure	Monetary Vul.	Labor Vul.	Water Vul.
898e62c28c7ffff	2,293.111257	0.004637	6.605670	0.0	0.0	9.010839
898e62d0937ffff	2,791.613705	0.000296	83.272295	0.0	0.0	18.271285
898e62d5acfffff	2,592.212726	0.001505	23.643137	0.0	0.0	8.423457
898e62d7227ffff	1,345.956608	0.000629	0.924561	0.0	0.0	97.529538
898e62d732fffff	598.202937	0.000046	68.200000	0.0	0.0	97.620593

Table 2. Accessibility, pressure and vulnerability summary within Miraflores

Hex ID	Population	Accessibility	Pressure	Monetary Vul.	Labor Vul.	Water Vul.
898e62c562bffff	1,388.426020	0.008930	2.782682	0.0	0.0	0.0
898e62ce5b7ffff	1,125.103844	0.027028	1.195638	0.0	0.0	0.0
898e62c0bafffff	837.843288	0.019017	1.239170	0.0	0.0	0.0
898e62ce597ffff	1,220.857362	0.028660	0.957121	0.0	0.0	0.0
898e62ce58bffff	1,077.227084	0.016751	1.666503	0.0	0.0	0.0

p	Buffer size	Build time (s)	CPU time (s)	Objective value
5	1,250	0.00	0.17	1.459656e+07
5	2,500	0.02	0.16	1.334495e+07
5	5,000	0.05	0.22	1.200104e+07
20	1,250	0.02	0.12	7.409369e+07
20	2,500	0.24	0.57	3.757340e+07
20	5,000	0.72	1.46	2.099214e+07
50	1,250	0.12	0.33	5.689734e+07
50	2,500	0.91	4.41	3.774712e+07
50	5,000	4.63	11.15	3.004802e+07
100	1,250	0.68	1.58	5.996508e+07
100	2,500	5.42	13.68	6.812555e+07
100	5,000	4.79	11.12	3.004802e+07
150	1,250	2.24	5.15	8.177861e+07
150	2,500	14.83	35.70	8.229656e+07
150	5,000	4.44	10.81	3.004802e+07
200	1,250	5.14	22.98	1.044296e+08
200	2,500	14.23	35.50	8.229656e+07
200	5,000	4.53	10.60	3.004802e+07

Table 3. Optimization tests and calibration

60-minte walking distance that collide (or are within a k-ring distance less than 2) increases significantly. This would reduce the total number of facilities, hence the lower build and solve time. Even so, all these models were of relatively quick build and solve times, which presents an opportunity for easy interaction within the SDSS.

4.4 Spatial decision support system development

The final set of results are related to the SDSS. Using the results from the previous sections, a web-based SDSS can be developed following the design shown in Figure 1. The SDSS has two main interactions: parameter selection and spatial analysis of the outputs, shown in Figure 8. In the left-most column, three kinds of parameters may be set. First, the parameters related to the hexagon selection procedure may be changed. These parameters include whether or not to use the whole city or only a district, how many candidate zones to select (max_candidates) and the minimum coverage by each candidate zone (buffer size).

The second set of parameters to select is which indicators (from those computed sections above) will be used within the hexagon selection procedure. Within this selection, the sorting method is required as well as a threshold for the primary indicator (*at* in Algorithm 1). On each parameter update, the SDSS will update the two figures shown in the right-most column by calling the selection procedure and the optimization engine. The optimization engine comprised an API [4] that by using standard web protocols, allows the platform to interact with the FLP model from the previous section. Once the parameters are set, a call to the API is made to get the optimization results and selected hexagons to visualize. First, the map of Lima is updated to show all hexagons selected with the procedure, as well as those in a k-ring distance of 2 (which results in approximately 19 hexagons per candidate). The additional elements to this map involve the public spaces available to be selected as facilities. As detailed in the previous section, the optimization of an FLP is based on the hexagon clusters as the customer set and the public spaces (in green) as facilities.

An additional property to the public spaces shown in the map is that they are related to the second figure. In this figure, given a set of selected hexagons (top 10 in blue and random in red), the radar chart shows different indicators such as population density,

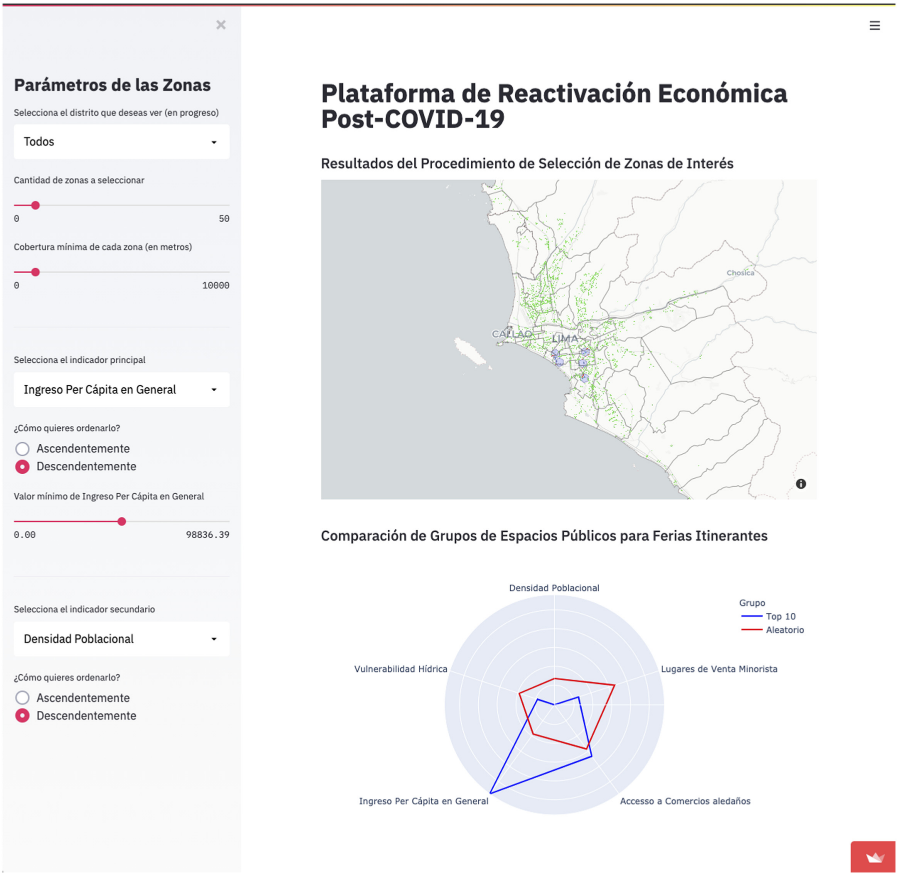

Figure 8.
Web-based SDSS application to interact with the computed indicators and the hexagon selection procedure

income and accessibility based on the public spaces and their surrounding hexagons. Both figures are updated simultaneously, where on each parameter change the hexagon set changes on the map and the radar chart adjusts to the selected hexagons. As mentioned in the previous section, when using the optimization API, another property would be added to these spaces, where the indicators of the optimal solution from the model will show as a third group.

The idea of showing a random selection of public spaces is to direct the attention of the user to a baseline that does not consider any information provided by the SDSS (which reflects a reality in which decision-makers do not have a rich data source from which to base their selection). The complete, interactive version of the platform is available within Lima's Observatory [5].

5. Conclusions and discussion

This paper presented a methodology to manage public spaces to increase the accessibility to essential goods and services by vulnerable populations using open data sources that was implemented into a web-based SDSS to increase the accessibility to essential goods and services during a pandemic using public spaces. Since the literature has shown strong relationships between accessibility and vulnerability, while lacking studies focused on using public spaces as disaster response facilities, this paper fills a literature gap on developing a methodology to identify vulnerable populations which have low accessibility to essential goods and services with geospatial data and applications of DSS in post-disaster public space management. The platform seeks to present relevant indicators related to accessibility and vulnerability, while presenting ways in which public spaces can be used to improve said indicators and ensuring an efficient allocation of resources in the response phase of a disaster.

The development of the platform was motivated by the COVID-19 pandemic, which added several constraints in terms of how accessible the response facilities may be given a city's restrictions. The development of the platform focused on presenting a set of indicators, such as population density, accessibility and vulnerability, and their spatial distributions. Using the H3 hexagonal system, different sources of data were aggregated into regular polygons, which in turn allows for a complete view of a city without settling for large spatial aggregations.

Using the hexagon layers, the SDSS was deployed so it can show interactive, web-based visualizations. To aid decision-makers in the process of selecting a public space (i.e. a park or a football field) as a response facility, two main alternatives were implemented. First, a selection procedure that prioritized the hexagons based on the indicators chosen by the user filters those hexagons which demand the most attention from the decision-maker. Second, taking these hexagons and the available database on public spaces, an FLP optimization API was implemented to identify the optimal spaces to select, which serves as an initial solution subject to other constraints within a municipality.

An important characteristic of this SDSS is the preference for open sources of data. This ensures that, for the most part, the indicators, selection procedures and deployments are reproducible across different cities in the world. The only proprietary sources of data relate to the location of businesses and demand, which usually comprised directories or private databases, or census data which may not be open in the spatial resolution required for the analysis made in this paper. Another potential limitation to the widespread use of this platform is the infrastructure needed to run the optimization API. Since it was designed for a relatively small test, a group of users would most likely overload the server if a set of large-scale instances is requested at once. To overcome this, algorithms for heuristic solutions (as presented in Section 2) may be implemented, but this is a future area for research and development.

Overall, the system was designed as an easy to use tool for decision-makers which are not necessarily well versed in accessibility, vulnerability or optimization. By providing indicator summaries of how an "optimal" solution may look like compared to picking a random set of spaces, the goal is to steer the managing authorities into a data-driven policy alternative, which, in turn, would encourage more data governance within the public sector and strengthen the collaboration with academia.

This was corroborated by testing the SDSS with local authorities. Within these tests, the different features of the SDSS were ranked by their importance in the decision-making process, where the indicators and their spatial distribution ranked highest. The interactivity and ease of use were also highlighted by the seven teams that tested the platform, where the possible interactions and results were clear and they can be integrated into their decision-making process without significant changes to either the SDSS or their IT suite. A recommendation from the discussion was that each local reality was different. Although the users understood the goal and usage of the platform, to reach its maximum potential, it is necessary to incorporate complementary local data since a great diversity of interests and needs were found. As such, a high-level overview like the one presented may not necessarily fit every single district within a city. This comes with the recommendation of a more mobile-based design, where more value can be added by designing the platform to work efficiently from a cellphone or tablet.

A future research avenue for this methodology (and the SDSS) is the adaptation of the hexagon selection procedure and FLP optimization to a multi-objective approach. Even though the current design of the hexagon selection does support a multiple indicators and priorities, the initial FLP formulation does not account for the multiple decision-making factors and objectives that may be considered by decision-makers. The most important improvements to this methodology in this regard are to (1) handle the multiple indicators and composite measures in the hexagon selection smoothly and (2) support multi-objective (or goal) programming approaches in the FLP to provide a Pareto frontier of solutions. This will allow enriching the end user's decision-making process, integrating more subjectivity from their domain knowledge into the methodology, which would synergize with the comments made by local authorities.

Notes

1. https://h3geo.org/docs/core-library/restable
2. http://project-osrm.org/docs/v5.24.0/api/
3. http://plato.asu.edu/ftp/milp.html
4. https://www.github.com/IngenieriaUP/prep_api
5. https://www.observatoriodelima.org/prep_covid19

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Appendix

Figure A1.
Resolution downsampling process. This allows to aggregate hexagons in coarse resolutions

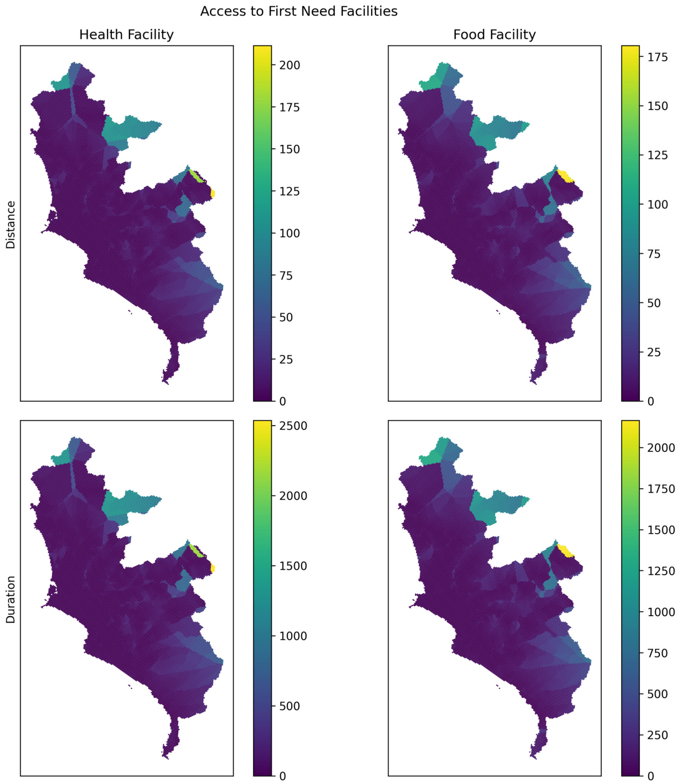

Figure A2.
Trip distance and duration time by foot to food and health facilities

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