Appendix

Table S1. Search strategies in PubMed, Scopus and Web of Science.

<table>
<tr><td>Source 1: PubMed</td><td>Retrieved citations: 448</td><td>Date: 10 Nov, 2021</td></tr>
<tr><td colspan="3">Search strategy: ("SARS-CoV-2"[Mesh]) OR ("COVID-19"[Mesh])) OR ("COVID-19 Testing"[Mesh])) OR ("COVID-19 Vaccines"[Mesh])) OR ("covid*"[Title/Abstract])) OR ("COVID-19"[Title/Abstract])) OR ("COVID19"[Title/Abstract])) OR ("Coronavirus"[Title/Abstract])) OR ("nCoV Infection"[Title/Abstract])) OR ("SARS-CoV-2"[Title/Abstract])) AND ((inequality[Title/Abstract]) OR (equality[Title/Abstract])) OR (equity[Title/Abstract])) OR (inequity[Title/Abstract])) OR (access*[Title/Abstract])) OR (inacces*[Title/Abstract])) OR ("travel time*"[Title/Abstract])) OR ("travel distance*"[Title/Abstract])) OR (availabl*[Title/Abstract])) OR ("catchment area"[Title/Abstract])) OR ("distribution"[Title/Abstract]))) AND ("Geographic Information Systems"[Mesh]) OR ("geographical distribution"[Title/Abstract])) OR ("geographic distribution"[Title/Abstract])) OR ("spatial access*"[Title/Abstract])) OR ("geospatial access*"[Title/Abstract])) OR ("geographic access*"[Title/Abstract])) OR ("spatial analysis"[Title/Abstract])) OR ("geospatial analysis"[Title/Abstract])) OR ("geographic mapping"[Title/Abstract])) OR ("geographic information system"[Title/Abstract])) OR ("geography information system"[Title/Abstract])) OR ("geographical information system"[Title/Abstract])) OR ("geographical mapping"[Title/Abstract])) OR ("travel time*"[Title/Abstract])) OR ("travel distance*"[Title/Abstract])) OR ("GIS"[Title/Abstract])) OR ("ArcGIS"[Title/Abstract])) AND (2019:2022[pdat])</td></tr>
<tr><td>Source 2: Scopus</td><td>Retrieved citations: 778</td><td>Date: 10 Nov, 2021</td></tr>
<tr><td colspan="3">Search strategy: (TITLE-ABS-KEY (sars-cov-2) OR TITLE-ABS-KEY (covid-19) OR TITLE-ABS-KEY (covid19) OR TITLE-ABS-KEY (covid) OR TITLE-ABS-KEY (covid*) OR TITLE-ABS-KEY (coronavirus) OR TITLE-ABS-KEY ("nCoV Infection*") OR TITLE-ABS-KEY ("SARS-CoV-2")) AND (TITLE-ABS-KEY (inequality) OR TITLE-ABS-KEY (equality) OR TITLE-ABS-KEY (equity) OR TITLE-ABS-KEY (inequity) OR TITLE-ABS-KEY (access*) OR TITLE-ABS-KEY (inacces*) OR TITLE-ABS-KEY ("travel time*") OR TITLE-ABS-KEY ("travel distance*") OR TITLE-ABS-KEY (availabl*) OR TITLE-ABS-KEY ("catchment area") OR TITLE ("distribution")) AND (TITLE-ABS-KEY ("Geographic Information Systems") OR TITLE-ABS-KEY ("geographical distribution*") OR TITLE-ABS-KEY ("geographic distribution*") OR TITLE-ABS-KEY ("spatial access*") OR TITLE-ABS-KEY ("geospatial access*") OR TITLE-ABS-KEY ("spatial analysis") OR TITLE-ABS-KEY ("geospatial analysis") OR TITLE-ABS-KEY ("geographic mapping") OR TITLE-ABS-KEY ("geography information system") OR TITLE-ABS-KEY ("geographical information system") OR TITLE-ABS-KEY ("geographical mapping") OR TITLE-ABS-KEY ("travel time*") OR TITLE-ABS-KEY ("travel distance*") OR TITLE-ABS-KEY (gis) OR TITLE-ABS-KEY (arcgis)) AND (LIMIT-TO (PUBYEAR,2022) OR LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2019))</td></tr>
</table>

Source 3: Web of Science	**Retrieved citations:** 491	**Date:** 10 Nov, 2021
Search strategy: (TS=("SARS-CoV-2" OR "COVID-19" OR covid* OR covid19 OR Coronavirus OR "nCoV Infection" OR "SARS-CoV-2")) AND (TS=(inequality OR equality OR equity OR inequity OR access* OR inacces* OR "travel time*" OR "travel distance*" OR availabl* OR "catchment area" OR "distribution")) AND (TS=("Geographic Information Systems" OR "geographical distribution" OR "geographic distribution" OR "spatial access*" OR "geographic access*" OR "geospatial access*" OR "spatial analysis" OR "geospatial analysis" OR "geographic mapping" OR "geography information system" OR "geographical information system" OR "geographical mapping" OR "GIS" OR "travel time*" OR "travel distance*" OR "ArcGIS")) *Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI Timespan=2019-2021*		

Table S2. Detailed information extracted from included articles.

ID	Author (Year)	Scale/ location	Population	Service	Main method	Software	Aim	Key findings
1	Bauer et al. (2020)	Continent 14 European countries	Populations at risk	ICU beds	Gravity models (E2SFCA)	ArcGIS Pro 2.5	Exploration of accessibility of ICU beds and its impact on CFR	Access to ICU beds varies significantly across countries; low ICU accessibility associated with a higher proportion of CFR
2	Alemdar et al. (2021)	City Istanbul, Turkey	Populations at risk	Vaccine	ED	ArcMap 10.6	Creation of a GIS-based multi-criteria decision approach for accessibility of vaccination centres	Efficiency, accessibility, availability and security of vaccination centres increase targeting them to population, hospital, police stations, public transportation stops and pharmacies
3	Boitrago et al. (2021)	Country Brazil	All population COVID-19 cases in particular	ICU beds	Gravity models (2SFCA) Spatiotemporal cluster analysis	ArcGIS PRO 2.5	Analysis of COVID-19 incidence and CFR; identify care gaps such as ICU bed accessibility; organization of emergency and urgency services	General provision of new beds failed to cover critical regions but could be optimized by spatial analysis, which also helped efforts to increase access to ICU beds in response to COVID-19outbreaks and identified regions with particularly high needs
4	Geldsetzer et al. (2020)	Continent 44 sub-Saharan countries	Adults aged 60 years and older	Hospital and healthcare facilities	CDNA with regard to travel time	AccessMod 5.6.33; R 3.6.3	Estimation of access to the nearest hospital or healthcare facility for adults aged 60 years and older	Localization of population groups most likely to under-report symptoms because of low physical access to healthcare facilities. Approximately 10% of adults ≥60 years across sub-Saharan Africa have estimated travel times to nearest hospital of ≥6 hours
5	Ghorbanzadeh et al. (2021)	State/Province Florida, USA	COVID-19 patients	ICU beds	Gravity models (2SFCA and E2SFCA)	CUBE; ArcGIS	Assessment of spatial accessibility of patients to which healthcare facilities with ICU beds are available in both urban and rural areas	2SFCA overestimates accessibility in areas with few ICU beds due to the “equal access” assumption of the population within the catchment area. Possibly related to the distance decay effect considered with E2SFCA. Both models reveal that many areas have low access to the facilities due to low access ratios
6	Guhlincozzi & Lotfata (2021)	City Chicago, Illinois, USA	People with disabilities and ≥65 years	Flu and COVID-19 vaccination sites	CDNA	ArcGIS Pro	Comparison of access to flu and COVID-19 vaccination sites before, during and post COVID-19	Geographical methods contribute to study of weaknesses and strengths of the health infrastructure; making COVID-19 vaccination sites available at flu shots (and vice versa) would improve access, in particular for people with limited mobility
7	Zheng et al. (2021)	State/Province Yunnan, China	COVID-19 cases	Hospitals	CDNA, Voronoi diagrams, OD cost matrix, IDW algorithm	Open Street Map; IDW algorithm	Investigation of the spatial scope of services and spatial accessibility of COVID-19-designated hospitals	Voronoi diagrams are effective for determining public health resources; weighted Voronoi diagrams can delineate services offered by designated hospitals. COVID-19 cases in Yunnan are concentrated in the central and northern regions. Medical resources in Yunnan should be shifted based on these findings
8	Lakhani & Wollersheim (2021)	State/Province Victoria, Australia	Populations at risk	POCT site	CDNA	R Software; ArcMap 10.7.1	Identification of impact of site location on the closest residents for each POCT site	The closest residents of POCT sites in urban locations would have a significantly lower travel time compared to the closest residents to POCT sites in rural locations.
9	Tao et al. (2020)	State/Province Florida, USA	Populations at risk	Testing site	Gravity models (2SFCA)	ArcGIS Pro	Identification of any disparities in accessibility to testing during the early stage of the pandemic	Accessibility scores were found to be heterogeneous across geographic regions and among different groups of people, in particular, those in rural areas and those without access to private transportation
10	Pereira et al. (2021)	Country Brazil (20 largest cities)	Vulnerable population (Low-income population >50 years)	ICU beds and mechanical ventilators	Gravity models (BFCA)	Open Trip Planner	Calculation of accessibility to ICU beds and mechanical ventilators	Low-income and black communities in urban peripheries have less healthcare access; 41% of the vulnerable population have poor access to ICU beds and mechanical ventilators, a particularly aggravated scenario when accounting for competition effects with regard to both supply and demand for health services

11	Silalahi et al. (2020)	City Jakarta, Indonesia	Populations at risk	Referral hospitals	CDNA, SDE, OD cost matrix)	ArcGIS 10.5; ArcGIS Pro 2.5.	Introduction of geographic distribution of COVID-19 care based on GIS; the nearest healthcare facility by service area and OD cost matrix; SDE modelling of study area	Additional referral hospitals needed; the SDE model was developed under assumption that the observed cases follow the normal distribution; hence, the variance of the data and the shape of the study area must be considered
12	Kim et al. (2021)	State/Province Florida, USA	COVID-19 cases	ICU beds	Gravity models (3SFCA)	R Software &OSRM	Identification of areas likely to be overwhelmed by the pandemic, and explore associations of low access areas with their socioeconomic and demographic characteristics	North Florida rural areas with Latino or Hispanic populations found likely to have lower access to health care than other regions; the number of cases can vary across time periods and areas with less developed transportation systems are more likely to be overwhelmed by the in the later period of the pandemic
13	Hernandez et al. (2021)	City New Orleans, Louisiana, USA	People tested at drop-in sites during 52 days (Vulnerable populations)	Testing sites	ED (Distance to nearest hub and distance matrix)	QGIS 3.10.8	Assessment whether drop-in to testing sites increased access, in particular for vulnerable populations including racial and ethnic minorities, poor and the elderly	Drop-in sites increased testing availability for some vulnerable populations who took advantage of site proximity, although inequalities appear at the metropolitan scale. Community-based strategies improve both coverage and access for hard-to-reach populations.
14	Mohammadi et al. (2021)	City Mashhad (second most populous city in Iran)	Populations at risk	Vaccination	Gravity models (Age-integrated E2SFCA)	ArcGIS v.10.8; QGIS v.3.20	Analysis of potential spatial access to vaccination centres	GIS can quantify the suitability of existing urban healthcare centres; The potential spatial accessibility results of the proposed GIS model indicate that, despite the selection of only 20% of high-capability centres for vaccination, more Census Tracts would have access to vaccination centres than in other scenarios.
15	Rocha et al. (2021)	Country Brazil	Populations at risk	Vaccination	CDNA	R software with WOPR; ArcGIS Pro 2.5.	Exploration of how artificial intelligence can support planning of local actions to ensure effective implementation of national vaccination plans.	Around 18% of Brazil's elderly population live more than 4 km from a vaccination point. The number of PCCs located more than 5 km from cell towers was largest in Brazil's North and Northeast
16	Leithauser et al. (2021)	Country Germany	Populations at risk	Vaccination	CDNA (Mathematical programming)	Python 3	Quantification of key indicators, number of required facilities, number of required physicians and patients‘ travel distance	In case of free assignments, the number of required physicians can be limited to 2, 000 but when travel distances are minimized, an increased number of physicians is unavoidable emphasizing the trade-off between travel distances and number of vaccination facilities.
17	Zhou et al. (2021)	City Wuhan, Hubei, China	Populations at risk	Medical Facilities	CDNA (Estimated travel distance and time)	Baidu Map API	Investigation of real-time accessibility of available travel modes; identify underserved areas and discern spatial disparity of facilities during emergency lockdown	Significant differences in service areas and load across facilities; accessibility of health care in peripheral areas was inferior to central areas; spatial inequality of health care within and across districts; number of community healthcare centres was insufficient; some communities were underserved regarding walking distance; while some could be overloaded; accessibility analysis can be rapid and relevant even with open-source data
18	Hu et al. (2020)	State/Province Massachusetts USA	Populations at risk	Testing site	CDNA (Google Maps Distance Matrix API)	Google Maps Distance Matrix API	Analysis of the relations between COVID-19 incidence rate and racial residential segregation regarding access to testing sites and socio-demographic & economic variables	Drive time to testing sites is significantly negatively associated with the incidence rate; African Americans have the shortest drive time to testing sites, followed by Hispanics, Asians, and Whites implying the importance of the accessibility to testing sites for all
19	Kang et al. (2020)	State/Province Illinois, USA	Populations at risk and COVID-19 patients	Healthcare resources	Gravity models (parallel - E2SFCA)	CyberGIS-Jupyter; Virtual ROGER	Analysis of the spatial accessibility of healthcare resources	Spatial accessibility measures for population at risk identifies geographic areas in need of additional healthcare resources and provides improved understanding of how well healthcare infra-structure is equipped to save people’s lives during the pandemic

20	Yong et al. (2021)	City Shenzhen, China	Populations at risk	Fever clinics	CDNA (OD time matrix, and LSCP model)	Baidu Map API	Use of travel time to link facilities and identify the dynamic allocation of patients' medical needs	Equal access to medical services (or reduced travel time) has improved while reducing the overutilization of high-quality medical resources. On this basis, during early screening for prevention and control of outbreaks, the specific suggestions for implementation in developing and less developed countries can be made optimized allocations
21	Kim et al. (2020)	Country South Korea	Populations at risk	NPIRs	Gravity models (2SFCA)	ArcGIS	Exploration of any insufficiency and spatial disparity of NPIRs in response to infectious disease outbreaks	NPIR allocation was found to be both suboptimal and inadequate for infectious risk; even a simple method of spatial allocation like 2SFCA can be used to discover potential lack of NPIRs and provide information where to establish this kind of facilities
22	Pecoraro et al. (2021)	Country Italy (20 regions)	Populations at risk	ICU beds	Gravity models (E2SFCA)	QGIS; OSRM	Investigation of spatial accessibility of ICU beds under inter- and intra-regional variability	Two main patterns of hospital distribution over the territory are highlighted: a) Regions with high density cities tend to concentrate hospitals and ICU beds in highly populated zones leaving rural areas underserved. b) Less populated regions have access to ICU beds better distributed localizing them at their borders to serve also neighbouring areas; overall access in almost all regions, however, still lack adequate critical care services.
23	Zhao et al. (2020)	City Beijing, China	Populations at risk	Hospitals	Gravity models (2SFCA)	Baidu Map API	Analysis of neighbourhood access to hospitals by means of public transportation or travel by car	Access for high-income neighbourhoods to secondary and tertiary hospitals is high but suburban areas are less well served; spatial inequality regarding health care in megacities is growing
24	Krzysztofowicz & Osinska-Skotak (2021)	City Warsaw, Poland	60–70 and 50–60 age groups as part of a planned approach	Vaccination	CDNA (Thiessen's tessellation)	ArcGIS Pro	Analysis of spatial access to vaccination sites to minimize the time needed to vaccinate specific age groups	Spatial inequalities and areas with poor access to vaccination sites was identified; activation of additional sites was proposed, either located at *ad hoc* places or using a mobile vaccination approach to achieve uniform coverage.
25	Lakhani (2020)	City Melbourne, Australia	Aging adults (>65 years) with disability	Palliative care and health services	CDNA (OD cost matrix)	ArcMap 10.4.1	Identification of priority areas with a high percentage and number of aging adults (>65 years) with disability and barriers to PCC access	Spatial analyse identified priority metropolitan areas of aging adults with disability and difficulties to access health services. Priority areas may require unique palliative care offerings
26	Whitehead et al. (2021)	Country New Zealand	Populations at risk	Vaccination	CDNA (OD Matrix)	ArcGIS 10.7	Analysis of the potential access for populations under different vaccine distribution scenarios	All potential vaccine delivery scenarios, except schools, resulted in travel barriers for a substantial proportion of various populations; a disproportionate impact of vaccine delivery location was seen for Māori, the elderly and people living in areas characterized by high socioeconomic deprivation

API=Application programming interface; BFCA= Balanced floating catchment area; CF= Case fatality ratio; CDNA= Cost Distance & Network Analysis; E2SFCA: ED=Euclidean distance; Enhanced two-step floating catchment area; GIS=Geographical information systems; ICU=Intensive care unit; IDW=Inverse distance weighting; LSCP=Location set covering problem; NPIR= Negative pressure isolation room; OD:=Origin destination; OSRM=Open source routing machine; PCC=Primary care centre; POCT:=Point of care test; SDE=Standard deviational ellipse; 2SFCA=Two-step floating catchment area.