A vulnerability index for COVID-19: spatial analysis to inform equitable response in Kenya

Peter M Macharia[†*1], Noel K Joseph[†1], Emelda A Okiro[1]

[1]Population Health Unit, KEMRI-Wellcome Trust Research Programme, Nairobi, Kenya

[†]joint first authors

*Corresponding author: PMacharia@kemri-wellcome.org

Abstract

Background: Response to the COVID-19 pandemic calls for precision public health reflecting our improved understanding of who is the most vulnerable and their geographical location. We created three vulnerability indices to identify areas and people who require greater support while elucidating health inequities to inform emergency response in Kenya.

Methods: Geospatial indicators were assembled to create three vulnerability indices; social (SVI), epidemiological (EVI) and a composite of the two (SEVI) resolved at 295 sub-counties in Kenya. SVI included nineteen indicators that affect the spread of disease; socio-economic inequities, access to services and population dynamics while EVI comprised five indicators describing comorbidities associated with COVID-19 severe disease progression. The indicators were scaled to a common measurement scale, spatially overlaid via arithmetic mean and equally weighted. The indices were classified into seven classes, 1-2 denoted low-vulnerability and 6-7 high-vulnerability. The population within vulnerabilities classes was quantified.

Results: The spatial variation of each index was heterogeneous across Kenya. Forty-nine north-western and partly eastern sub-counties (6.9 m people) were highly vulnerable while 58 sub-counties (9.7 m people) in western and central Kenya were the least vulnerable for SVI. For EVI, 48 sub-counties (7.2 m people) in central and the adjacent areas and 81 sub-counties (13.2 m people) in northern Kenya were the most and least vulnerable respectively. Overall (SEVI), 46 sub-counties (7.0 m people) around central and south-eastern were more vulnerable while 81 sub-counties (14.4 m people) that were least vulnerable.

Conclusion: The vulnerability indices created are tools relevant to the county, national government and stakeholders for prioritization and improved planning especially in highly vulnerable sub-counties where cases have not been confirmed. The heterogeneous nature of the vulnerability highlights the need to address social determinants of health disparities, strengthen the health system and establish programmes to cushion against the negative effects of the pandemic.

Keywords: Kenya, COVID-19, vulnerability, sub national, social, epidemiological, inequities

Summary

Key questions

What is already known?

- Disasters and adverse health events such as epidemics and pandemics disproportionately affect population with significantly higher impacts on the most vulnerable and less resilient communities.

- Significant health, socio-economic, demographic and epidemiological disparities exist within Kenya when considering individual determinants, however, little is known about the spatial variation and inequities of their concurrence.

What are the new findings?

- Sub-counties in the north-western and partly eastern Kenya are most vulnerable when considering social vulnerability index while central and south-east regions are most vulnerable based on the epidemiological vulnerability index affecting approximately 6.9 million and 7.2 million people respectively.

- The combined index of social and epidemiological vulnerabilities shows that on average, 15% (7.0 million) of Kenyans reside in the most vulnerable sub-counties mainly located in the central and south-eastern parts of Kenya.

What do the new findings imply?

- Targeted interventions that cushion against negative effects to the most vulnerable sub-counties are essential to respond to the current COVID-19 pandemic.

- Implementation of strategies that address the socioeconomic determinants of health disparities and strengthening health systems is crucial to effectively prevent, detect and respond to future adverse health events or disasters in the country.

- Need for better quality data to define a robust vulnerability index at high spatial resolution that can be adapted and used in response to future disasters and adverse health events in the long run.

Introduction

There has been growing recognition of the threat that epidemics, disasters and public health emergencies pose to global health security and the livelihoods of people, beyond their impact on human health [1]. Under the umbrella of the global health security agenda, countries have come together to advance a world safe and secure from infectious disease threats. Hence, countries are expected to be prepared to weather disease outbreaks and natural disasters with Africa having a history of dealing with emerging diseases [2,3] most recently the Ebola epidemic in West Africa and DRC [4].

Epidemics, disproportionally impact vulnerable populations as can be witnessed with the coronavirus disease 2019 (COVID-19) in the United States and the United Kingdom where Black, Asian and minority ethnic communities are being disproportionately affected [5–7] as are poorer communities [8,9]; during the Ebola outbreak the disease was linked to rural and remote areas [10]. The reasons behind this disparity are complex and varied however, one of the biggest underlying factors driving this disproportionate impact is socioeconomic inequities [8,11]. Several factors, including poverty, lack of access to healthcare and transportation, and certain aspects of housing may weaken a community's ability to prevent significant human and financial loss when a disaster such as the current COVID-19 pandemic strikes. A framework that provides a detailed understanding and location of population groups that are either vulnerable to increased risk of infection or inferior health outcomes and that are also marginalized from health services can inform where additional resources are most needed. These factors are collectively identified as vulnerability and aim to identify people that are disproportionally exposed to the risk of infection and/or disease severity.

COVID-19 rapidly spread worldwide and while low testing numbers do not allow for a reliable appraisal of the extent of the epidemic in Africa, 115,616 cases and over 3,479 deaths had been reported in Africa as of May 26th, 2020 [12]. Health officials expect that it is only a matter of time before infections begin to rise in Africa with growing concerns about risks in a continent that faces unique challenges in dealing with the current outbreak [2]. WHO has estimated that between 83,000 and 190,000 people could die of COVID-19 and 29 million to 44 million could get infected during the first year of the pandemic if containment measures fail in Africa [13]. However, although cases are increasing, most countries in Africa are not documenting the same exponential growth rate in confirmed cases as seen in Europe and the United States [11,14].

The first case of COVID-19 in Kenya was confirmed on March 13th, 2020. Since then 1,348 cases have been reported with 52 deaths confirmed by May 26th 2020 [15]. The Kenyan government, through the Ministry of Health, has responded quickly by taking proactive public health measures to combat the spread of the disease. These measures have been through intensive tracking of contacts, isolation of confirmed cases, halting non-essential services, and cutting

off routes of transmission through suspension of international flights, dusk-to-dawn curfew, partial lockdowns and most recently closing borders with high intensity neighbouring countries of Tanzania and Somalia [15]. However, certain challenges face the implementation of some of these measures. There has been widespread growth of informal settlement in Kenya which typically are characterized by high-density neighbourhoods and poor infrastructure common across the continent where self-isolation and social distancing are proving extremely challenging. A substantial number of people work in the informal sector [16] where working from home is not realistic and the risks of a sudden loss of income is a constant threat with many more suffering from insecure food supplies [17].

Often people living in these settings often have malnutrition, infectious diseases such as HIV/AIDS and some may suffer from non-communicable diseases putting these individuals at greater risk of more severe clinical infection and mortality due to COVID-19 [18]. Other challenges include high poverty rates, weaker health systems and minimal access to healthcare with most countries having inadequate financial leeway to provide an effective response without external assistance. While the scarcity of resources is a matter of concern, it is equally important to look at whether the resources available support the most affected communities. This time presents an opportunity to reduce overall inequities by supporting the most vulnerable groups. Some level of prioritization and targeting of resources will prove useful in this context to identify those people and places that face the highest risk.

Using a wide range of spatially referenced indicators to enumerate a varied range of social constraints and assess risk, we developed three COVID-19 specific vulnerability indices to enumerate both social vulnerability (affects the risk of infection and spread) and epidemiological vulnerability (affects the risk of progression to severe disease) defined at the sub-county level in Kenya. This will facilitate identification of vulnerable groups and elucidate health inequities to help public health response by identifying and mapping communities that will most likely need greater support during the current outbreak.

Data and methods

Geographic analysis unit: In 2013, Kenya adopted a decentralized system of governance where the units of administration and health planning were revised to 47 counties with broad policy directions maintained at the national level [19,20]. The counties are further sub divided to sub-counties [21] and was adopted as the unit of analysis. A geospatial layer of all sub-counties was created by digitizing sub-county maps available for each county from the county integrated development plans (CIDPs) [21]. Additional file 1 shows all the 295 sub-counties of Kenya derived from the CIDPs.

Three indices were defined, social vulnerability index (SVI), epidemiological vulnerability index (EVI) and a composite of the two, the social-epidemiological vulnerability index (SEVI). SVI broadly refers to the resilience of communities in face of external stresses such as disasters and disease outbreaks on human health [22]. The indicators used to define SVI entail socio economic inequalities [17,23,24], population dynamics [23] and access to services [23–26] which are likely to affect the risk of infection and spread of the disease at different rates in different sub national areas.

The EVI encapsulates diseases and comorbidities that affect the likelihood of disease progression hence affecting the severity of COVID-19 disease [18,27–30]. They include underlying medical conditions such as liver disease, chronic kidney disease, obesity, hypertension, diabetes, smoking, cardiovascular disease, chronic respiratory disease, cancer and people who are immunocompromised including HIV/AIDS [18,27–30]. The SVI and EVI were combined to generate SEVI in order to explore the overall resilience and risk of developing severe COVID-19 disease in Kenya.

Data assembly

To create the indices at subnational level in Kenya, 24 data layers were assembled from various sources (Table 1) based on data availability, Kenya's epidemiological context and preliminary findings suggesting an association with COVID-19 disease [17,18,23–30]. Nineteen datasets were used to define the SVI while five were used to construct the EVI. The datasets were available in different formats and at different spatial resolution necessitating pre-processing and/or modelling before being input to the framework for constructing a vulnerability index.

------------------Table 1 here ---------------------------------

The 24 layers of data fall into three broad groups. The first group comprised of twelve data layers available as gridded surfaces at 1 x1 km or 5 x 5 km spatial resolutions [31–40] [Table 1]. The mean value per indicator and subcounty was extracted using the *zonal statistics* function of the Spatial Analyst tool of ArcMap 10.5 (ESRI Inc., Redlands, CA, USA). The second group comprised of seven variables whose coverage was estimated using small area estimation (SAE) models [41] based on the 2014 demographic and health survey (DHS) [42] and the 2015 stepwise survey for non-communicable diseases (NCD) [43] conducted in Kenya [Table 1 denoted as B]. DHS 2014 and NCD survey were designed to provide precise estimates at county and provincial level respectively. Therefore, SAE models were used to smooth estimates at subcounty (DHS 2014) and county level (NCD survey) using R-INLA package [44] in R software (version 3·4·1). The remaining five data layers were derived through a combination of geospatial techniques (Table 1 footnote).

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Constructing SVI

COVID-19 disease vulnerability indices have been created using different approaches ranging from technical [45–47] to simpler approaches [48–50]. In the current analysis, the indices were created following approaches used to define universal health coverage (UHC) and equity in maternal and child health [51–55], infectious disease vulnerability index [56] and some of the recent COVID-19 vulnerability indices [48–50].

To create SVI for Kenyan sub-counties, three sub domain indices were first defined based on major thematic areas related to COVID-19 vulnerability (Table 1 and Figure 1). They included socioeconomic inequality, population characteristics and access to services. The subdomains facilitate a finer and detailed viewpoint that would have been masked by a single averaged index. A similar approach was used when creating an infectious disease vulnerability index for African countries [56] and a composite coverage index for measuring UHC [53].

Nine indicators (Table 1 and Figure 1) were used to define socioeconomic inequality sub domain. People of low socioeconomic status including those under casual employment and physical labour are unlikely to have resources to actualize measures put in place by the government such as social distancing viz-a-viz earning a daily livelihood [7,17,24]. Further, households need to have access to a basic handwashing facility, soap and detergents as a first line of protection against infection [17]. The population characteristics subdomain included six indicators related to population dynamics (Table 1 and Figure 1). As population density increases, the rate of transmission of infectious diseases increases [57], informal settlements, refugee and internally displaced people (IDP) camps are vulnerable mainly due to shared community facilities such as water points and toilets while rural areas maybe at a lower risk [58]. The risk of COVID-19 increases with age especially after sixty years [17,18,59].

Finally, four indicators were used to define access to services (Table 1, Figure 1). About 8% of the Kenyan population lives outside two-hour travel of the nearest facility capable of offering hospital and emergency care [38] that might be needed to deal with severe COVID-19 cases with significant gaps in hospital capacity to accommodate a surge due to COVID-19 [26]. Further, commodities and services that might be needed by people during the COVID-19 era are likely to be concentrated in urban areas with marginalized areas associated with poorer health and education outcomes [39].

The geospatial data layers in each subdomain had different scales with different minima and maxima values. Therefore, to make the values comparable, they were first rescaled to a common scale ranging between 0 (least vulnerable) and 100 (most vulnerable) (Equation 1). The scaled indicators were used to create a unique index for each of the three subdomains

through an arithmetic mean and were equally weighted. The arithmetic mean of the three subdomains indices was used to create the SVI.

Equation 1: Rescaling of coverage and or prevalence values for each determinant to a common scale ranging from 0 (least vulnerable) to 100 (most vulnerable)

$$\text{Scaled value} = \left(\frac{m - r_{min}}{r_{max} - r_{min}} \right) * \left(t_{max} - t_{min} \right) + t_{min}$$

M - the value to be scaled; r min- the minimum value in the original range; r max- the minimum value in the original range; t min - the minimum value in the new scale (0) and t max - the maximum value in the new scale (100)

Constructing EVI and SEVI

Five indicators on underlying health conditions and comorbidities, risk factors for severe disease [18,27–30] were available including the prevalence of HIV, smoking, obesity, diabetes and hypertension (Table 1, Figure 1). Similarly, these layers were first rescaled (Equation 1) and spatially overlaid using arithmetic mean and equally weighted to generate EVI. Finally, the generated SVI and EVI were averaged to generate the composite final index, SEVI.

Each index was grouped into seven classes ranging from the least vulnerable to the most vulnerable. The classes were grouped using the natural Jenks classification method which identifies "natural" groups within the data by reducing the variance within classes and maximizing the variance between classes [60]. A higher group (the sixth and seventh class) indicated high vulnerability while a lower group (the first and the second class) represented low vulnerability. The groups are unique within each index since the distribution of data among the indices are different. The proportion of the population within each band of vulnerability was then computed based on the 2019 Kenya's census data.

Figure 1 summarizes the input data and methods used to define the indices in Kenya across the 295 sub-counties. The analysis and visualizations were done using StataCorp. 2014 [Stata Statistical Software: Release 14. College Station, TX: StataCorp LP], R software (version 3·4·1) and ArcMap 10·5 (ESRI Inc., Redlands, CA, USA).

------------------Figure 1 here ---------------------------------

Patient and public involvement
Our study does not involve the participation of patients or any members of the public. All data used in this study are aggregated and publicly available as listed in Table 1.

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Results

The spatial variation of the social vulnerability index (SVI) was heterogeneous across the 295 sub-counties (Fig 2A). The least vulnerable sub-counties are mainly located in the western and central parts of Kenya while sub-counties in north-eastern and southern parts are moderately vulnerable. North-western and parts of eastern Kenya have the most vulnerable sub-counties (Figure 2A). Approximately fifteen per cent (6.9 million) of Kenya's total population resides in the 49 sub-counties that that were classified as highly vulnerable. Almost two-thirds (65%) of Kenya's population (30.9 million) live in 188 sub-counties that are moderately vulnerable while only circa 21% live in the 58 least vulnerable sub-counties.

The most vulnerable sub-counties in north-western and partly eastern Kenya with reference to SVI are characterized by poor geographic access to health care services, marginalized in terms of access to the nearest urban areas and economically disadvantaged (mainly poor households, poor access to improved water and sanitation and low education attainment) (Additional file 2, and Additional file 3). However, despite being the most vulnerable, the region has a low population density and fewer families with single parents relative to other parts of Kenya (Additional file 2).

The least vulnerable sub-counties based on SVI mainly in central and western Kenya have a lower proportion of the poor households, improved access to water and handwashing soaps/detergents, higher education attainment while most settlements are near urban areas and within 2 hours of the nearest hospital (Additional file 3). Despite having on average low vulnerability, both central and western Kenya sub-counties have a high population density and higher proportion of the elderly population. In addition, sub-counties in central Kenya and adjacent areas have a slightly higher number of urban population and families with a single parent (Additional file 2).

-------------------Figure 2 here ----------------------------------

Conversely, based on the EVI, 48 sub-counties in central, south-east and partly western Kenya where approximately 7.2 million people reside were the most vulnerable (Figure 2B). Approximately thirteen million (13.2) people residing in 81 sub-counties mainly located in the northern and eastern parts were classified as the least vulnerable. Majority of the sub-counties in the south of the equator have higher epidemiological vulnerability mainly driven by a high prevalence of hypertension and smoking. High prevalence of obesity and diabetes is only evident in fewer sub-counties around central and south-east Kenya while HIV is more prevalent in the western Kenya (Additional file 2, and Additional file 3). There are exceptions in north-eastern, where Wajir county has a higher prevalence for both diabetes and hypertension while Turkana county has a higher prevalence of smoking (Additional file 2).

The spatial variation of the overlay between social vulnerability and epidemiological vulnerability (SEVI) is shown in Figure 3. The resulting patterns are smoother than EVI and SVI since its average of the two which were had fewer areas of concurrence of the high or low vulnerable sub-counties. Consequently, majority of Kenya's population (55%) reside in moderately vulnerable sub counties mainly in north-western and eastern parts of Kenya.

Forty-six sub-counties in the central and adjacent areas, south-east and partly western Kenya were the most vulnerable affecting 15% (7.0 million) of Kenya's population. More importantly, a few sub-counties that are highly vulnerable due SEVI, have a dual burden of SVI and EVI. Notable cooccurrence of EVI and SVI include parts of Kitui (central-east), Elgeyo Marakwet (partly western) and Narok (south-west). These areas have a high prevalence of smoking, hypertension and stunting, higher proportion of elderly population, low access to improved water and sanitation and smaller proportion of people within 2-hours of the nearest hospital.

Approximately 30% of the population reside in sub-counties classified as the least vulnerable based on SEVI. These sub-counties are not localized in one geographic but scattered across Kenya mainly in western (e.g. Bungoma county) and a few in north-eastern (e.g. Wajir county) and central (e.g. Kiambu county) Kenya. The localized areas of low vulnerability have different variable factors contributing to the least vulnerable score. For example, in Kiambu, central Kenya, all 24 indicators have low scores (meaning least vulnerable) except five, namely, high population density, high urban population, elderly population, shared toilets and high prevalence of smoking whose effect is masked in the combined index. On the other hand, Wajir county in north-eastern, only crowded and poor households, poor spatial access to hospitals, water and sanitation had higher scores (meaning more vulnerable) whose effect was neutralized by low scores from the rest of the indicators.

--------------------Figure 3 here ---------------------------------

Discussion

Emerging and re-emerging diseases with pandemic potential continue to challenge countries and health systems, causing enormous human and economic losses [1,3]. Health security calls for the need for all countries to invest in improving their global health preparedness in the phase of emerging epidemics including stronger health infrastructure as the best defence against disease outbreaks and other health threats [2,61]. Not surprisingly most countries are struggling to mitigate the impact of the current COVID-19 pandemic with varied levels of success with increasing fears or re-emergence in those places that have managed to contain the pandemic [62]. It remains uncertain how Africa is going to come through this pandemic. Compared with the rest of the world, the virus has arrived later, providing an opportunity to learn from other contexts that could help guide Africa's fight. Social distancing and basic hygiene measures are proving to be the most effective tools to slow down the rate of transmission. Yet, in many contexts throughout Africa, social distancing and frequent handwashing are privileges that not everyone has access to [7,63].

In Kenya, the expectation is that nearly all communities will be affected by COVID-19 to yet undetermined degrees; however, the impact of the pandemic will not be the same in each locality. Meanwhile, Kenya does not have a preexisting granular vulnerability index such as the CDC's US social vulnerability index [22]. Such an index would have been used to assess vulnerability or identify vulnerable populations that can be used to inform decisions on the disbursement of social support measures or identify those areas that require improved health services. In the current analysis three indices have been developed to identify which communities may need the most support as COVID-19 spreads in the country. Mapped to the sub-county, the vulnerability indices provide information that is useful for emergency response planning and mitigation at a relatively granular level and can help support response planning for the current epidemic.

Once introduced, outbreaks spread faster in vulnerable communities than in less vulnerable areas. Some communities in Kenya were identified to be more vulnerable than others and would exhibit compromised ability to manage the spread and limit the economic and social impact of the outbreak. The social vulnerability index identified sub-counties in the northern and south east parts of Kenya as the most vulnerable while majority of the sub-counties in central and western Kenya were observed to be less vulnerable (Figure 2A). The 49 most vulnerable sub-counties account for 6.9 million (15%) of Kenya's total population require greater focus and prioritization in terms of response.

There is a divergence between sub-counties that had high social vulnerability indices and those defined as epidemiologically most vulnerable (Figure 2). Most of the sub-counties in western, central and parts of south east were observed to have high EVI hence when applied

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to COVID-19, these areas are likely to have sub populations at higher risk of developing severe disease and increased mortality rates [18,27–30]. While the Kenyan population has hypertension, obesity and diabetes, the prevalence is generally not high compared to other settings where severe disease and increased mortality have been observed. Conversely these regions appear to be less vulnerable with respect to social vulnerability (Figure 2A).

Though sparsely populated, northern and south eastern parts of Kenya were less epidemiologically vulnerable and are therefore generally less vulnerable to severe diseases but more susceptible to infections and spread when considering their socioeconomic context. They have poor access to hospitals and urban areas, high number of poor households, constrained access to water and sanitation and low education attainment. These metrics allow for identification of geographic areas that are most likely to harbour large numbers of undocumented COVID-19 cases due to lack of access to care (Additional file 2, Additional file 3), which in turn can inform the geographic targeting of testing and surveillance efforts and for the deployment of temporary hospitals based on projected need.

The government of Kenya has put in place several measures to curb the spread of COVID-19. Some of these measures lead to reduced social interaction hence reduced production and demand across all the sectors which are costly to the economy and will have negative impacts on the livelihoods of people. The national government, the county governments and other stakeholders are implementing programmes to cushion against adverse socio-economic impacts. These include reduction of taxes, provision of masks and hand sanitizers, distribution of food, water and other commodities. Further the government will inject Kenya shillings 53.7 billion into the economy to stimulate growth and cushion families and companies during COVID-19 pandemic in eight thematic areas including infrastructure, education, small and medium enterprises, health, agriculture, tourism, environment and manufacturing [64]. This analysis identifies areas that should be prioritized for different interventions when programmes to ease vulnerability and mitigate the effects of COVID-19 are being rolled out across the country. This is important especially in areas that are highly vulnerable and are yet to experience an escalation of cases. These indices have the potential to pave the way for data driven informed planning to tackle vulnerability.

The epidemic is shaped by many factors, testing capacity and social distancing, as well as population density, age structure, wealth and other social behavioral factors. In Kenya the spread of the virus is uneven with most of the cases identified in the capital city, larger towns and a few border towns. By overlaying the number of confirmed cases of COVID-19 onto the vulnerability indices, we can begin to explore the spread of the virus in communities with different levels of vulnerability. We have preliminary explored how vulnerability relates to the numbers of confirmed cases of COVID-19 using case data at the county level made available by of May 14th.Identified hotspots (Mvita subcounty, Dagoretti north and Kamukunji sub-

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counties) are in highly vulnerable areas when considering their population characteristics which include being largely urban, high population density with a high proportion of people living within informal settlements. Further they have most people within informal employment and shared sanitation facilities. This is somewhat confounded by the fact that we are unable to separate out imported cases which comprise a substantial percent of the total case count.

Countries are starting to ease lockdown measures to limit the negative impact on the economy [62,65]. These decisions need to be informed by the trends in new cases, the potential risk of resurgence and the strength of public health systems including the capacity to detect new cases. The vulnerability index delivers a measure through which to better appreciate factors that enable communities to remain resilient, inform on their ability to carry out personal protective measures, practice both hand hygiene and hygiene in the household and the possibility of social distancing in different context. Importantly these indices have identified indicators that shed light on factors that would drive the continued spread of disease and inform prediction on the burden of severe disease and mortality due to COVID-19 in Kenya. Importantly, the indices developed are versatile and can be repurposed for use in varied emergency response situations.

The indices showed widespread inequities across sub-counties of Kenya. While the interim measures will help ease the pressure and reduce vulnerability, there is a need to reduce inequities in the longer term, beyond the current COVID-19 pandemic in preparation for future epidemics which are inevitable [66]. Africa must invest heavily in relevant data systems and preparedness by increased government investments. Programmes to ensure access to improved water and sanitation, targeted social programmes such as raising awareness for proper hygiene, improvement of housing facilities in the informal settlements and IDP camps are needed. Strengthening health systems remains at the core of reducing health inequities [66]. The system should also be redesigned to deal with surge capacity by absorbing the increase in the demand of healthcare services due to epidemics and pandemics [26].

The prevalence and recurrence of epidemics and disasters in Africa should be the impetus for greater investment in preparedness. Disasters such as COVID-19 pandemic [67,68], Ebola epidemic [4] , flooding in East and Southern Africa [69], ongoing floods and recurrent malaria epidemics in Kenya [70] have become common. Investments on measures such as early warning systems should be put into place to detect, respond and effectively contain these threats. Strategic actions that were recommended against influenza could potentially inform better preparation in case of a viral disease; capability to develop pandemic strain vaccines, stockpiles of broad-spectrum antiviral drugs, surge capacity for rapid vaccine production and developing models that could inform effective means of delivering therapies during an outbreak [71].

The indicators used in the current analysis to derive vulnerability indices were based on the priori understandings of who is a risk and vulnerable from information available so far, however, COVID-19 is evolving and more insights will become increasing available and the indices can be adapted. Further the classification of indicators into sub domains should be adapted to context and the data availability. For example, Wilkinson *et al.,* (2020), proposes categorizing the indicators into epidemiological vulnerability (based on underlying health conditions), transmission vulnerability (for example social mixing and hygiene infrastructure), health system vulnerability (for example hospitals beds and health workers etc) and vulnerability to control measures [72].

Limitations

There were data related limitations when computing the vulnerability indices. Several variables such as access to mobile phones, access to insurance cover, and mobility between counties could not be accessed during the analysis. Further, due to the lack of granular data despite using SAE techniques, obesity, diabetes and hypertension could only be resolved at the county level. Therefore, we assumed the estimates within sub-county were equal for these three variables. Some of the datasets are not updated to 2020 and their trends are likely to have changed between 2014 and 2020. Further the analysis was conducted at the sub county level, it's likely that that some variation and heterogeneity was masked in the relatively bigger polygons.

An equal weighting scheme was implemented for all the determinants. While variables can be weighted through epidemiological (amount of variation a variable explains in the outcome), subjective (from experts) or statistical approaches, there is neither a gold standard approach nor a predefined way of implementing the weights [51,53,73]. During the creation of an infectious disease vulnerability index [56], different weighting schemes were explored, and the results indicated the most vulnerable countries did not change substantially. However, the determinants employed in the current analysis are likely to have varying contribution, severity and impact to COVID-19 disease. The weighting scheme can be revised as more individual COVID-19 data with attributes become available in Kenya and other countries across Africa. This will allow a better definition of how the risks associated with different variables vary in across different population and settings [18].

The preliminary overlay between indices and the cases may have been limited. Cases were allocated in counties where they were recorded, however, these might not have been the residential counties for the last several years. Some might have been living outside Kenya and other counties. On the hand, the data layers used refer to the specific counties for the period between 2014 and 2020.

Conclusions

Fighting the COVID-19 pandemic calls for precision public health reflecting our improved understanding of who is most vulnerable and what makes them more vulnerable, where the disease is spreading or likely to spread fastest, and where current interventions may not work as intended. COVID-19 is spreading at different rates across Kenya, most probably working its way through all 47 counties. The indices estimated presents tools that can be used by the Kenyan government and stakeholders to better plan especially in areas where COVID-19 has not been confirmed by prioritizing sub-counties that are moderately to highly vulnerable. The heterogenous nature of the vulnerability indices highlight the need to address social determinants of health disparities, strengthening of the health system and related programmes.

Declarations

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Authors' contributions

All authors contributed to the development of the project, analysis, interpretation of the study findings and writing of the manuscript. All authors read and approved the final manuscript.

Availability of data and materials

All the datasets used in the current analysis are publicly available and can be accessed through references listed in Table 1

Ethics approval and consent to participate

This study used secondary data only, all publicly available and can be accessed from different data repositories via references listed in Table 1. No individual patient level data used in this publication.

Consent for publication

Not applicable. The manuscript does not contain any individual person's data.

Competing interests

The authors declare that they have no competing interests

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Tables and figures legends

Table 1: Data layers used to define COVID-19 vulnerability index in Kenya including their definition, sources, spatial resolution, year of they refer to and pre-processing done. The layers are classified into 4 thematic areas

Figure 1: Schematic representation of data layers and approaches used to define social vulnerability index (SVI), epidemiological vulnerability index (EVI) and the combination of the two, social-epidemiological vulnerability index at subnational level in Kenya.

Figure 2: Social vulnerability index (SVI) (A) and epidemiological vulnerability index (EVI) (B) across 295 sub-counties in Kenya grouped into seven ranks. Rank 1 and 2 are the least vulnerable sub-counties while rank 6 and 7 are the most vulnerable.

Figure 3: Social- epidemiological vulnerability index (SEVI) across 295 sub-counties in Kenya grouped into seven ranks. Rank 1 and 2 are the least vulnerable sub-counties while rank 6 and 7 are the most vulnerable.

Table 1

Index	Sub index	Domain	ID	Indicator and definition	Definition	Year /source	Resolution
SEVI	SVI	Socioeconomic inequality	1	Informal employment	Percent aged 15-49 years who work in a manual labour profession	2014 [31]	1x1 km
			2	Detergent availability	Percent of households where no soap/detergent was observed		
			3	Car ownership	Percent living in a household that does not own a private car		
			4	Place for handwashing	Percent living in a household with no place for handwashing		
			5	Education attainment	Mean years of school attainment	2015 [32]	5x5 km
			6	unimproved water source	Proportion of households without access to improved water sources	2014 [33,34]	
			7	Malnutrition	Prevalence of stunting among children	2015 [35]	
			8	Poor households	Proportion of households within the poorest and poorer wealth quintile	DHS 2014 [42]	Subcounty [B]
			9	Shared sanitation facilities	Percentage in the households sharing a toilet facility		
		Population characteristics	10	Informal settlements	Percentage of people living in informal settlements and IDP camps	2019 [74–76]	See footnote
			11	Elderly population	Percentage of the population aged 65+	2019 [36,37]	1x1 km
			12	Single parent families	Percentage of the population headed by a single parent	DHS 2014 [42]	Subcounty [B]
			13	Crowded households	Percentage in the population with 3+ persons per bedroom		
			14	Log Population density	Total population per unit area	2019 [16]	See footnote
			15	Urban population	Proportion of population living in urban areas		
		Access to services	16	Access to hospitals	Proportion of population outside 2 hours travel of a hospital	2019 [38]	1x1 km
			17	Health workforce	Number of clinicians and medical officers per population	2019 [16,77]	See footnote
			18	Hospital beds	Number of hospital beds per population		
			19	Access to urban areas	Travel time to the nearest urban centre with at ≥ 5000 people	2015 [39]	1x1 km
	EVI	Epidemiological factors	20	HIV	HIV prevalence among adults (5x5 km grids)	2017 [40]	5x5 km
			21	Smoking	Percent of households with least a daily or weekly smoker	2014 [31]	1x1 km
			22	Obesity	Percentage of adults categorized as obese	NCD survey 2015 [43]	County [B]
			23	Diabetes	Percentage of adults diagnosed with diabetes		
			24	Hypertension	Percentage of adults diagnosed with high blood pressure		

Footnote: The methods used to create each dataset are detailed in the references provided in Table 1 and fall in to three broad categories. 1) Methods used to create gridded surfaces (denoted with a resolution of either 1x1 km or 5x5 km spatial resolution), using model-based geostatistics which produces probabilistic inference on a spatially continuous phenomenon based on data collected over a finite set of geo-referenced locations [78] or the use of a cost distance algorithms to define travel time (spatial access) to either the nearest urban area or health facility[38,39]; 2) Generated from household surveys using small area estimation (SAE) techniques (denoted by letter B), SAE smooths estimates by borrowing strength from adjacent units and weights predictions towards the estimated prevalence of neighbouring areas. The spatial dependence was represented through a queen adjacency [79] and modelled via the Besag-York -Molliè (BYM) 2 conditional autoregressive (CAR) model. 3) The remaining datasets required a combination of steps to derive them. Lists of informal settlements were extracted from online portals [74,75] and their extents digitized using Google Earth. Population density maps [76] were used to define the proportion of the population living in the digitized settlements by subcounty. Similarly, the proportion of the population living in urban areas by subcounty was derived based on a list of urban areas according to Kenya's 2019 census [16]. Population per unit area(population density) were available by subcounty [16] while the number of health workers and hospital beds per population available from the 2018 Kenya harmonized health facility assessment [77] were divided by the total population per subcounty [16] to derive health workers and beds per 10, 000 population.
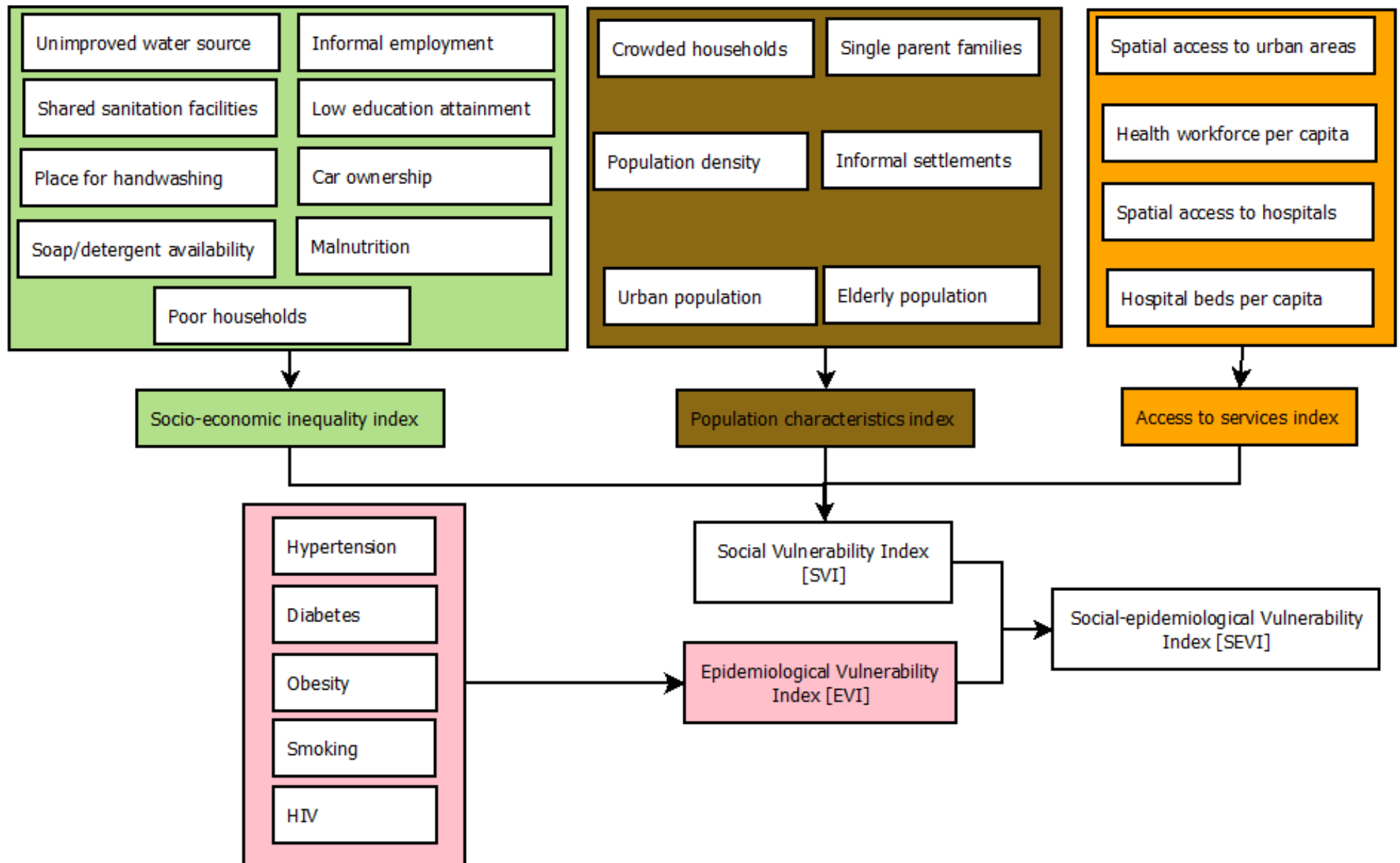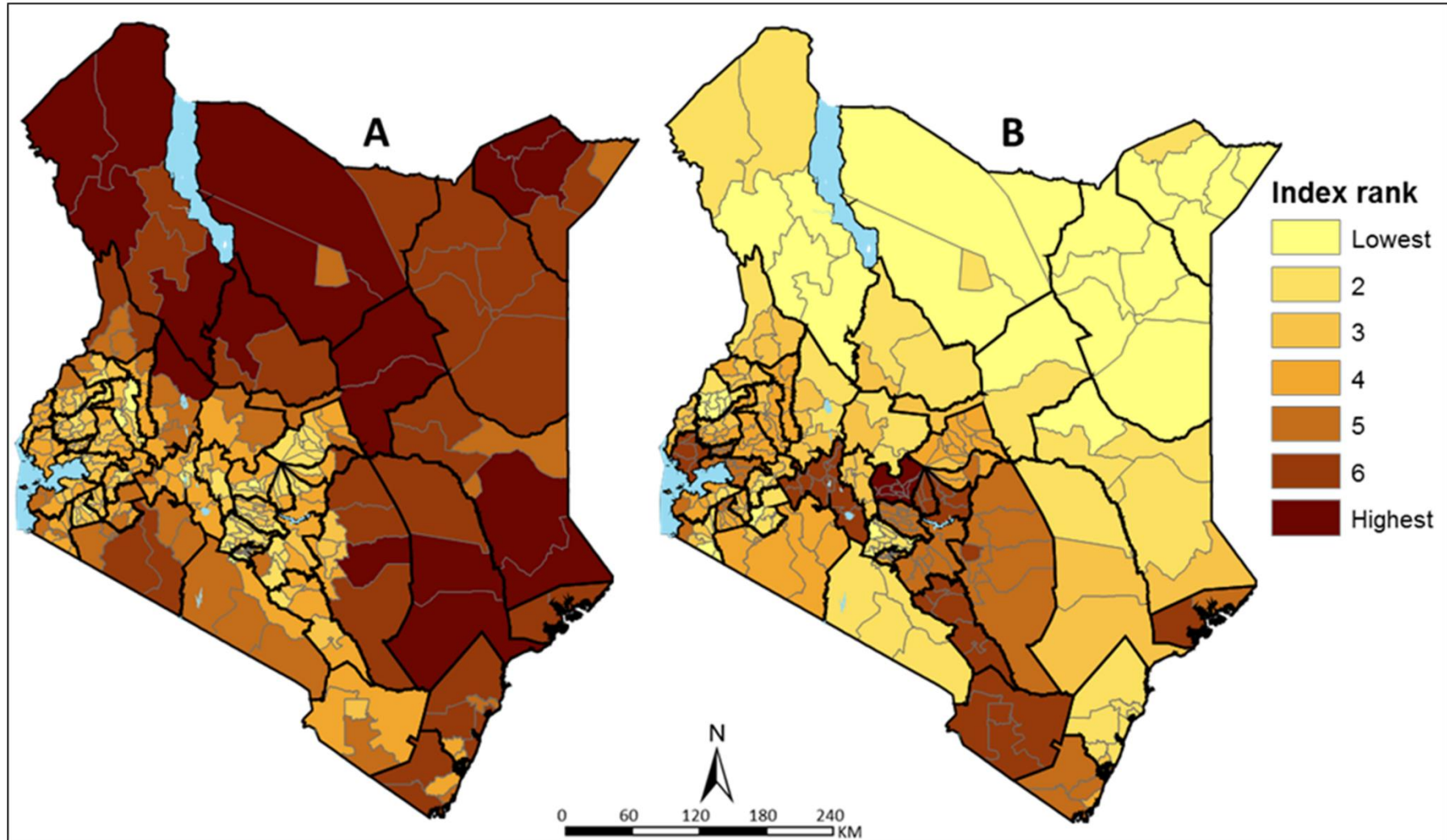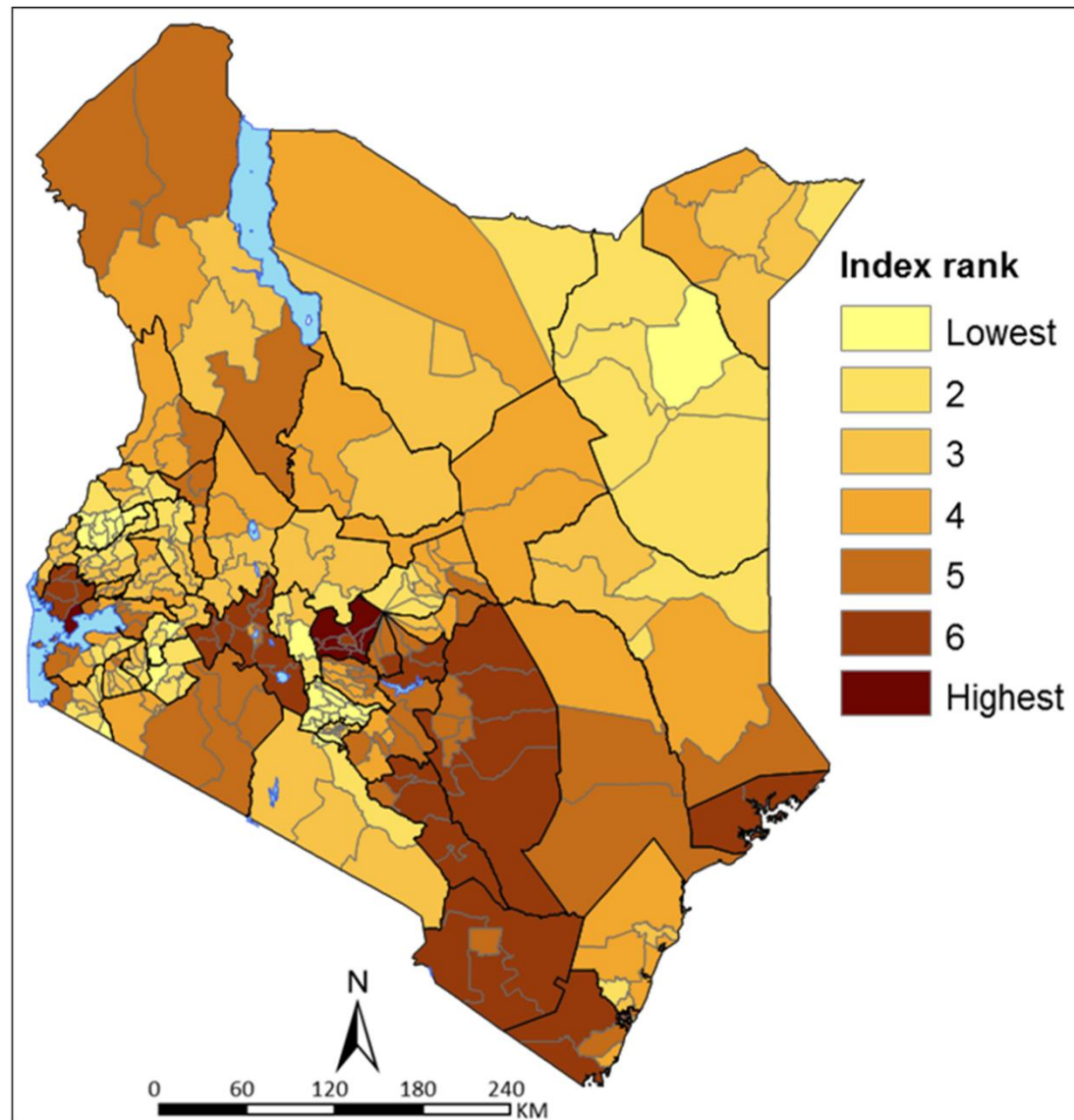
Figure 1

Figure 2

Figure 3

References

1   WHO. A Safer Future: Global Public Health Security in the 21ST Century.
     2007.https://www.who.int/whr/2007/whr07_en.pdf (accessed 22 May 2020).

2   Ihekweazu C, Agogo E. Africa's response to COVID-19. *BMC Med* 2020;**18**:151.

3   Talisuna AO, Okiro EA, Yahaya AA, *et al.* Spatial and temporal distribution of infectious disease
     epidemics, disasters and other potential public health emergencies in the World Health
     Organisation Africa region, 2016-2018. *Global Health* 2020;**16**:1–12. doi:10.1186/s12992-019-
     0540-4

4   Dixon MG, Schafer IJ. Ebola viral disease outbreak - West Africa, 2014. *Ann Emerg Med*
     2015;**65**:114–5. doi:10.1016/j.annemergmed.2014.10.010

5   Williamson E, Walker AJ, Bhaskaran KJ, *et al.* OpenSAFELY: factors associated with COVID-19-
     related hospital death in the linked electronic health records of 17 million adult NHS patients.
     medRxiv 2020;:2020.05.06.20092999. doi:10.1101/2020.05.06.20092999

6   Dorn A van, Cooney RE, Sabin ML. COVID-19 exacerbating inequalities in the US. *Lancet*
     2020;**395**:1243–4. doi:10.1016/s0140-6736(20)30893-x

7   Whitehead M, Barr B, Taylor-Robinson D. COVID-19: We are not "all in it together"-less
     privileged in society are suffering the brunt of the damage. BMJ Opin.
     2020.https://blogs.bmj.com/bmj/2020/05/22/covid-19-we-are-not-all-in-it-together-less-
     privileged-in-society-are-suffering-the-brunt-of-the-damage/

8   Ahmed F, Ahmed N, Pissarides C, *et al.* Why inequality could spread COVID-19. *Lancet Public
     Heal* 2020;**5**:e240. doi:10.1016/S2468-2667(20)30085-2

9   Rose TC, Mason K, Pennington A, *et al.* Inequalities in COVID19 mortality related to ethnicity
     and socioeconomic deprivation. *medRxiv* 2020;:2020.04.25.20079491.
     doi:10.1101/2020.04.25.20079491

10   WHO. Emergencies preparedness, response: Factors that contributed to undetected spread of
     the Ebola virus and impeded rapid containment.
     2015.https://www.who.int/csr/disease/ebola/one-year-report/factors/en/ (accessed 20 May
     2015).

11   Winskill P, Whittaker C, Walker P, *et al.* Equity in response to the COVID-19 pandemic: an
     assessment of the direct and indirect impacts on disadvantaged and vulnerable populations in
     low- and lower middle-income countries. 2020.https://doi.org/10.25561/78965 (accessed 22
     May 2020).

12   CDC Africa. Coronavirus Disease 2019 (COVID-19): Latest updates on the COVID-19 crisis.
     ;:2020.https://africacdc.org/covid-19/ (accessed 15 May 2020).

13   WHO. Up to 190 000 people could die of COVID-19 in Africa if not controlled.
     https://www.afro.who.int/news/new-who-estimates-190-000-people-could-die-covid-19-
     africa-if-not-controlled (accessed 22 May 2020).

14   WHO. Africa COVID-19 cases top 100 000. 2020.https://www.afro.who.int/news/africa-covid-
     19-cases-top-100-000 (accessed 23 May 2020).

15   MoH/GoK. Ministry of Health Republic of Kenya COVID-19. 2020.https://www.health.go.ke/
     (accessed 8 May 2020).

16   KNBS. Kenya National Bureau of Statistics: 2019 Kenya Population and Housing Census
     Reports. 2020.https://www.knbs.or.ke/?p=5732 (accessed 6 May 2020).

17   Rosenthal PJ, Breman JG, Djimde AA, *et al.* COVID-19: Shining the Light on Africa. *Am J Trop
     Med Hyg* 2020;**00**:1–4. doi:10.4269/ajtmh.20-0380

18   Jordan RE, Adab P, Cheng KK. Covid-19: Risk factors for severe disease and death. BMJ.
     2020;**368**:1–2. doi:10.1136/bmj.m1198

19   KPMG. Devolution of Healthcare Services in Kenya: Lessons Learnt from Other Countries. 2013.https://www.kpmg.com/Africa/en/IssuesAndInsights/Articles-Publications/Documents/Devolution of HC Services in Kenya.pdf (accessed 22 May 2015).

20   GoK. The Constitution of Kenya, 2010. 2010.http://kenyalaw.org/kl/index.php?id=398 (accessed 23 May 2016).

21   COG. County Integrated Development Plan. 2020.https://maarifa.cog.go.ke/cidps/ (accessed 5 May 2020).

22   CDC. Social Vulnerability Index. 2018.https://svi.cdc.gov/ (accessed 5 May 2020).

23   Wadhera RK, Wadhera P, Gaba P, *et al.* Variation in COVID-19 Hospitalizations and Deaths Across New York City Boroughs. *JAMA - J Am Med Assoc* 2020;**April**:29–31.https://jamanetwork-com.ezproxy.cul.columbia.edu/journals/jama/fullarticle/2765524

24   Smith JA, Judd J. COVID-19: Vulnerability and the power of privilege in a pandemic. *Heal Promot J Aust* 2020;**31**:158–60. doi:10.1002/hpja.333

25   Rader B, Astley CM, Sy KTL, *et al.* Increased travel times to United States SARS-CoV-2 testing sites: a spatial modeling study. *medRxiv* 2020;:2020.04.25.20074419. doi:10.1101/2020.04.25.20074419

26   Barasa E, Ouma PO, Okiro EA. Assessing the Hospital Surge Capacity of the Kenyan Health System in the Face of the COVID-19 Pandemic. *medRxiv* 2020;:2020.04.08.20057984. doi:10.1101/2020.04.08.20057984

27   Chen T, Wu D, Chen H, *et al.* Clinical characteristics of 113 deceased patients with coronavirus disease 2019: Retrospective study. *BMJ* 2020;**368**. doi:10.1136/bmj.m1091

28   Wu Z, McGoogan JM. Characteristics of and Important Lessons from the Coronavirus Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72314 Cases from the Chinese Center for Disease Control and Prevention. *JAMA - J Am Med Assoc* 2020;**323**:1239–42. doi:10.1001/jama.2020.2648

29   CDC. COVID-19: People who are at higher risk for severe illness. 2020.https://www.cdc.gov/coronavirus/2019-ncov/specific-groups/people-at-higher-risk.html (accessed 6 May 2020).

30   Zhou F, Yu T, Du R, *et al.* Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. *Lancet* 2020;**395**:1054–62. doi:10.1016/S0140-6736(20)30566-3

31   Fraym. Local Data to Optimize Delivery of Public Health Messages for COVID-19. 2020.https://fraym.io/covid_comms_data/ (accessed 6 May 2020).

32   Graetz N, Friedman J, Osgood-Zimmerman A, *et al.* Mapping local variation in educational attainment across Africa. *Nature* 2018;**555**:48–53.

33   DHS Program. Spatial Data Repository, The Demographic and Health Surveys Program. Modeled Surfaces. ICF International. Funded by the United States Agency for International Development (USAID). 2019.https://spatialdata.dhsprogram.com/modeled-surfaces/ (accessed 6 May 2020).

34   Burgert-Brucker CR, Dontamsetti T, Gething PW. The DHS Program's Modeled Surfaces Spatial Datasets. *Stud Fam Plann* 2018;**49**:87–92. doi:10.1111/sifp.12050

35   Osgood-Zimmerman A, Millear AI, Stubbs RW, *et al.* Mapping child growth failure in Africa between 2000 and 2015. *Nature* 2018;**555**:41–7. doi:10.1038/nature25760

36   Pezzulo C, Hornby GM, Sorichetta A, *et al.* Sub-national mapping of population pyramids and dependency ratios in Africa and Asia. *Sci Data* 2017;**4**:1–15. doi:10.1038/sdata.2017.89

37   Tatem AJ, Garcia AJ, Snow RW, *et al.* Millennium development health metrics: where do Africa's children and women of childbearing age live? *Popul Health Metr* 2013;**11**:11. doi:10.1186/1478-7954-11-11

97 98 99	38	Ouma PO, Maina J, Thuranira PN, *et al.* Articles Access to emergency hospital care provided by the public sector in sub-Saharan Africa in 2015 : a geocoded inventory and spatial analysis. *Lancet Glob Heal* 2018;:1–9. doi:10.1016/S2214-109X(17)30488-6
100 101	39	Nelson A, Weiss DJ, van Etten J, *et al.* A suite of global accessibility indicators. *Sci data* 2019;**6**:266. doi:10.1038/s41597-019-0265-5
102 103	40	Dwyer-Lindgren L, Cork MA, Sligar A, *et al.* Mapping HIV prevalence in sub-Saharan Africa between 2000 and 2017. *Nature* 2019;**570**:189–93. doi:10.1038/s41586-019-1200-9
104	41	Rao JNK. *Small Area Estimation*. 1st Editio. New Jersey: : John Wiley & Sons, Ltd 2003.
105 106	42	KNBS, MoH, NACC, *et al.* Kenya Demographic and Health Survey 2014. 2015.https://dhsprogram.com/pubs/pdf/FR308/FR308.pdf (accessed 20 Jan 2020).
107 108	43	KNBS. Kenya National Data Archive. 2016.http://statistics.knbs.or.ke/nada/index.php/home (accessed 21 Apr 2020).
109 110	44	Bakka H, Rue H, Fuglstad GA, *et al.* Spatial modeling with R-INLA: A review. *Wiley Interdiscip Rev Comput Stat* 2018;**10**:1–24. doi:10.1002/wics.1443
111 112	45	DeCaprio D, Gartner JA, Burgess T, *et al.* Building a COVID-19 Vulnerability Index. *medRxiv* 2020;:2020.03.16.20036723. doi:10.1101/2020.03.16.20036723
113 114 115	46	Barda N, Riesel D, Akriv A, *et al.* Performing risk stratification for COVID-19 when individual level data is not available, the experience of a large healthcare organization. *medRxiv* 2020;:2020.04.23.20076976. doi:10.1101/2020.04.23.20076976
116 117 118	47	NIEHS. COVID-19 Pandemic Vulnerability Index (PVI). 2020.https://www.niehs.nih.gov/research/programs/coronavirus/covid19pvi/details/index.cfm (accessed 17 May 2020).
119 120 121	48	Africa Center for Strategic Studies. Mapping Risk Factors for the Spread of COVID-19 in Africa. 2020.https://africacenter.org/spotlight/mapping-risk-factors-spread-covid-19-africa/ (accessed 6 May 2020).
122 123	49	Surgo Foundation. The COVID-19 Community Vulnerability Index (CCVI). 2020.https://precisionforcovid.org/ccvi (accessed 6 May 2020).
124 125	50	OCHA. Iraq COVID-19 Camp Vulnerability Index. 2020.https://data2.unhcr.org/en/documents/details/75660 (accessed 5 May 2020).
126 127 128	51	Boerma JT, Bryce J, Kinfu Y, *et al.* Mind the gap: equity and trends in coverage of maternal, newborn, and child health services in 54 Countdown countries. *Lancet* 2008;**371**:1259–67. doi:10.1016/S0140-6736(08)60560-7
129 130 131	52	Barros AJD, Victora CG. Measuring Coverage in MNCH: Determining and Interpreting Inequalities in Coverage of Maternal, Newborn, and Child Health Interventions. *PLoS Med* 2013;**10**. doi:10.1371/journal.pmed.1001390
132 133 134	53	Wagstaff A, Neelsen S. Articles A comprehensive assessment of universal health coverage in 111 countries : a retrospective observational study. *Lancet Glob Heal* 2020;**8**:e39–49. doi:10.1016/S2214-109X(19)30463-2
135 136 137	54	Faye CM, Wehrmeister FC, Melesse DY, *et al.* Large and persistent subnational inequalities in reproductive , maternal , newborn and child health intervention Saharan Africa coverage in sub- Saharan Africa. *BMJ Glob Heal* 2020;**5**:e002232. doi:10.1136/bmjgh-2019-002232
138 139 140	55	Wehrmeister FC, Restrepo-Mendez MC, Franca GVA, *et al.* Summary indices for monitoring universal coverage in maternal and child health care. *Bull World Health Organ* 2016;**94**:903–12. doi:10.2471/BLT.16.173138
141 142 143 144	56	Moore M, Gelfeld B, Okunogbe A, *et al.* Identifying Future Disease Hot Spots: Infectious Disease Vulnerability Index. 2016.https://www.rand.org/content/dam/rand/pubs/research_reports/RR1600/RR1605/RAND_RR1605.pdf (accessed 7 May 2020).

145   57   Heesterbeek JAP, Dietz K. The concept of R0 in epidemic theory. *Stat Neerl* 1996;**50**:89–110.
146   doi:10.1111/j.1467-9574.1996.tb01482.x

147   58   Diop BZ, Ngom M, Pougue Biyong C, *et al.* The relatively young and rural population may limit
148   the spread and severity of Covid-19 in Africa: a modelling study. *medRxiv*
149   2020;:2020.05.03.20089532. doi:10.1101/2020.05.03.20089532

150   59   Lloyd-Sherlock P, Ebrahim S, Geffen L, *et al.* Bearing the brunt of covid-19: Older people in low
151   and middle income countries. *BMJ* 2020;**368**:1–2. doi:10.1136/bmj.m1052

152   60   Jenks GF. Optimal data classification for choropleth maps Occasional Paper No 2. In: *University*
153   *of Kansas, Department of Geography*. 1977.

154   61   Kluge H, Martín-Moreno JM, Emiroglu N, *et al.* Strengthening global health security by
155   embedding the International Health Regulations requirements into national health systems.
156   *BMJ Glob Heal* 2018;**3**:1–7. doi:10.1136/bmjgh-2017-000656

157   62   Cyranoski D. 'We need to be alert': Scientists fear second coronavirus wave as China's
158   lockdowns ease. *Nature* Published Online First: 2020. doi:10.1038/d41586-020-00938-0

159   63   Barasa E, Mothupi MC, Guleid F, *et al.* Health and Socio-Economic Impacts Of Physical
160   Distancing For COVID-19 In Africa. 2020.https://kemri-wellcome.org/wp-
161   content/uploads/2020/05/DFID-Report-Rapid-Review-of-Physical-Distancing-in-Africa-
162   19052020-compressed.pdf (accessed 22 May 2020).

163   64   GoK. The seventh presidential address on the coronavirus pandemic: the 8-point economic
164   stimulus programme. 2020.https://www.president.go.ke/2020/05/23/the-seventh-presidential-
165   address-on-the-coronavirus-pandemic-the-8-point-economic-stimulus-programme-saturday-
166   23rd-may-2020/ (accessed 23 May 2020).

167   65   WHO. African countries start easing COVID-19 confinement measures. 2020.http://whotogo-
168   whoafroccmaster.newsweaver.com/JournalEnglishNewsletter/p52h8rfrk0gy48iiujdam4?email=t
169   rue&lang=en&a=11&p=56942028 (accessed 22 May 2020).

170   66   Kelley M, Ferrand R, Muraya K, *et al.* An appeal for practical social justice in the COVID-19
171   global response in low-income and middle-income countries. *Lancet Glob Heal*
172   2020;**2019**:2019–20. doi:10.1016/S2214-109X(20)30249-7

173   67   WHO. WHO Director-General's opening remarks at the media briefing on COVID-19 - 11
174   March 2020. 2020.https://www.who.int/dg/speeches/detail/who-director-general-s-opening-
175   remarks-at-the-media-briefing-on-covid-19---11-march-2020 (accessed 8 May 2020).

176   68   Zhu N, Zhang D, Wang W, *et al.* A novel coronavirus from patients with pneumonia in China,
177   2019. *N Engl J Med* 2020;**382**:727–33. doi:10.1056/NEJMoa2001017

178   69   Manhique AJ, Reason CJC, Silinto B, *et al.* Extreme rainfall and floods in southern Africa in
179   January 2013 and associated circulation patterns. *Nat Hazards* 2015;**77**:679–91.
180   doi:10.1007/s11069-015-1616-y

181   70   Harris MJ, Hay SI, Drake JM. Early warning signals of malaria resurgence in Kericho, Kenya. *Biol*
182   *Lett* 2020;**16**:1–6. doi:10.1098/rsbl.2019.0713

183   71   Breiman RF, Evans M, Preiser W, *et al. Learning from SARS, preparing for the next disease*
184   *outbreak: workshop summary*. National Academies Press 2004.

185   72   Wilkinson A, Ali H, Bedford J, *et al.* Local response in health emergencies: key considerations
186   for addressing the COVID-19 pandemic in informal urban settlements. *Environ Urban* 2020;:1–
187   20. doi:10.1177/0956247820922843

188   73   Lozano R, Soliz P, Gakidou E, *et al.* Benchmarking of performance of Mexican states with
189   effective coverage. *Lancet* 2006;**368**:1729–41. doi:10.1016/S0140-6736(06)69566-4

190   74   SDI. The Know Your City Campaign, Community-driven data on slums.
191   2020.https://knowyourcity.info/explore-our-data/country/?country=kenya (accessed 6 May
192   2020).

193   75   UNHCR. Operation portal refugee situations. 2020.https://data2.unhcr.org/en/situations/covid-

194   19 (accessed 6 May 2020).

195   76   Stevens FR, Gaughan AE, Linard C, *et al.* Disaggregating census data for population mapping
196   using Random forests with remotely-sensed and ancillary data. *PLoS One* 2015;**10**:e0107042.
197   doi:10.1371/journal.pone.0107042

198   77   MoH/GoK. Kenya Harmonized Health Facility Assessment (KHFA).
199   2019.https://www.health.go.ke/wp-content/uploads/2020/01/KHFA-2018-19-Community-
200   Systems-Report-Final.pdf (accessed 6 May 2020).

201   78   Diggle PJ, Tawn JA, Moyeed RA. Model-based geostatistics. *J R Stat Soc Ser C (Applied Stat*
202   2002;**47**:299–350. doi:10.1111/1467-9876.00113

203   79   Getis A, Aldstadt J. Constructing the Spatial Weights Matrix Using a Local Statistic. *Geogr Anal*
204   2004;**36**:90–104.

205