# An index to map feasibility of social distancing within urban areas

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## 1. Introduction

The COVID-19 pandemic has brought factors affecting disease transmission into the spotlight, and required widespread use of public health measures to reduce transmission and contain outbreaks. Urban areas inherently have large concentrations of people, providing high potential for large outbreaks and rapid disease spread, necessitating extensive use of measures to reduce transmission. Social distancing, also called physical distancing, is a public health measure intended to reduce infectious disease transmission, by maintaining physical distance between individuals or households. In the context of the COVID-19 pandemic, populations in many countries around the world have been advised to maintain social distance, with distances of 6ft or 2m commonly advised. The feasibility of social distancing is affected by the availability of space and the number of people, which varies geographically. In locations where social distancing is difficult, a focus on alternative measures to reduce disease transmission should be prioritised. To help identify and map such locations at high spatial resolution, this paper describes an index to quantify ease of social distancing, applied to urban areas across sub-Saharan Africa.

## 2. Methodology

### 2.1 Method

The index is calculated from two variables: (1) mean population density and (2) the proportion of space occupied by buildings. In applying this index to urban areas in sub-Saharan Africa, index values were calculated for small spatial units, created from bounding features including roads, rivers and railways. These features were intersected to create polygons, enabling the urban area to be sub-divided into relatively homogeneous spatial units.

For each spatial unit, values of mean population density were classified based on the theoretical maximum possible population density with different distancing parameters. Distancing parameters were based on a hexagon tessellation, with the hexagon representing the space available for one person, and distance between people measured in terms of the apothem (the distance between the hexagon centroid and mid-point of a side). A maximum value of 10 for the population density score is assigned to spatial units with population density in excess of 32,075.01 people per km$^2$, corresponding to an apothem of less than 3 metres (**Table 1**). Based on a hexagon tessellation, an apothem of 3 metres enables a person to move 2 metres in any direction, and still maintain a distancing of 2 metres from any other person. Remaining population density scores are classified based on the maximum population density possible when increasing the apothem distance incrementally by 1 metre (**Table 1**).

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**Table 1** Classification of population density, based on distancing parameters

| Apothem [m] | Hexagon area [$m^2$] | Population density [pop per $km^2$] | Population score |
|---|---|---|---|
| < 3 | < 31.18 | > 32,075.01 | 10 |
| (3 – 4] | (31.18 - 55.43] | (18,042.20 - 32,075.01] | 9 |
| (4 – 5] | (55.43 - 86.60] | (11,547.01 - 18,042.20] | 8 |
| (5 – 6] | (86.60 - 124.71] | (8,018.75 - 11,547.01] | 7 |
| (6 – 7] | (124.71 - 169.74] | (5,891.33 - 8,018.75] | 6 |
| (7 – 8] | (169.74 - 221.70] | (4,510.55 - 5,891.33] | 5 |
| (8 – 9] | (221.70 - 280.59] | (3,563.89 - 4,510.55] | 4 |
| (9 – 10] | (280.59 - 346.41] | (2,886.75 - 3,563.89] | 3 |
| (10 – 11] | (346.41 - 419.16] | (2,385.74 -2,886.75] | 2 |
| > 11 | > 419.16 | (0.0 -2,385.74] | 1 |
| - | - | 0.0 | 0 |

Values for the second variable: proportion of space occupied by buildings, were classified linearly with a score of 10 assigned to any spatial units where in excess of 90% of the area was built-up, and a value of 1 corresponding to 10% or less of the area being occupied by buildings.

To calculate the ease of social distancing index, the two variables were combined by calculating the mean of the two scores, with index values ranging from 0-10; higher index values indicating greater difficulty in social distancing.

### 2.2 Data

The application of this index to countries in sub-Saharan Africa, utilised two GHS (Global Human Settlement) datasets to define the spatial extent of urban areas: GHS Urban Centre Database 2015 v1.2 (Florczyk et al., 2019) and GHS-SMOD v2.0 (Settlement Model grid; Pesaresi et al. 2019). Within each urban extent, sub-division into small spatial units was based on OpenStreetMap data (OpenStreetMap contributors, 2020), primarily using roads, rivers, railways and boundaries of different landuse types and features.

The population density variable is calculated from gridded (raster) population datasets, based on WorldPop 2020 population counts, constrained to settled areas (Bondarenko et al., 2020) with a spatial resolution of 3 arc seconds. The proportion of space occupied by buildings is calculated based on building footprint (vector) polygons (Ecopia.AI and Maxar Technologies, 2020). Recent developments in machine-learning based feature extraction techniques and increasing coverage of high-resolution satellite imagery has meant that the number of countries for which building footprint datasets exist, has grown rapidly and increasingly now include datasets for less-developed countries. Such datasets can provide new insights into the structure of urban areas (Jochem et al., 2020; Lloyd et al., 2020).

## 3. Results

Preliminary results include mapped outputs for 10 countries in sub-Saharan Africa (Burkina Faso, Botswana, Lesotho, Mozambique, Malawi, Namibia, Niger, Rwanda, Sierra Leone and Zambia). In these 10 countries, ease of social distancing index values were calculated for 170 urban areas, covering a total of 23,052 $km^2$ with index values calculated for 166,776 spatial units. Examples for 9 cities are shown in **Figure 1**, with a larger scale map showing index values for part of Lusaka, Zambia shown in **Figure 2**. Output datasets are openly available from the WorldPop Open Population Repository (https://wopr.worldpop.org/?/SocialDistancing).

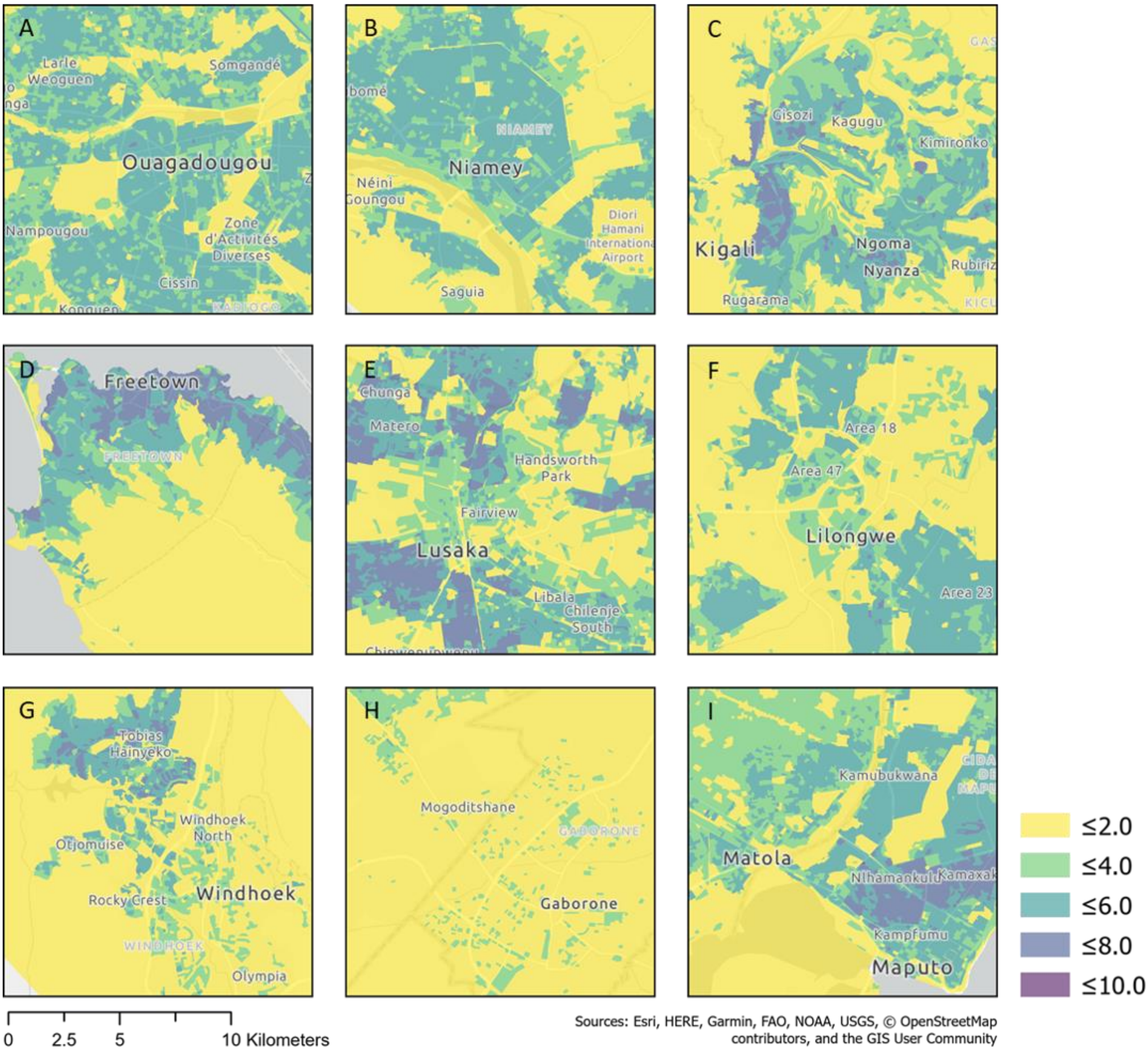


**Figure 1** Ease of social distancing index mapped outputs for 9 cities: Ougadougou, Burkina Faso (A), Niamey, Niger (B), Kigali, Rwanda (C), Freetown, Sierra Leone (D), Lusaka, Zambia (E), Lilongwe, Malawi (F), Windhoek, Namibia (G), Gaborone, Botswana (H) and Maputo, Mozambique (I).

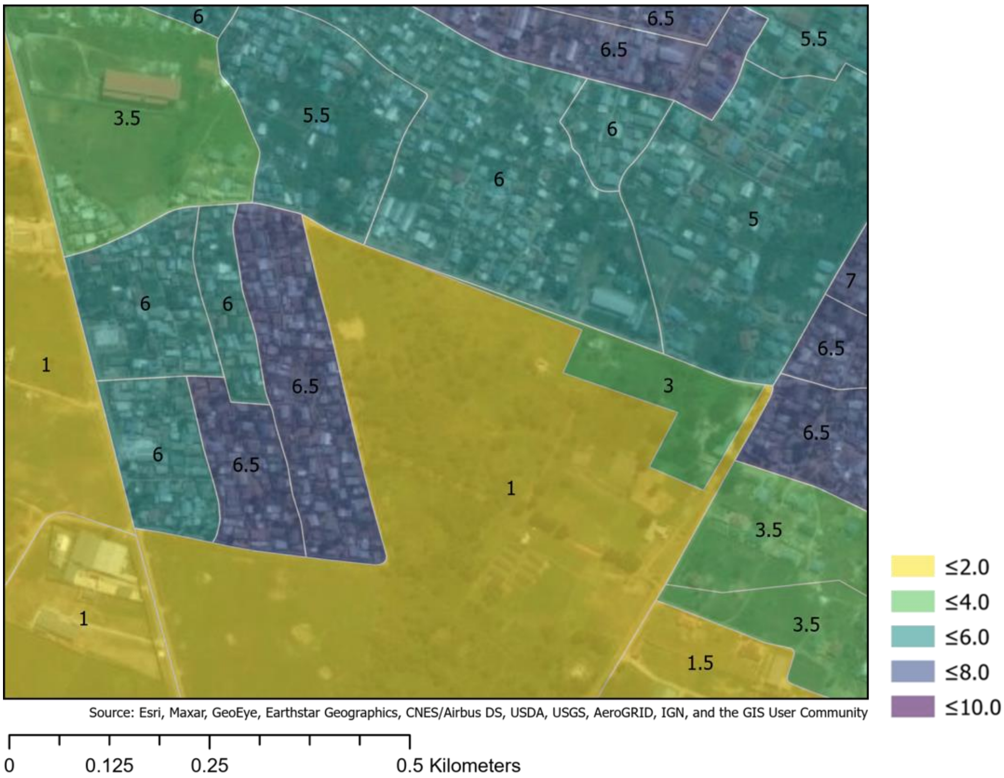


**Figure 2** Ease of social distancing index values for an area in the west of Lusaka, Zambia. The index values for spatial units are shown overlaid on satellite imagery; higher values indicate a greater difficulty in social distancing.

## 4. Discussion

The application of the ease of social distancing index to small spatial units, highlights how the feasibility of social distancing, driven by population density and the layout of buildings, varies within urban areas. Capital cities, or other major cities in the ten countries for which mapped outputs have been produced, tend to have considerable spatial heterogeneity with high index values in close proximity to lower values. The highest index values commonly are calculated for spatial units associated with informal settlements, with both a high density of built structures and high population density. In smaller urban areas, the ease of social distancing index values vary more between countries with some urban areas having relatively homogeneous, consistently low index values. In Burkina Faso for example, outside of the capital Ouagadougou, index values in urban areas were generally low (<4) with the highest values often corresponding to major markets.

Mapped outputs highlight locations where there is potentially high risk of COVID-19 transmission within and between households. In the context of urban areas in sub-Saharan Africa, such locations are often associated with high-density informal settlements. As well as being locations at high risk of disease transmission, residents in high-density informal settlements often have poor access to health systems and are economically highly vulnerable (Corburn et al., 2020), compounding the impact of the COVID-19 pandemic on residents. Aside from COVID-19, the use of the index in identification of high-density informal settlement areas has wider relevance, including in relation to management of other infectious diseases.

Future directions for this work will include expansion in geographical coverage to produce mapped outputs for all urban areas in sub-Saharan Africa and potentially development of a gridded version of the index, to cover both rural and urban contexts.

## 5. Conclusion

In conclusion, the ease of social distancing index can be calculated for small spatial units within urban areas, providing high spatial resolution mapped outputs which can highlight locations where social distancing may be difficult. Within major cities in particular, this has applicability in identifying where additional measures may need to be prioritised in order to reduce COVID-19 transmission.

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## Biographies

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