Heterogeneity and scale of sustainable development in cities

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Rapid worldwide urbanization is at once the main cause and, potentially, the main solution to global sustainable development challenges. The growth of cities is typically associated with increases in socioeconomic productivity, but it also creates strong inequalities. Despite a growing body of evidence characterizing these heterogeneities in developed urban areas, not much is known systematically about their most extreme forms in developing cities and their consequences for sustainability. Here, we characterize the general patterns of income and access to services in a large number of developing cities, with an emphasis on an extensive, high-resolution analysis of the urban areas of Brazil and South Africa. We use detailed census data to construct sustainable development indices in hundreds of thousands of neighborhoods and show that their statistics are scale-dependent and point to the critical role of large cities in creating higher average incomes and greater access to services within their national context. We then quantify the general statistical trajectory toward universal basic service provision at different scales to show that it is characterized by varying levels of inequality, with initial increases in access being typically accompanied by growing disparities over characteristic spatial scales. These results demonstrate how extensions of these methods to other goals and data can be used over time and space to produce a simple but general quantitative assessment of progress toward internationally agreed sustainable development goals.

neighborhoods | slums | urban services | spatial correlations | inequality

The current worldwide growth of cities presents at once an unprecedented historical opportunity for universal socioeconomic development and an immense challenge to global sustainability (1, 2). The mechanisms that generate improved living conditions and economic growth in cities—and that typically also increase overall energy and resource consumption—are still only partially understood (1–5) and remain hard to disentangle.

Many recent studies have emphasized the environmental and geophysical adverse consequences of an increasing proportion of the planet's population living in cities and of the acceleration of this transformation in recent decades (6–8). The type and scope of these impacts vary but include air and water pollution, land-cover change, loss of natural habitats, strain on water resources, higher demand for energy, and rising greenhouse gas emissions (1, 8, 9).

Conversely, the positive correlation between urbanization and many important dimensions of human development has also become increasingly clear. At the national level, the association between higher levels of urbanization and per capita economic productivity has been clear for some time (2). More recently, as city-scale data have become available, evidence has emerged for broader relationships between urbanization and better health, education, longer lifespans, and greater access to basic services, such as water or electricity, at lower nominal costs (2, 10).

Regardless of whether the positive or negative outcomes of urbanization are emphasized, a more systematic, empirically based understanding of processes of (sustainable) development is still missing. To fill this gap, we must focus on how and where development takes place (11): inside cities and in terms of changes experienced by households and neighborhoods (12–14). Initial steps in this direction point to a large heterogeneity and inequality of outcomes between people or places, manifested by the unprecedented scale and growth of vast informal settlements (slums) in low- and middle-income cities (9, 11, 15–17). However, local analysis of change also reveals paths toward more sustainable human development, especially in connection to expanded access to urban services (4, 5, 9, 10, 15, 18), which improve health conditions and allow for greater energy and water consumption with much reduced adverse environmental impacts in terms of land use, contaminated effluents, or emissions.

The present paper seeks to address this critical need for connecting processes of change at their sources, by creating a simple framework for the integrated analysis of sustainable development patterns in cities with an emphasis on empirical quantitative measurements across scales—from households to nations—that track progress toward recently agreed sustainable development goals (19).

Critical to the understanding and measurement of sustainable development is the construction of empirically based indicators that capture many aspects of the process simultaneously. The Human Development Index (HDI) has been a forerunner of this methodology by emphasizing standards of health and education in addition to rising incomes (20, 21). Another example is UN-Habitat's Secure Tenure Index (STI) (9), which characterizes poor (informal) neighborhoods. In both cases, index construction is based upon a capabilities approach to development (22), where high values for indices reflect the attainment of universally desirable goals, guaranteeing minimal decent standards of living. This approach is different from and contrasts with the representation of consumption of the same quantities in terms of utility

Significance

Most nations worldwide have recently committed to solving their most severe challenges of sustainability by 2030, including eradicating extreme poverty and providing universal access to basic services. But how? Rapid urbanization is creating the conditions for widespread economic growth and human development, but its consequences are very uneven. We show how measures of sustainable development—identified by residents of poor neighborhoods—can be combined into a simple and intuitive index. Its analysis reveals that challenges of development are typically first addressed in large cities but that severe inequalities often result as patterns of spatially segregated rich and poor neighborhoods. A new systematic understanding of these processes is critical for devising policies that produce faster and more equitable universal sustainable development.

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Data deposition: All data are available at www.santafe.edu/~bettencourt/heterogeneity-scale-sustainable-development.

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functions common in economic modeling, which requires assumptions about individual-level behaviors and preferences. Our approach below parallels the development of the HDI and STI toward assessing the universal attainment of broad development goals in cities (19).

A critical problem in any assessment of development is tied to inequality (14). Average quantities over large populations, such as nations or metropolitan areas (MAs), hide extremes (18, 23). Depending on our understanding of these processes and the scale at which they are measured, proposed solutions may take different forms. Specifically, during the transition between extreme poverty and total absence of services to greater affluence and widespread provision of basic needs the creation of extreme inequalities is common (24, 25). Thus, any intervention is likely to affect distinct groups in different ways, an issue often described in terms of distributional effects (*SI Appendix*). The distributional effects literature makes it clear that impacts are more varied than they seem when evaluated by averages (26) and that policies that target average effects risk producing unintended consequences that are often regressive, placing disproportionate burdens on disadvantaged populations (27). To identify these issues, we will introduce simple ways to measure and assess distributional effects via the statistical analysis of sustainable development indices.

We illustrate our approach through the analysis of detailed data from Brazil and South Africa to characterize three fundamental aspects of sustainable development in cities. First, we ask whether there is a general relationship, and expected feedbacks, between agglomeration effects associated with higher economic productivity in larger cities and improving living conditions. Second, we ask whether there are general quantitative sustainable development paths for units of analysis at different scales (neighborhoods to nations), characterized not only by averages but also by associated levels of heterogeneity. Finally, we assess the importance of space and specifically ask what sets the scale for the observed socioeconomic heterogeneity within cities.

Results

We now provide a detailed spatial and socioeconomic characterization of development patterns in a range of low- and middle-income cities. Fig. 1*A* gives a first impression by showing a map of South Africa highlighting its large cities (MAs), each consisting of hundreds of neighborhoods (see also *SI Appendix*, Figs. S1–S8). Measuring any sustainable development characteristic at different scales results in different levels of heterogeneity expressed by measures of inequality such as the Gini index, which is typically larger at the metropolitan level but smaller within neighborhoods (Fig. 1*B* and *SI Appendix*, Figs. S9–S11). To better understand how sustainable development takes place in cities, we start by summarizing results from recent neighborhood surveys expressing slum dwellers' self-identified development priorities followed by an analysis of agglomeration effects in income and provision of the same priorities using detailed data from MAs of Brazil and South Africa. We conclude by analyzing how these patterns change across different scales of analysis, emphasizing the connections between heterogeneity, inequality, and spatial structure.

Neighborhood Priorities in Developing Cities. Slums constitute a substantial fraction of all neighborhoods in cities of South and Southeast Asia and in sub-Saharan Africa (9) and illustrate the

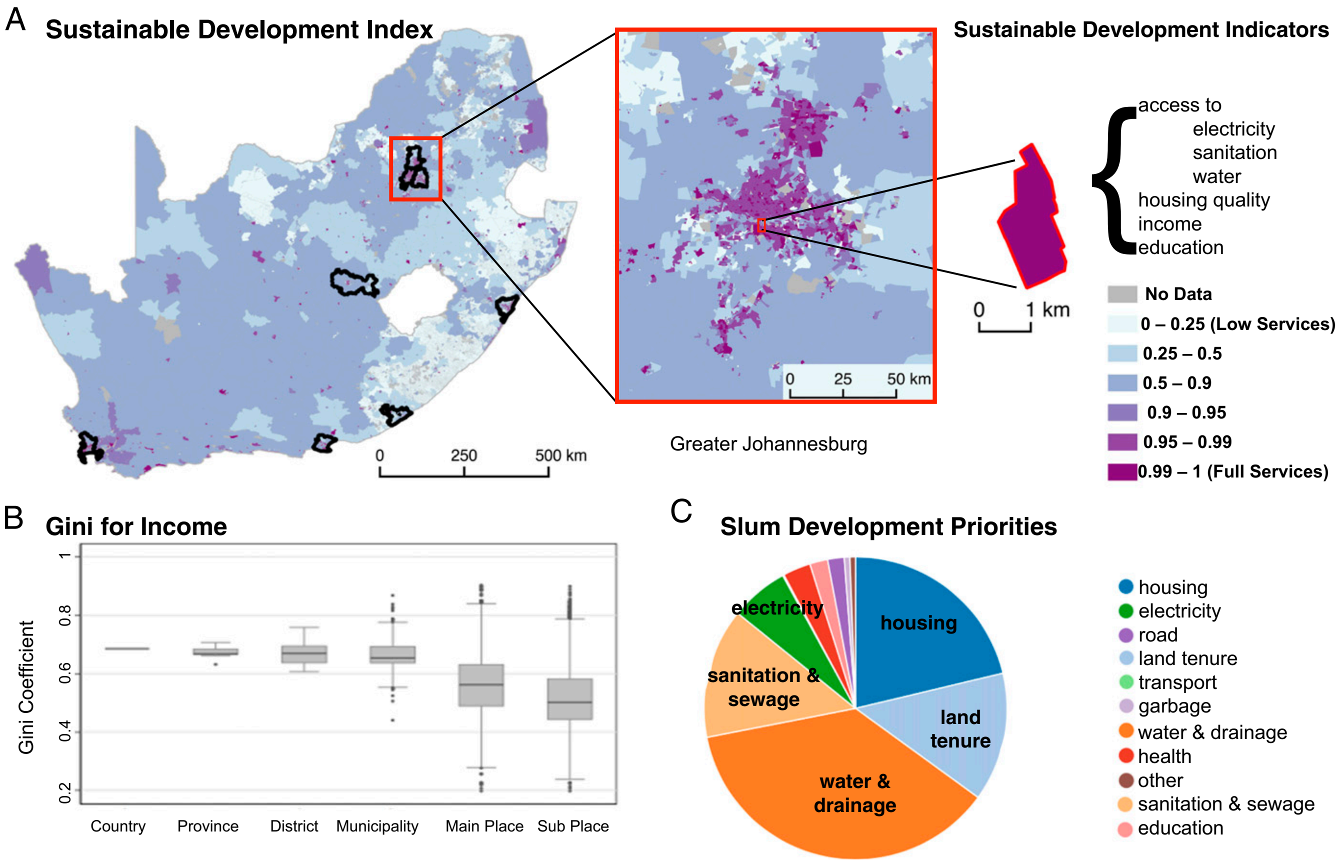

Fig. 1. Heterogeneity and scale of sustainable development in cities. (*A*) The Sustainable Development Index, X_i, at the subplace level for all of South Africa, the Johannesburg MA, and a single subplace. (*B*) The values of the Gini coefficient for income across scales for South Africa. The median across all units of analysis within a class is shown by a horizontal black line, with the 25th to 75th percentiles shown by the gray box. (*C*) Development priorities identified by slum residents in the 10 countries in Table 1.

Table 1. Summary of slum development priorities

		Nations							
Priorities	Total	South Africa, %	Tanzania, %	Kenya, %	Uganda, %	Malawi, %	Namibia, %	Sierra Leone, %	Nigeria, %
All	677	26.90	26.70	22.20	13.10	4.40	2.70	1.60	1.50
Water and drainage	36.90%	20.30	43.50	33.30	57.30	76.70	11.10	81.80	10.00
Housing	21.30%	44.00	2.80	32.00	5.60	0	11.10	0	10.00
Sanitation and sewage	13.90%	8.20	14.90	10.70	27.00	16.70	27.80	0	0
Land tenure	13.70%	18.70	4.40	21.30	4.50	3.33	33.30	9.10	60.00
Electricity	6.20%	8.20	8.30	1.30	4.50	0	16.70	0	20.00
Others	7.80%	0.50	27.10	1.30	1.10	0	0	9.10	0.00

There are 10 nations and 59 cities in the dataset. Four neighborhoods in the Philippines and two in Ghana are not shown but are included in the totals.

direst challenges of urban sustainable development. Worldwide one in seven people is presently estimated to live in slums, but this number rises to one in two or more in parts of South Asia and Africa (2, 9). International development agencies have stressed the critical need for better understanding the nature of human and economic development in these poor neighborhoods, and of acquiring detailed empirical information on their primary needs and priorities (2, 9). However, extensive direct information on residents' priorities is still rare. Recent efforts provide us with some new insights on the most important development needs expressed by slum residents (15, 28). Table 1 and Fig. 1*C* show residents' priorities in 677 neighborhoods in 10 nations and 59 cities mostly in low-income nations in sub-Saharan Africa (*Materials and Methods* and *SI Appendix*, Fig. S12). Most of these data pertain to large and fast-growing urban areas, such as Lagos, Nairobi, Dar-es-Salam, Kampala, Blantyre, Freetown, Johannesburg, Cape Town, or Windhoek.

Although there is broad agreement on the most important priorities, there are also a number of differences across nations (and cities). Overall, water and drainage is the most frequent problem, mentioned 36.9% of the time, followed by issues of housing (21.3%), sanitation and sewage (13.9%), land tenure (13.7%), and electricity (6.2%). These priorities emphasize the dual role of basic services and improved housing in promoting the resilience of communities against both chronic stresses and extreme events, such as flooding and diseases associated with local environmental degradation (15, 29). Other issues, related to health access, transportation, waste collection, jobs, and education, also come up frequently but are stated as less critical. Apart from land tenure, all other issues deal with daily living challenges and are intimately connected to access to improved basic services and local environmental conditions. These findings resonate with recent definitions of sustainable development (9, 29) to which we now turn using extensive neighborhood data from two large middle-income nations: Brazil and South Africa.

City Size and Agglomeration Effects. Agglomeration effects are at the root of the advantages of larger cities at creating greater resources per capita, which historically have led to innovation and development along a broad range of human and environmental issues (2, 30, 31). Cities are characterized by two general phenomena: agglomeration effects and high socioeconomic and spatial heterogeneity (32–35). Both have long been understood as having a strong scale (population size) dependence (36). The strength of these scaling effects and the nature of urban heterogeneity have, however, remained poorly studied in rapidly developing cities, in large part due to the absence of systematic data for appropriate units of analysis.

Scaling effects are expressed in terms of the mean expected values for urban quantities, such as the size of the overall economy (gross domestic product, GDP), personal income, amounts of infrastructure, rates of innovation, and so on, as functions of city population size (31, 34, 35). Nonlinear scaling of all these quantities is predicted for functional cities, defined as spatially embedded networks of socioeconomic interaction (35, 37), known as MAs. MAs are integrated labor markets circumscribing areas of work and residence for most of their inhabitants. For other definitions of cities, whether political or resulting from density thresholds, agglomeration effects may vanish or seem inconsistent, possibly because not all heterogeneity is included (38, 39).

To illustrate these effects, Fig. 2*A* shows total income for MAs in South Africa and Brazil, versus their population size (see also Table 2). In Brazil, MAs typically include many (political) municipalities, whereas in South Africa they are made up of a single large municipality, with the exception of Greater Johannesburg (*SI Appendix*, Figs. S1–S5 and Table 2).

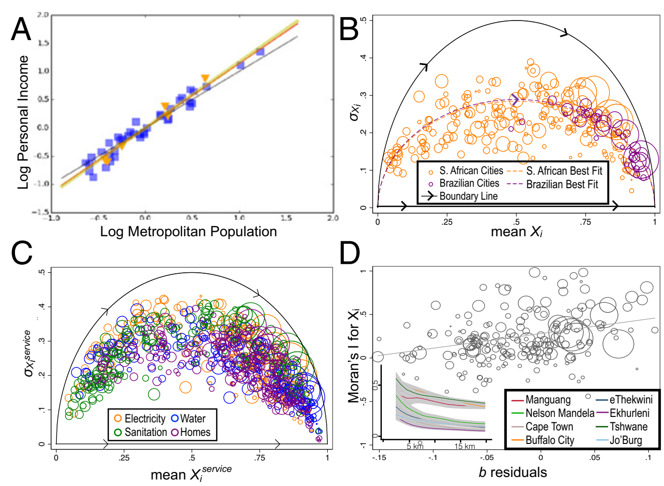

Fig. 2. Agglomeration effects and heterogeneity of sustainable development in cities of Brazil and South Africa. (*A*) Scaling of personal income with population for Brazil (squares) and South Africa's MAs (triangles). The yellow line shows the theoretical slope of 1 + 1/6 (35), the red shows the best fit, and the gray line shows the 1:1 line for reference. The best fit demonstrates that larger cities have on average higher resources per capita, at least in nominal terms, which can be invested in sustainable development. (*B*) The relationship between the SD, σ_i, and mean, $\bar{X}_i$, of the Sustainable Development Index, X_i, for Brazil's 38 MAs (purple) and 207 South African municipal regions (orange), where the size of the circle is proportional to population. The two black lines bind the area in which ($\bar{X}_i, \sigma_i$) pairs can exist, with the upper curved line showing maximal inequality (Kuznets curve, $b = 1$) and the horizontal line corresponding to total equality ($b = 0$). The dashed line shows the estimated best fit for the mean heterogeneity index b. (*C*) The decomposition of X_i into subcomponents: $X_i^{electricity}$ (orange), X_i^{water} (blue), $X_i^{sanitation}$ (green), and X_i^{homes} (purple) for Brazil's metropolitan regions, which allows us to see the role of larger cities at providing improved services. (*D*) The positive association between Moran's *I* (distance threshold = 5km) and σ_i for South African municipalities, showing that higher spatial clustering is associated with higher inequality of access to services. (*Inset*) The variation of Moran's *I* with the distance threshold *s* for South Africa's major metropolitan regions.

Table 2. Agglomeration and heterogeneity of sustainable development indicators

	Summary statistics			
MAs	N_units	Estimate	95% CI	Fit
Brazil (metros)				
Income exponent β	39	1.11	[1.03, 1.20]	$R^2 = 0.90$
Heterogeneity index *b*	38	0.58	[0.56, 0.60]	$R^2 = 0.99$
South Africa				
Income exponent (metros) β*	8	1.35	[1.19, 1.53]	$R^2 = 0.97$
Heterogeneity index (municipalities) *b*	207	0.57	[0.54, 0.60]	$R^2 = 0.96$

*The scaling fit without aggregation of the three municipalities in the Johannesburg area gives $\beta = 1.49$, with 95% CI [1.17, 1.81], $R^2 = 0.87$. The best fit for the combined dataset after centering is $\beta = 1.14$, 95% CI [1.06, 1.23], $R^2 = 0.89$, statistically indistinguishable from the simplest theoretical expectations (yellow line) in Fig. 2*A*. One MA in Brazil was excluded from *b*'s estimate because of data completeness issues.

As in many other urban systems, total personal income, Y_j, for each urban area, j, is well described statistically by a scale-free function of the form

$$Y_j = Y_0 N_j^{\beta} e^{\xi_j}, \quad [1]$$

where the prefactor, Y_0, is independent of city population size, N_j, and where β is a scaling exponent (or elasticity: $\beta = dlnY/dlnN$). The quantities ξ_j are (scale-independent) deviations from the mean (scaling) expectation and are characterized by a zero mean and a small variance. Fig. 2*A* and Table 2 show the scaling results for the two nations as well as their combined behavior (after centering the regression and pooling the data; see ref. 37). The scaling exponent $\beta = 1.11$ estimated for Brazil is very similar to that of the United States and to the GDP of Brazilian MAs (35). The relatively large number of MAs in Brazil and their size range allows us to establish with high confidence that this result is broadly consistent with theory (35), which derives quantitative expectations for scaling exponents from calculating rates of socioeconomic interactions for a population in a spatial steady state, determined by the balance of benefits and transportation costs in the tradition of urban economic geography (37). The smaller number of South African MAs show stronger scaling effects with a larger $\beta = 1.35$ but also with a wider confidence interval. The combined dataset, Fig. 2*A*, shows scaling that is statistically indistinguishable from the simplest prediction of urban scaling theory, $\beta = 7/6$ (35), shown as a yellow line in Fig. 2*A*.

A consequence of this scaling behavior is that larger cities have greater average incomes per capita and thus may exhibit greater capacity to dedicate more resources to services and infrastructure (34–36, 40). Such allocations may happen directly via local taxes or indirectly via higher receipts and reinvestments managed at the national level (30). To investigate this issue empirically, we define a sustainable development index, X_i, characterizing a population in a given spatial unit of analysis i, as

$$X_i = \sqrt[n]{\prod_{j=1}^{n} X_i^j}. \quad [2]$$

This index spans a number of dimensions n of sustainable development. Because much of the underlying data for assessing sustainable development goals (SDGs) remain to be collected, we illustrate here its properties in terms of access to basic services and housing (SDG goals 6, 7, 11; or 4 of the STI's components):

$$X_i = \left[X_i^{water} X_i^{electricity} X_i^{sanitation} X_i^{homes}\right]^{1/4}, \quad [3]$$

where X_i^{water} is the fraction of the population in unit i with access to an improved water source. Similarly the superscripts *electricity*, *sanitation*, and *homes* refer to access to electrical power, improved sanitation, and permanent housing. Descriptions and emerging international standards for their use as indicators are given in *Materials and Methods* and *SI Appendix*.

This index is bounded between $X_i = 0$, when one or more services are totally absent, and $X_i = 1$, when there is universal access within area i. The multiplicative character of the index follows the construction of the HDI and emphasizes that all components are essential for achieving a set level of development (41) and are not substitutable. This form is also consistent with the HDI (20, 21) and UN-Habitat's definition of a "slum household" as a household that lacks access to any one of these services in the composite STI (9). For purposes of illustration, we show in *SI Appendix*, Figs. S13–S16 and section 1.5 the comparison between the multiplicative and additive forms of X and refer the reader to the relevant discussions leading to changes in the definition of the HDI to a multiplicative form, which motivate Eq. **2** (20, 21).

Fig. 2*B* shows the average value of X_i for urban areas of different population sizes in Brazil and South Africa. In general, the level of services increases with city size (*SI Appendix*, Figs. S17 and S18), a trend that is especially clear in South Africa. In some parts of Brazil, service provision has expanded more systematically to smaller cities and rural areas (*SI Appendix*, Fig. S8). These results answer our first question: The relative performance of larger cities in terms of access to services and thus some of the dimensions of sustainable development is consistent with advantages derived from urban agglomeration effects and points to a wide range of reasons why urbanization continues to grow in low- and middle-income nations beyond strictly economic motives. As *SI Appendix*, Figs. S17 and S18 show, living in larger cities means that, on average, residents obtain access to many dimensions of sustainable development sooner. However, these averages hide large heterogeneities, to which we now turn.

Heterogeneity of Development Across Scales. Measures of heterogeneity within MAs are especially important because at this scale residents share the same labor and real-estate markets and thus face many of the same opportunities and costs (35, 42).

Measures of heterogeneity may be spatially explicit or they may consider only variation within a population. The Gini coefficient (Fig. 1*B* and *SI Appendix*, Figs. S9–S11) is a well-known nonspatial measure of heterogeneity. A simpler measure of variation is the SD, σ, and its relation to the mean of any socioeconomic variable. Moran's I, by contrast, is the most widely used measure of spatial heterogeneity (43): It accounts for the level of correlation between characteristics at two spatial locations separated by a distance. The Gini coefficient (or the SD) and Moran's I are not necessarily correlated because this depends on the spatial structure of mixing between different people. Any resource within a population may be spatially distributed in a manner that is maximally clustered, meaning that Moran's I approaches $I = 1$, or perfectly anticorrelated (like a checkerboard), so that Moran's I approaches $I = -1$, or a random (well-mixed) pattern, when Moran's I approaches $I = 0$ (see *SI Appendix*, Figs. S19 and S20 for illustrations).

These quantities, taken together, characterize the heterogeneity of sustainable development indices in cities. From its definition, we see that the variance of X must be a function of the mean, and vanish when everyone in unit i has services, $X = 1$, or when they are nonexistent, $X = 0$. It typically is maximal when the mean $\bar{X}= 1/2$, because then there are more configurations possible, for example by having households with different levels of access within and across neighborhoods i. Thus, we can parameterize the SD of X_i, σ_i, as

$$\sigma_i = b_i\sqrt{\bar{X}_i\left(1-\bar{X}_i\right)}, \qquad [4]$$

where the square root corresponds to the SD of a random Bernoulli process. This relation means that $b = 1$ gives the maximal variance at each value of the average $\bar{X}$(Fig. 2 *B* and *C*). Note also that it follows from the properties of the SD that $b \geq 0$. Thus, we can characterize two-dimensional trajectories in the space of $(\bar{X}_i, \sigma_i)$ as levels of development change in each unit, i, and the values of $(\bar{X}_i, \sigma_i) \rightarrow (1{,}0)$. Given $\bar{X}_i$, these trajectories are characterized by a single number: the value of b_i as a function of place and time. There are two special trajectories—of maximal and minimal heterogeneity—characterized by $b_i = 1$ and $b_i = 0$, respectively, indicated in Fig. 2 *B* and *C* by solid black lines. Because of these properties we refer to b_i as a (normalized) heterogeneity index.

Although our present data are cross-sectional, we can compare different urban areas by estimating levels of heterogeneity in terms of b. Fig. 2*B* shows the plot of $\bar{X}$ versus σ for Brazilian MAs and South African municipalities (see also *SI Appendix*, Figs. S21 and S22). Across different urban areas, we observe a Kusnetz-curve type behavior (24), where intermediate levels of access are associated with the greatest variance. We estimated the values of b (*SI Appendix*, Figs. S21–S23) to determine the expected value of b = 0.58 for Brazil and b = 0.57 for South Africa, which are statistically indistinguishable from each other (Table 2). The frequency of residuals (*SI Appendix*, Figs. S24 and S25) shows that the variation of b across different cities is small and slightly left-skewed so that trajectories with considerably lower inequality are possible. It is also important to realize that levels of heterogeneity are scale-dependent, as shown in Fig. 1*B*. Adopting smaller units of analysis, such as neighborhoods, obtains lower values of b. These results answer our second question: They suggest that there are generic trajectories of local development (Fig. 2 *B* and *C*). Empirically, the variation between neighborhoods is closer to the case where access is distributed in an all-or-nothing manner ($b \rightarrow 1$) rather than when access, though limited, is provided equally to everyone ($b \rightarrow 0$). These results provide a set of specific expectations for local urban development as longitudinal data become available.

To explicitly take into account the effects of space, we now use Moran's I to measure the similarity of conditions between nearby neighborhoods (*SI Appendix*, Figs. S19 and S20 and *Materials and Methods*). We varied the distance between neighborhoods to measure the corresponding strength of spatial correlation for various quantities (Fig. 2*D*, *Inset*, *SI Appendix*, Fig. S26, and Table 2). In all cases, we find clear evidence of strong spatial clustering in access to services with a magnitude that is strongest at a "walkable" distance below a few kilometers (Fig. 2*D*, *Inset*). This spatial correlation is even higher for socioeconomic quantities, such as income and racial composition (*SI Appendix*, Fig. S26). These results suggest that assortative dynamics, which generate strong spatial economic and racial inequalities in US cities (25, 33), are likely also at play in urban areas of Brazil and South Africa. Higher levels of spatial clustering, measured by the magnitude of I, are also statistically associated with higher levels of heterogeneity in access to services, measured via the magnitude of b (Fig. 2*D*). These findings answer our final question: Heterogeneity between people is expressed spatially as differences between places within a city defined at about a kilometer scale, rather than differences within spatially well-mixed populations. In other words, heterogeneity is expressed in these cities systematically as spatially concentrated (dis) advantage (14, 25, 33).

Discussion and Outlook

We have shown how several central features of sustainable development are intimately connected to agglomeration and heterogeneity effects in cities and how the scale of spatial units of analyses matters to measure inequality and inform more effective assessments and policy. We expressed these connections in terms of three general questions, which we answered through empirical analysis using data from Brazil and South Africa. First, we have demonstrated that despite environmental challenges larger cities tend to exhibit greater economic productivity and expanded access to housing and urban services (2), which nucleate solutions for sustainable development within their nations. Second, large inequality typically results as improvements are initially expanded (15). Such patterns of inequality are scale-dependent, being larger between different neighborhoods within MAs. Nevertheless, high levels of inequality are not inevitable and several places offer counterexamples of development with low inequality. Importantly, we observe that stronger heterogeneities are associated with more spatially concentrated outcomes at characteristic scales of about a kilometer.

The indicators and statistical analyses introduced here provide a general roadmap for better understanding and assessing sustainable development in cities across scales. The construction of the sustainable development index X_i is general and should be improved and expanded to additional sustainability measures as data become available, for example relating to access to education, gender equity, health, clean energy, and environmental quality, measured within cities and globally.

To this end, it is important to emphasize several shortcomings of present data, which we expect will be gradually overcome in the near future. First, our analysis was focused on neighborhoods and cities of Brazil and South Africa, two middle-income nations with well-established urban systems and state-of-the-art census practices (*SI Appendix*). Other cities in lower-income nations may show much more incipient processes of sustainable development (9, 15, 29). It will be critical to identify and track such situations over time. Second, local sustainability indicators must be expanded to include associated quality of service. Measures associated with safety, health, environmental impacts, effort allocation, and pecuniary costs will need to be better factored in so as to promote meaningful progress (15, 29). This approach requires measurements of the several components, X_i^j, that are closer to the experience of individuals and to the spirit of each development goal and should mirror the process by which components of the HDI have been improved over time in contact with a growing availability of data and case studies (20, 21).

A third area of concern is time. We used census data for Brazil and South Africa because they are consistent and well-documented and cover every neighborhood in these large nations. However, these are decennial census data, and 10 years is too long to assess change in fast-growing MAs given the timeline to meet sustainable development goals. Two new sources of such data may come from remote sensing and citizen-generated maps and surveys. More-frequent and higher-resolution imagery may help identify the type and quality of housing and physical infrastructure and track new construction (44–46). Working collaborations between local governments, communities, and civic organizations using new data collection, mapping, and reporting technologies will be essential to create detailed evidence that is accurate, verifiable, and expressive of residents' priorities (47, 48). These collaborations also generate possibilities for supporting training and education, while providing a mechanism for local knowledge and experiences to guide change (15, 28, 47, 48).

The ultimate objective of a scientific understanding of sustainable development is to decouple improving living standards from environmental degradation. Cities play a crucial role in both processes (2, 4–6, 9, 15, 30). They create increased socioeconomic productivity and a greater intensity of environmental impacts in ways that are at once connected but also place- and scale-dependent (9, 14, 29). As emphasized by the evidence documented here, the continued improvement of theory and practices that exploit the joint dynamics created by scaling effects, heterogeneity, and spatial structure across a large number of socioeconomic and physical dimensions will be critical for harnessing the transformative power of cities toward faster and more equitable processes of socioeconomic and environmental change.

Materials and Methods

Development Priorities Surveys. Data on informal settlement development priorities were extracted from "informal settlement profiles"—neighborhood surveys of population and services (28)—conducted during 2014–2015 by Slum/Shack Dwellers International (knowyourcity.info/) national federations in collaboration with neighborhood communities and our group. Table 1 derives from 677 neighborhood profiles in 10 nations and 59 cities, including 4 neighborhoods in the Philippines and 2 in Ghana, which are included in the total data but not as individual countries. Among other questions, communities were asked to discuss and identify their most pressing needs in ranked order. The data shown refer to their highest self-identified priority.

Small Area Statistics Data for Brazil. Data for small area statistics in Brazil were obtained from the 2010 national census, available at www.ibge.gov.br. The data are provided in a hierarchical set of spatial units (*SI Appendix*, Fig. S6). The base unit of analysis is the *setor* (average population = 695), modeled after US census tracts. The municipality and the metropolitan region are the geographic levels at which we report statistics. There are currently 39 metropolitan regions in Brazil, made of sets of municipalities ranging in population from about 1/4 to almost 20 million (São Paulo). There are 121,030 urban *setores* in Brazil, characterized in the main text and *SI Appendix*. Data contain detailed information on demographic and household characteristics in addition to construction and access to services.

Neighborhood Statistics for South Africa. South African neighborhood data are drawn from the 2001 national census, available at www.statssa.gov.za. South Africa produces universal coverage census data relevant for assessing sustainable development indicators reported in small geographical units, called "subplaces" (average population = 2,100; median population = 770). We report statistics on municipalities, defined by Statistics South Africa, which also designates eight functional cities as metropolitan municipalities (*SI Appendix*, Figs. S1–S5). The contiguous metropolitan municipalities of Johannesburg and Ekurhuleni (East Rand) are often aggregated into a single large urban area of Greater Johannesburg, and there is discussion as to whether Tshwane (Pretoria), with a city center 35 km away, should also be included.

Sustainability Index Definition. Indices accounting for the degree of attaining each development goal were constructed for the smallest units of analysis (*setor* in Brazil, and subplace in South Africa) and composed multiplicatively (Eq. **2**) to generate a composite index. Measures of access to each service category follow the definitions developed by the Joint Monitoring Program and UN-Habitat; see Satterthwaite (29) and *SI Appendix*, section 1.3 for additional details.

Scaling Analysis. Scaling parameter estimation was performed using ordinary least-squares regression of logarithmically transformed variables. Fig. 2*A* shows centered data, obtained by subtracting the average logarithmically transformed population and income (see ref. 39).

Heterogeneity Analysis. Estimates of the heterogeneity index b were obtained from Eq. **4**, given the estimated mean and SD of X or $X^{service}$ for each spatial unit i. Moran's I estimates were obtained using the smallest available units (*setor* or subplace). A matrix of nearest neighbors j, w_{ij} for each neighborhood i was constructed as $w_{ij} = 1/d_{ij}$, cut off at distance s, which is varied to explore the strength of I (Fig. 2*D*, *Inset*).

ACKNOWLEDGMENTS. We thank Anni Beukes and members of Slum Dwellers International for discussions and use of informal settlement profiles data, and the Arizona State University/Santa Fe Institute Center for Biosocial Complex Systems for partial support. This work was partially funded by MacArthur Foundation Grant 13-105749-000-USP and Army Research Office Minerva Program Grant W911NF1210097.

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Supplementary Information Appendix

Heterogeneity and Scale of Sustainable Development in Cities

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1. Supporting Information

1.1 Distributional Effects in Sustainability Urban Indicators

In the main text, we characterize several aspects of the heterogeneity of personal income and access to basic services as fundamental measures of sustainable development as defined by the recent *Sustainable Development Goals*. We emphasized the strong spatial and socioeconomic heterogeneity of these indicators across entire nations, and specifically within functional urban areas whose inhabitants share the same labor and real estate markets.

Here we provide a more comprehensive description of related work. In this section, we concentrate on a literature that refers to these issues in terms of so called *distributional effects*. As the term indicates distributional effects consider quantities beyond the mean, by analyzing higher statistical moments (such as the variance), inequality indices (such as the Gini coefficient) or indeed by characterizing frequency or probability distributions.

The discussion of distributional effects has become particularly relevant in the context of environmental and public goods provision policies and their differential effects on distinct segments of the population, especially when stratified by income (*1*–*3*). A pervasive concern in the literature on distributional effects is whether such policies are regressive, meaning that they impose a disproportionate burden on poorer populations, such as happens with (flat) consumption taxes (*1*, *4*–*8*). Though the problem analyzed in the main text is somewhat different – heterogeneity in *access* to services, rather than specifying policies for service revenue or taxes—we provide the reader here with a brief introduction to issues of distributional effects as they make clear that knowledge of the disaggregated impacts, whether by social and economic groups and by place, is critical for the design of urban sustainability policies.

This literature can be characterized in terms of the i) types of policies attempted, ii) the typology of the population to be served (e.g. income groups), and iii) the level of spatial aggregation in the analysis. Most past studies rely on relatively high levels of spatial aggregation within developed nations or are limited to just a few places. The results in the main text are novel with respect to our treatment of space as they produce, to the best of our knowledge, the first comprehensive analysis across all scales (neighborhood to country) in two large middle-income nations and show the way such analysis can be performed in any city or nation with similar, neighborhood level data.

One of the earliest literatures to emphasize distributional effects was focused on policies aimed at creating sustainable solutions related to air quality in the USA (*1*, *9*–*11*). It was established that poor air quality disproportionally impacted the poor (and certain other populations at risk) and, as such, that policies for improving air quality should be more targeted in order to truly affect the lives of the poor.

Similar concerns and more contemporary methods of analysis have been used to foresee or measure the impacts of other sustainable development policies. For example, Bitler and colleagues (*12*) analyzed the distributional consequences of specific welfare reforms in Connecticut, to find that policy results are more varied and more extensive then when evaluated in terms of means. Similarly, Hammer and colleagues have studied the impacts of social sector policies in Malaysia (*13*) between 1974-89, and in particular investments in education, finding that those targeted at universal primary education have had tremendous progressive consequences over the long term, while others less so. Thus, the analysis of the heterogeneity of effects as a result of policies or events provides a finer and more insightful view of processes and aids policy design and assessment.

A number of recent studies have analyzed distributional effects resulting from the privatization of services in Bolivia (*14*) and the United Kingdom (*6*), of water pricing models in São Paulo (*15*), or environmental and renewable energy policies in Germany (*16*, *17*), and of road congestion charges in the USA (*2*, *3*). Studies of household consumption, as they relate to greenhouse gas emissions, have also been analyzed in terms of their heterogeneity (*18*).

The overall conclusions from all these studies is that there is strong heterogeneity in patterns of consumption and emissions across households with different socioeconomic status, and that policies and assessments that forego distributional analyses will be unnecessarily blunt and may generate unintended consequences, such as being regressive.

Another important line of enquiry has analyzed the distributional impacts of changes in international trade and globalization on personal incomes. These studies tend to be tied to international policies, e.g. connected to World Bank Investments, World Trade Organization guidelines and others. For example, Goldberg and Pavcnik (*19*) conducted a large empirical study of measures of income inequality in developing nations (including skill wage premiums, wage and income Gini indices and other measures of heterogeneity). Garuda (*20*) performed a similar analysis of distributional effects across several nations as a result of International Monetary Fund policies to find adverse distributional effects in many cases. Such studies fit into a broader literature on progress in international policy targeted at eliminating poverty (*21*) and other sustainability goals and an increasing recognition that such effects need to be studied in greater detail across populations and places.

Most past analyses of the distributional impacts of specific development policies, however, apply to entire nations at once, without performing a scale-dependent disaggregation or emphasizing diverse urban areas, as we do here. Thus, in the main text, we establish and illustrate a systematic procedure to measure and evaluate sustainable development goals across scales, from neighborhoods to nations. In our view --supported by the results of numerous distributional effects studies -- only such systematic approaches can capture local variation and context in a way that renders the analysis general, and not merely circumstantial.

1.2. The Value and Role of Public Services for Sustainability Assessment

In this section, we discuss the importance of tracking service access as a fundamental component of sustainable development at the local level, and discuss how it gives us a window into local development beyond that provided by income assessments.

The inaccuracies introduced by ignoring non-cash income and the benefits of access to public goods and infrastructure have long been noted by economists (*22*, *23*). The neglect of non-cash sources of income when analyzing the prevalence of poverty, poverty rates and income distribution stem largely from the difficulties inherent in the measurement, valuation, and imputation of non-cash income to individual households on the basis of the data typically collected by governmental agencies (*24*).

Considering that most welfare transfers in developed countries are in the form of in-kind benefits (health insurance, education, subsided housing and other services), an excessive focus on cash income yields not only an incomplete but also misleading picture of the distribution of economic wellbeing (*25*). Measuring "extended income" (defined as the sum of disposable cash income, the value of access to public infrastructure and the value of public services received by households) leads to smaller differences in the calculated poverty rates among the developed economies but with increased heterogeneity of income inequality for households within countries (*26*).

The arguments in favor of using extensive income for analyzing poverty rates and income distribution in and among poor communities in developing economies are also compelling but the empirical challenges are even more severe. Surprisingly little is known about patterns of income distribution and poverty rates in urban areas of the developing world, especially within slums (*27*, *28*). A World Bank comparative study of slums in Dakar, Nairobi and Johannesburg based on survey data of slum dwellers socioeconomic and housing conditions, which tried to estimate "extensive income", finds much heterogeneity of poverty within slums and even that not all slums dwellers can be considered poor with respect to cash income (*29*).

There is a striking discrepancy when poverty alleviation programs for the urban poor and slum upgrading projects are discussed. Poverty is usually identified and measured on the basis of income with poverty reduction been identified with an increase in household income. Slums are identified primarily through non-income measures, the presumption being that slum dwellers have low cash (or pecuniary) incomes. But an accurate assessment of poverty in slums necessitates not only the identification of income levels (hard to do when a large proportion of a population is economically engaged in the informal sector) but also the valuation of the public services and infrastructure a slum population has access to. An important step in the right analytical direction is to measure the spatial heterogeneity of income and access to services within and across *all* neighborhoods inside a city. The main text shows how this can be done extensively for entire nations, and how distributional effect by place, income and race can be readily identified. It also shows that present policies create strong adverse distributional effects on their way to providing greater access to services.

1.3 Additional Details of the Construction of the Sustainable Development Index

While, from a purely accounting perspective, an additive form provides a possible definition of a sustainable development index, *X*, such a choice has two major disadvantages: i) it must be renormalized by the number of objectives every time a new dimension is added, and ii) it conveys a sense that different dimensions are strict substitutes for each other (e.g. electricity for sanitation), which is incorrect. A multiplicative index, instead, emphasizes the simultaneous importance of all its dimensions. Multiplicative indices are usually written as geometric means of several, such as the Human Development Index.

To construct *X* in practice, we used four different dimensions identified by slum dwellers as major priorities and available in census data: Access to improved water, improved sanitation, electricity, and permanent housing. The quantification of access to any service category in both Brazil and South Africa follows the measures identified by the Joint Monitoring Program and UN Habitat, described by Satterthwaite (*30*), as closely as is permitted by the available data:

For the case of South Africa, we defined a household as having access to an *improved water source*, if it has access to piped water inside the dwelling, through a tap inside the yard, or via a community tap less than 200m away. We define a household as having access to *improved sanitation* if its main type of toilet facility empties to a sewer system or septic tank, or is a ventilated improved pit latrine. We define the rate of *electricity access* in each sub-place as the combined maximum rate of use of electricity for heating, cooking, or lighting. Finally, we define a household as having *permanent housing* if the household lives in an apartment in a multi-unit building, in semi-detached housing such as townhouses or duplexes, or in a permanent structure on its own lot or in a back yard. All these terms correspond to *categories of access* characterized and measured by the Census of South Africa, household by household.

For Brazil, we defined a household as having access to an *improved water source* if it has access to piped water, well water, or rain water on their premises. We defined a household as having *improved sanitation* if it has access to a toilet where waste is disposed of into the municipal sewer system, a septic tank, or a pit. Sanitary sewage waste disposal via ditch or an open water body is not considered improved sanitation. *Access to electricity* and *adequacy of housing* are directly measured in the Census.

Note that in most cases these classifications do not necessarily require formal (municipal) services, and express instead the quality of the service households have access to, regardless of the manner in which the service is provided. In particular, in many cases improved services may result from informal business models or practices. This is in the spirit of a "capabilities approach" to development, which frames this work as discussed in the main text.

We note that the technology and type of infrastructure necessary to provide improved access to urban services varies substantially across different population densities. This is especially true for sanitation and fresh water access. For example, a *ventilated improved pit* is clearly an inappropriate technology for a dense urban neighborhood in a flood prone location. Similarly, a single community tap may not have the capacity to serve the entire population within a 200m radius. Better future metrics should include notions accounting for the ratio of actual population using some service to the design capacity of that service.

The issue of land tenure, which is a component of UN-Habitat "slum indices" (*31*) and is an important priority to slum dwellers, could not be evaluated as this information is not collected in either Census.

It is important to note that these measures exclude important considerations relating to safety, time use, quality of service and its durability, which are relevant to better assessing development capabilities and neighborhood resilience but are not currently reported in either Census.

1.4 Census of Brazil and South Africa: Assessments of quality and coverage

Both Census datasets for Brazil and South Africa are comprehensive counts of population and their living conditions and strive to account for every person, in each household and place of residence throughout their entire nations. Assessments of success of these practices, in terms of accounting for the entire population and controlling for possible biases, by place or socioeconomic characteristics, are always difficult to gauge in detail and must rely on smaller samples that test for such issues in specific places.

Data from the Census of Brazil and South Africa are highly regarded among national statistical bureaus and follow the worldwide state of the art. Their methods are based on and are very similar to those implemented by the US Census Bureau. The *Brazilian National Institute of Geography and Statistics* (IBGE), Brazils' counterpart to the United States Census Bureau, is highly respected by international agencies and itself provides technical advice to other middle and low-income nations on how to conduct population counts and surveys.

To check for accuracy and biases, the Brazilian and South African Census agencies follow the practice of the U.S. Census Bureau and conduct "post-enumeration surveys." A "post enumeration survey" (PES) is a smaller survey run a short time after a Census in order to compare counts in specific places and thus determine how many people may have been missed or counted more than once. A PES is run independently from the Census and it is intended to provide a methodologically independent assessment of the completeness of a Census. Both the IBGE an Statistics South Africa conduct PES following the guidelines provided by the *U.N. World Population and Housing Programme* (*32*). While not providing an overall margin of error for the population count, post-enumeration surveys often allow for the estimation of error margins and corrections for some specific sub-population thereby helping to validate the methodology and count accuracy of nation-wide census.

In the case of South Africa the PES conducted after the 2010 Census estimates that about as many as 16% of households and 15% of the total population were not included in the Census (*33*). For Brazil the results of the PES are not reported in a manner that allows for a succinct evaluation of accuracy but a recent study indicates that around 5% of households might have been missed in the 2010 Census (*34*). Within the caveats that no population Census (including the one conducted in the U.S.) can or is expected to be perfectly accurate, there are no serious doubts raised based on these findings for the Census of Brazil, especially regarding biases. For South Africa there has been some controversy in the media about the level of population coverage, but the post enumeration survey points to slightly better coverage in cities relative to rural areas and of black populations relative to white, for example.

For these reasons, while some undercount is likely in both Censuses , we have no reason to expect significant biases in coverage by place or socioeconomic characteristics, and can therefore expect that comparative conclusions across neighborhoods and more aggregated units of analysis are warranted in both nations.

1.5 Sensitivity Analysis for the Construction of the Sustainable Development Index

Although the multiplicative form of *X* in the main text is motivated by its mathatematical properties and well as a long history of lessons learned from the construction of the Human Development Index and others, it may be interesting to compare several possible definitions of *X*, using the same underlying data.

To illustrate this comparison, we show in Fig S13 the within-municipality standard deviation for the mean access rate for the different constituent components of the Sustainable Development Index. In addition, Fig S14A shows an index where the components have been combined into their arithmetic mean, and Fig S14B shows this manuscript's definition, where the components have been combined into their geometric mean, which is the same strategy used in the construction of the HDI.

The maps of Fig S15 refer to the Johannesburg and Tshwane Metro areas in South Africa. The left panel shows an index based on the arithmetic mean of the four urban services measures, while the right shows the geometric mean of the same services. The maps in Fig S16 refer to a small part of the city of Rio de Janeiro, again showing the arithmetic and geometric means. Figs S15A and B are quite similar because in South Africa, if an area is has low levels of service for one of the components of *X*, it is also likely to have low levels of service for the other categories. As a result, the difference between the arithmetic mean and geometric mean is small.

Fig S16A and B show much larger differences than Fig S15A and B. This occurs because in this part of Brazil the components of urban services are less likely to be provided together than they are in South Africa. As a result, the lack of substitutability between different services expressed by the geometric mean implies lower values of sustainable development.

2. Supplementary Figures

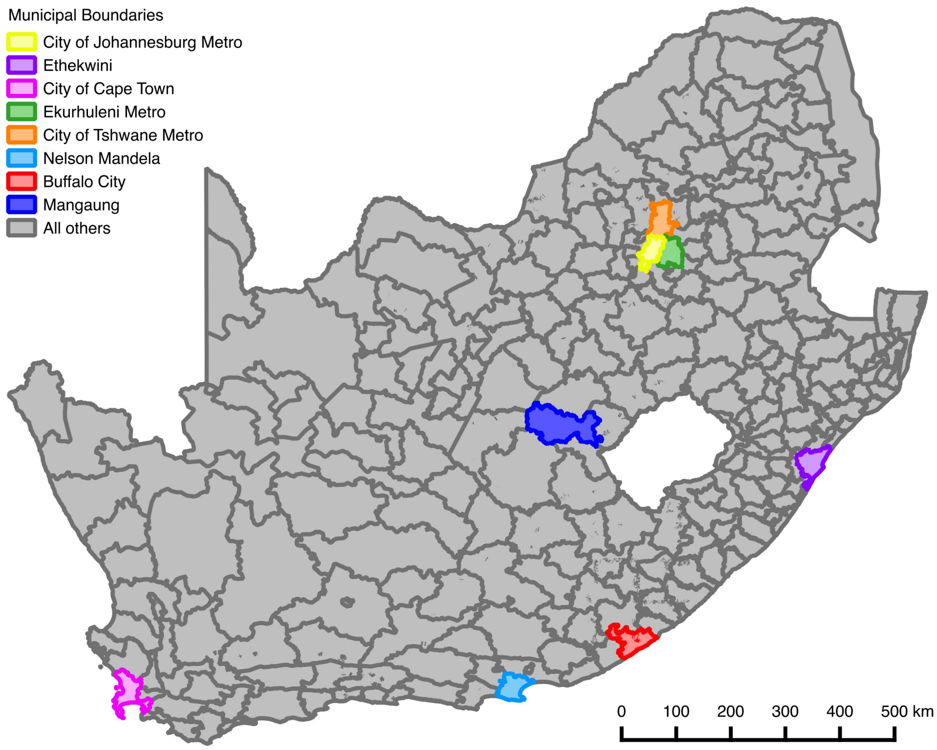


Figure S1 – A Map of South Africa showing municipal boundaries and main cities. The eight officially designated Metropolitan Areas are indicated in color (see legend). Details of their urban fabric and sustainability indices are developed in the main text and shown in Figs. S4-5, below.

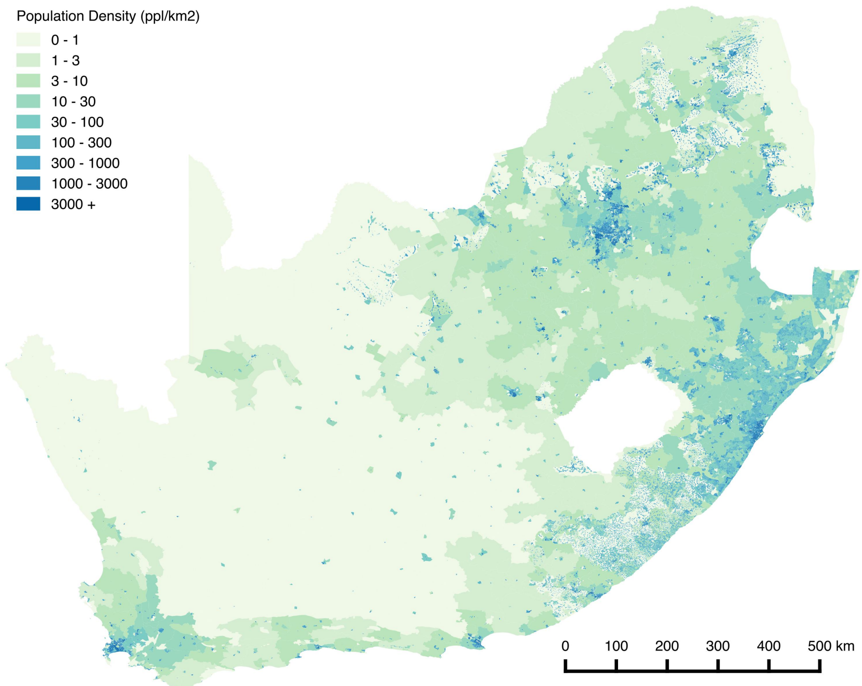


Figure S2 – Population Distribution in South Africa. Large cities clearly stand out as dense population agglomerations, compare with Figure S1. However note that there are several areas of relatively dense rural populations, especially along the Eastern Cape (southeast) and Limpopo (northeast). These have been areas of large out-migration to the largest cities in the country, especially greater Johannesburg and Cape Town.

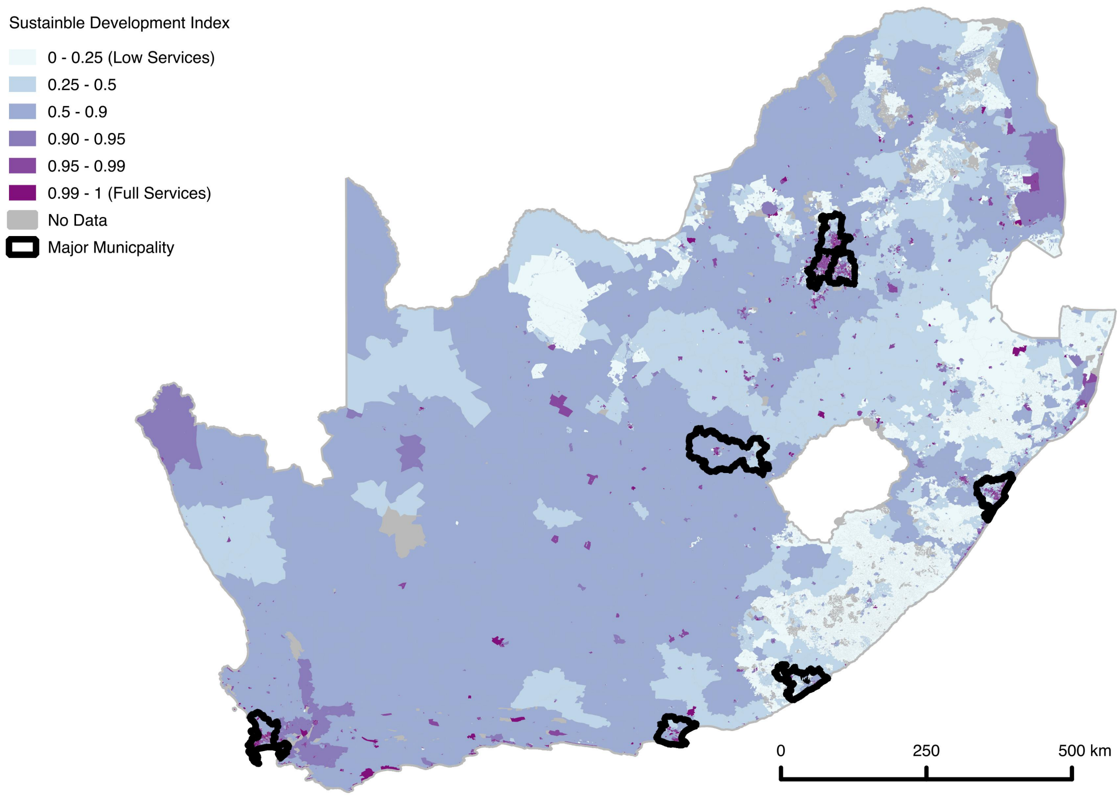


Figure S3 – A Map of South Africa showing the nationwide distribution of the Sustainability Index. Colors show the values of the Sustainable Development Index, X (see main text), which varies from the total absence of services (white) to universal access (dark purple). Note that despite their small geographic size, large cities are much more likely than rural areas to have high levels of services, see also Figures S4-5. Note, however, the role played by other small cities and by a few low density areas, especially in the North of the country.

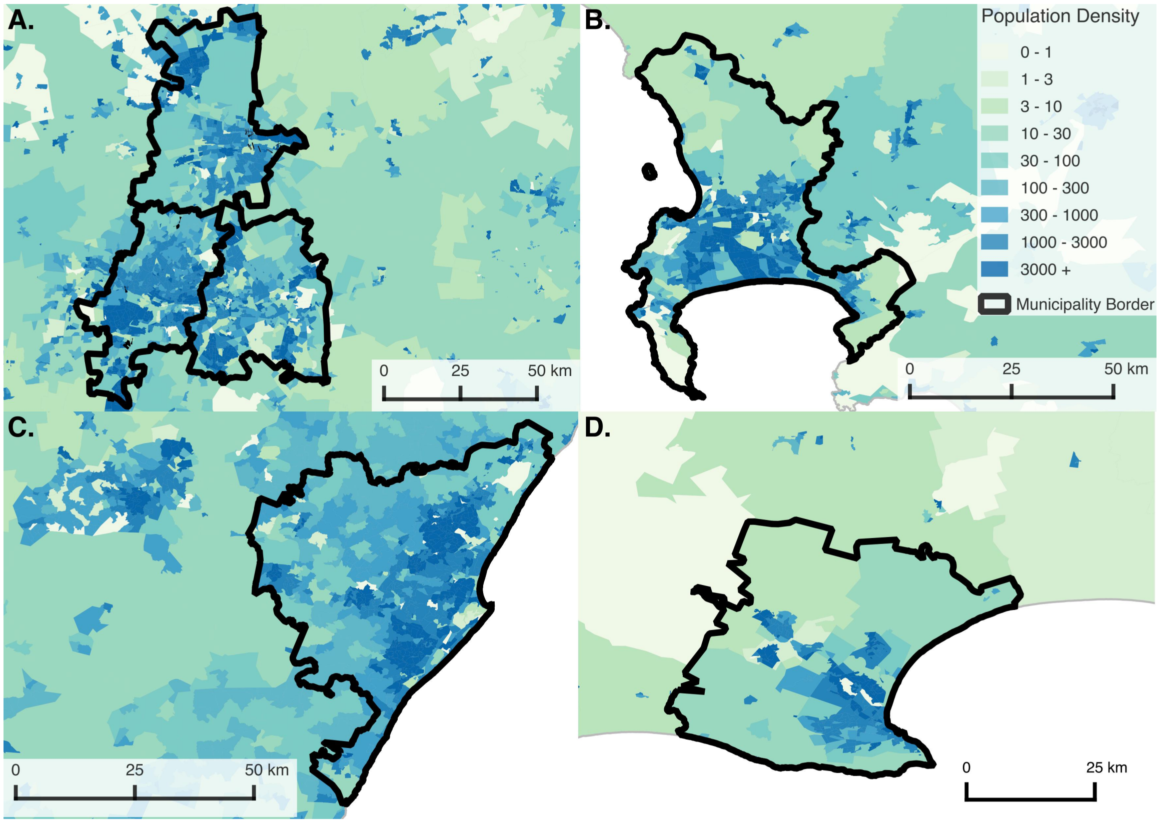
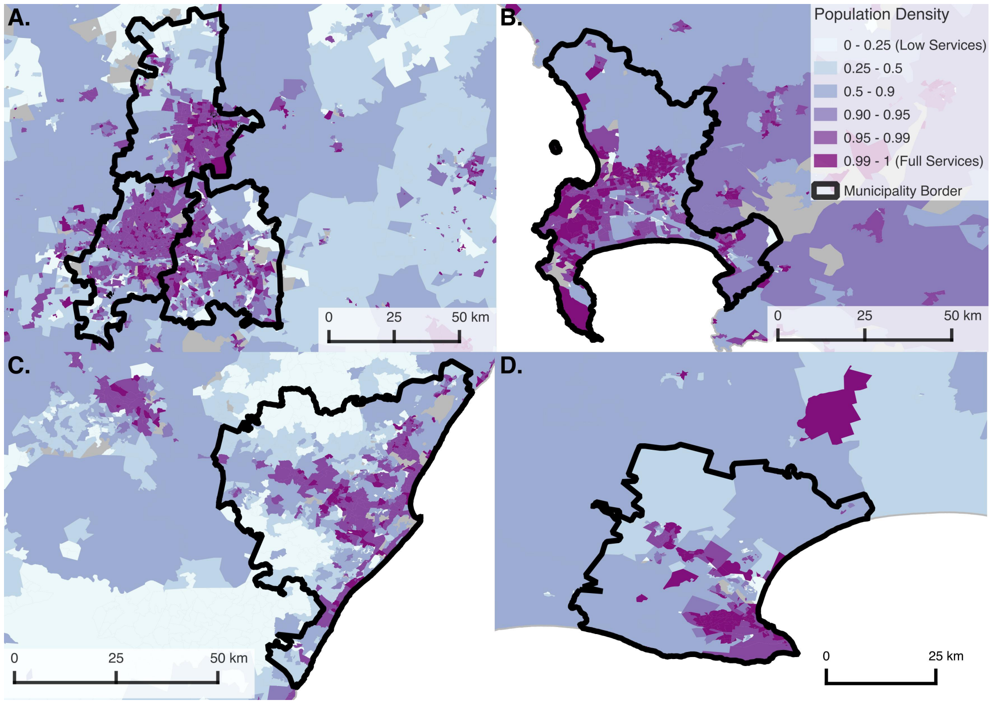


Figure S4: Population Distribution in selected South African Metropolitan Areas. In each panel, we show the estimated population density (people/km^2) at the sub-place level. Panel A shows the Greater Johannesburg area, which includes the City of Johannesburg Metropolitan area, Ekurhuleni Metropolitan area (East Rand), and the City of Tshwane Metropolitan area (Pretoria). Panel B shows the City of Cape Town Metropolitan area. Panels C and D show the Metropolitan areas for eThekwini (Durban), and Nelson Mandela (Port Elizabeth), respectively.



Figures S5: Sustainability Index Distribution in selected South African Metropolitan Areas. In each panel, we show the estimated sustainable development index, *X,* at the sub-place level. Panel A shows the broader Johannesburg area, which includes the City of Johannesburg Metropolitan area, Ekurhuleni Metropolitan area (East Rand), and the City of Tshwane Metropolitan area (Pretoria). Panel B shows the City of Cape Town Metropolitan area. Panels C and D show the Metropolitan areas for eThekwini (Durban), and Nelson Mandela (Port Elizabeth), respectively. With the exception of Cape Town, widespread access to services is generally concentrated within metropolitan areas, and in the denser more central parts of those cities. However, the correlation is not perfect and many dense poor areas remain underserviced. In informal areas (slums), some of the official census numbers are disputed by resident communities.

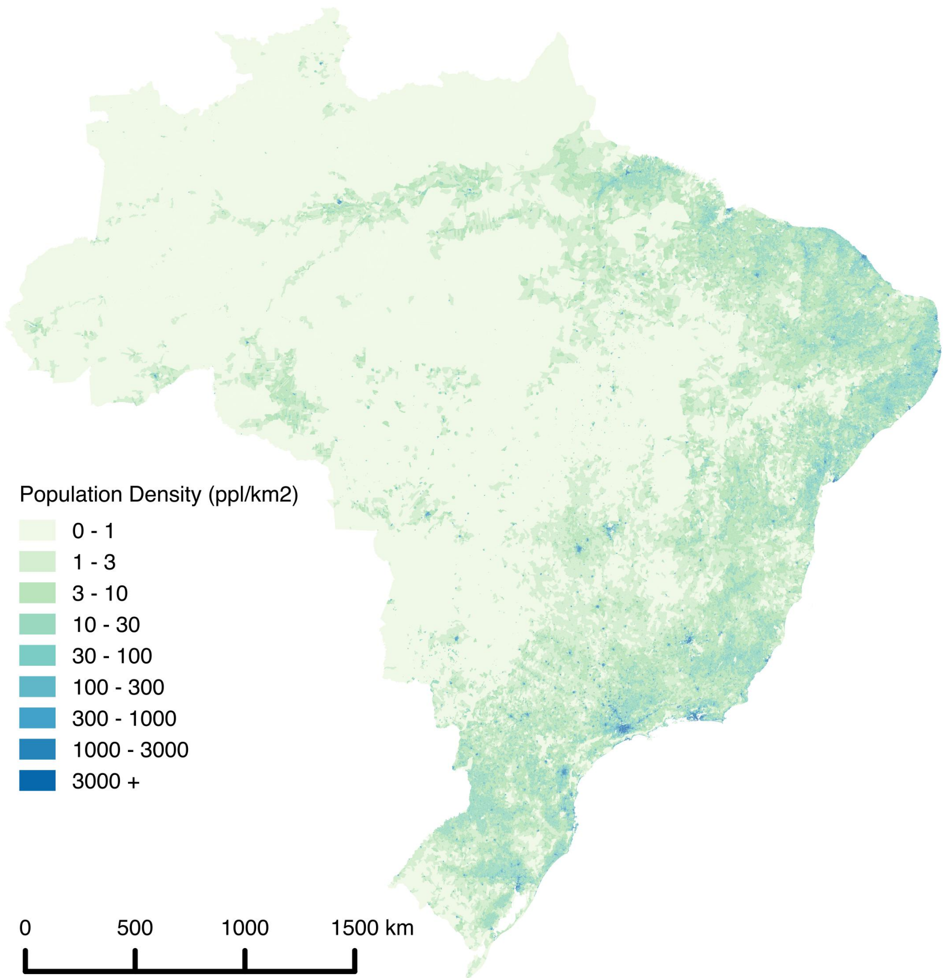


Figure S6: Population Distribution in Brazil. Brazil's population is clearly concentrated towards the coast, with the interior and Amazon very sparsely populated. Brazil's large cities, such as São Paulo and Rio de Janeiro, are visible through their large population density, but their area is small relative to the country as a whole.

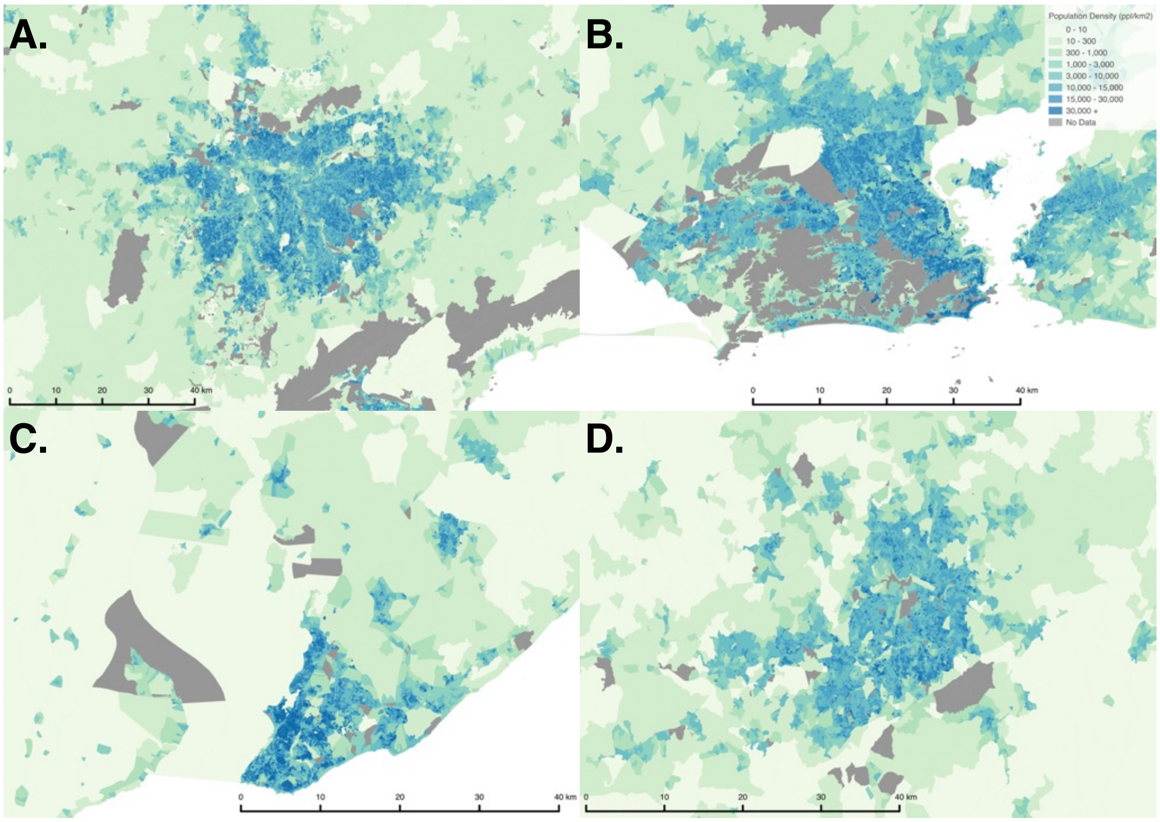


Figure S7: Population Distribution in selected Brazilian Metropolitan Areas. In each panel, we show the estimated population density (in people/km^2) at the *setor* level. Note the color scale used to show population density for urban environments breaks out much higher population densities than the color scale used at the national level in Figure S6. Panel A shows São Paulo. Panel B shows Rio de Janeiro. Panels C and D show Salvador and Belo Horizonte, respectively.

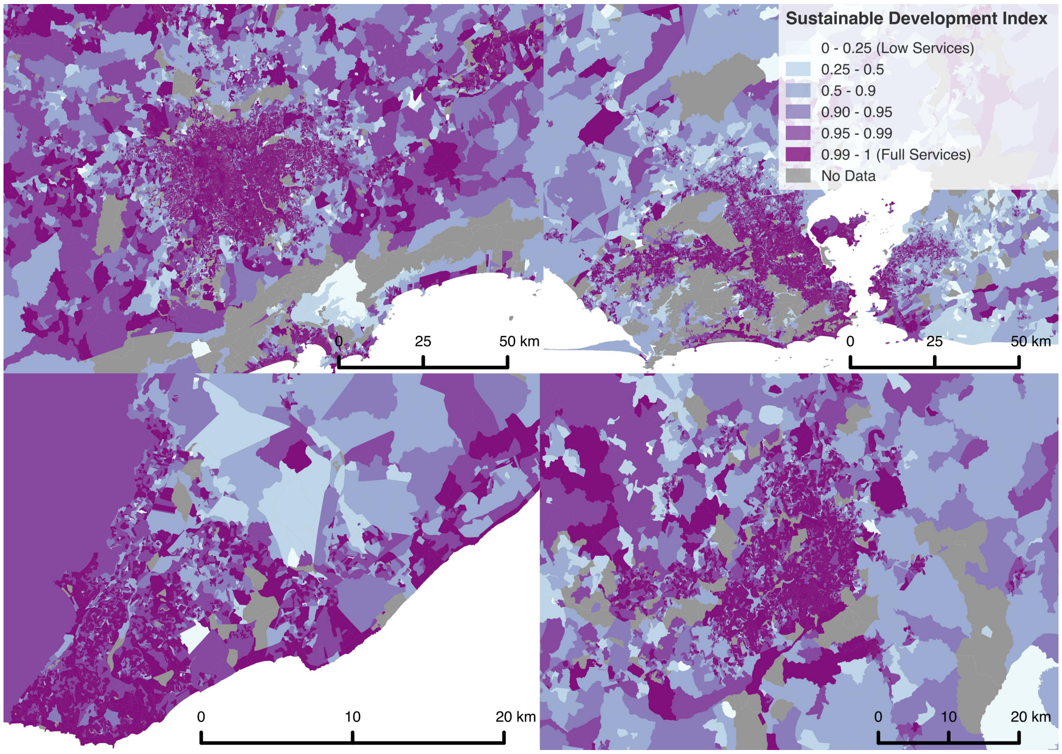


Figure S8: Sustainability Index Distribution in selected Brazilian Metropolitan Areas. In each panel, we show the estimated sustainable development index, *X,* at the *setor* level. Panel A shows São Paulo. Panel B shows Rio de Janeiro. Panels C and D show Salvador and Belo Horizonte, respectively. We observe that, relative to South African cities, Brazilian Metropolitan Areas have higher overall levels of services, which is particularly visible for São Paulo, the nation's largest Metropolitan Area.

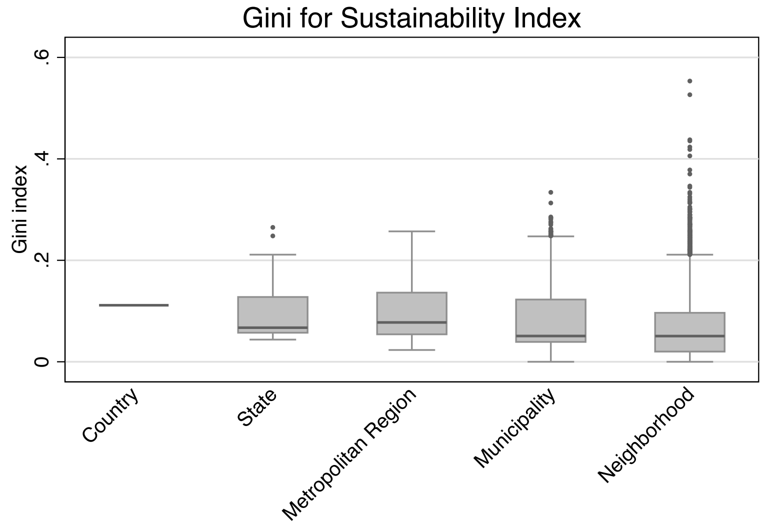


Figure S9: The Gini coefficient for the sustainable development index, *X*, at the neighborhood (*bairro*), municipality, metropolitan region, state, and national level for Brazil. The population weighted median across all units of analysis within a class is shown by a horizontal black line, with the 25th to 75th percentiles shown by the grey box. Whiskers reach to the most extreme data point that is less than 1.5 times the distance between the 25th and 75th percentiles from the grey box. Any remaining outlying points are plotted individually. We see that, in analogy to Fig. 1B, the spread in inequality across neighborhoods is greater than the spread in inequality across cities and larger areas. Metropolitan regions show level of services inequality that are consistent with the nation at large and are greatest for an integrated labor and real estate market.

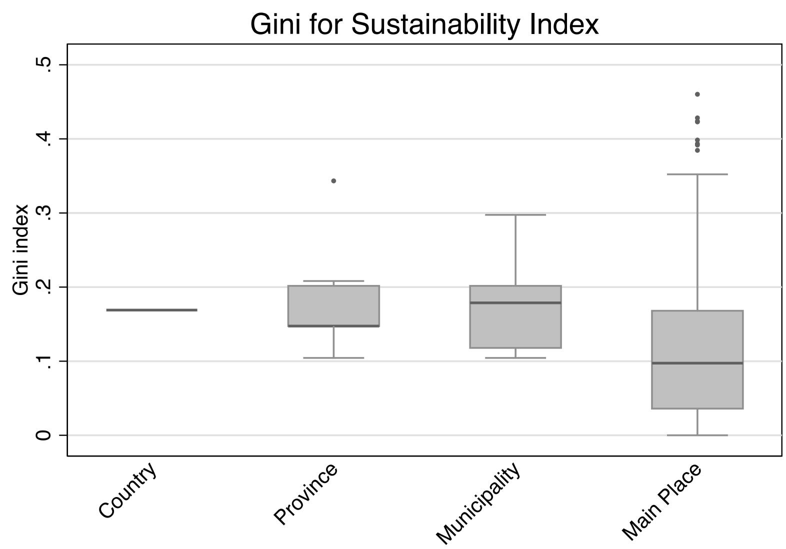


Figure S10: The Gini coefficient for Sustainable Development Index at the main-place, municipality, province and national level for South Africa. The population weighted median across all units of analysis within a class is shown by a horizontal black line, with the 25th to 75th percentiles shown by the grey box. Whiskers reach to the most extreme data point that is less than 1.5 times the distance between the 25th and 75th percentiles from the grey box. Any remaining outlying points are plotted individually. We see that inequality is somewhat lower within "Main Places" than it is at spatial scales of the municipality or larger.

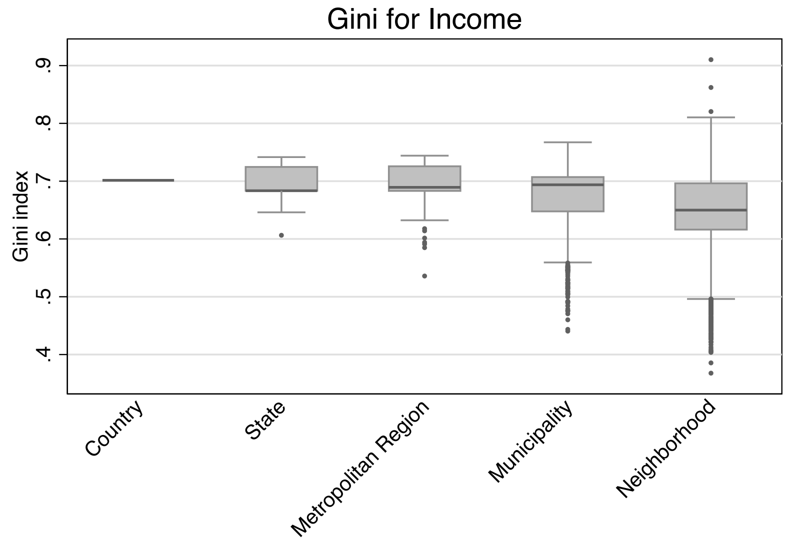


Figure S11: The Gini coefficient for personal income at the neighborhood, Municipality, Metropolitan, State, and national level for Brazil. The population weighted median across all units of analysis within a spatial class is shown by the horizontal dark line. The 25th to 75th percentiles are bounded by the grey box. Whiskers reach to the most extreme data point that is less than 1.5 times the distance between the 25^{th} and 75^{th} percentiles from the grey box. Any remaining outlying points are plotted individually. Similarly to the Sustainable development index, *X*, we find levels of inequality at the city level similar to the nation, but see somewhat lower inequality for neighborhoods (though still high by international standards), with larger variations. Thus, cities show the highest level of inequality within units that are integrated labor markets**.** Note that the Gini coefficients at all scales for both Brazil **and South Africa is very high**, around 0.7.

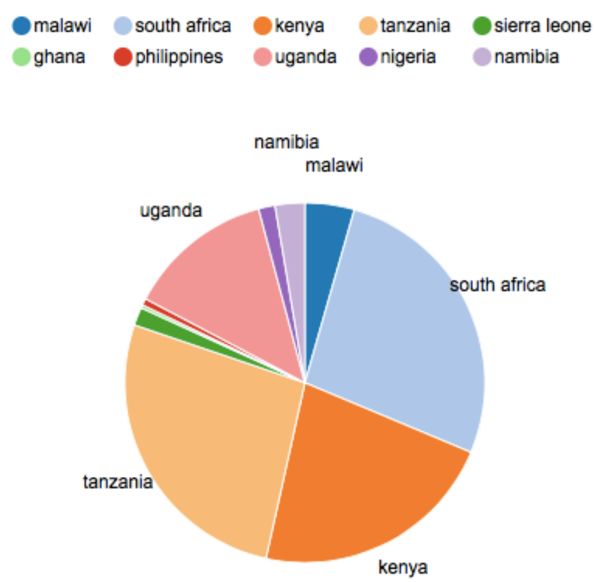


Figure S12: National breakdown of slum upgrading priority surveys. The pie chart gives a visual depiction of the fraction of neighborhoods surveyed by nation in Table 1 and Fig. 1C**.**

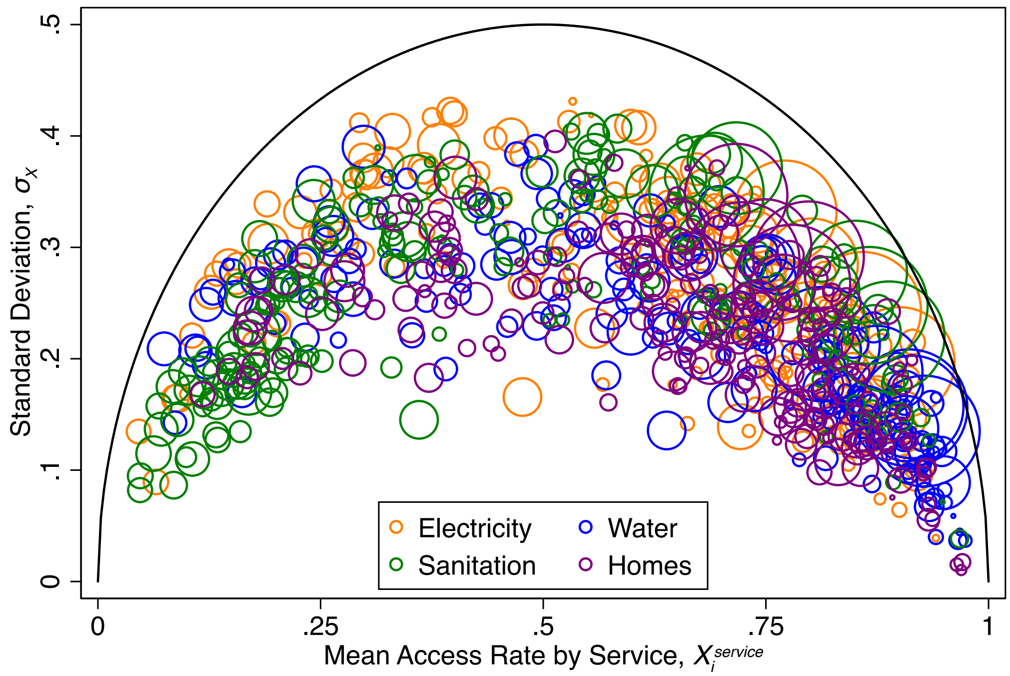


Figure S13: The mean access rate within Municipalities against the standard deviation in access rate for that service within a municipality for each of the four services for South African Municipalities. This is also shown in Fig S18A, right panel.

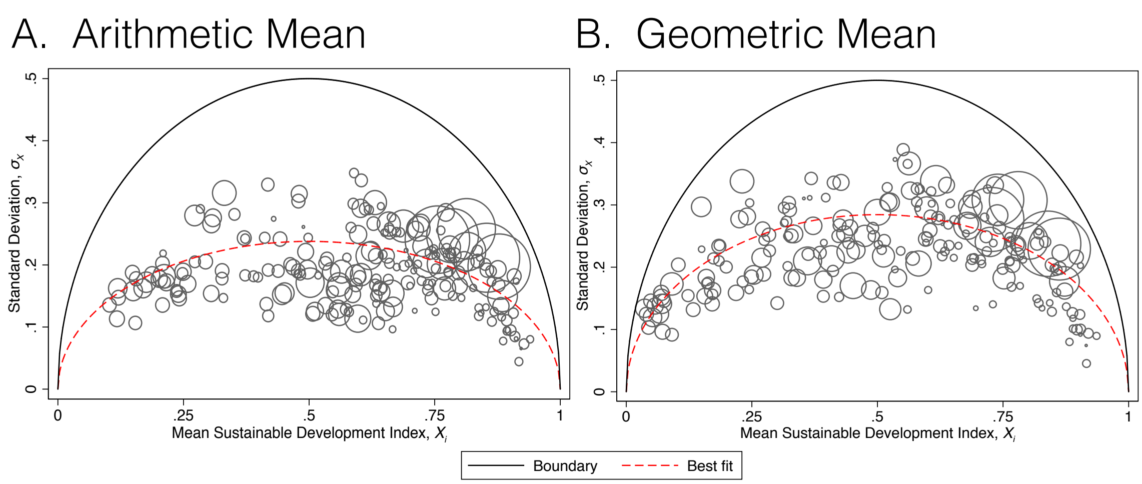


Figure S14 Comparison between multiplicative and additive forms o the Sustainability Index, X. Panel A shows the arithmetic mean for the data shown in Fig S13. Panel B shows the geometric mean for the same data.

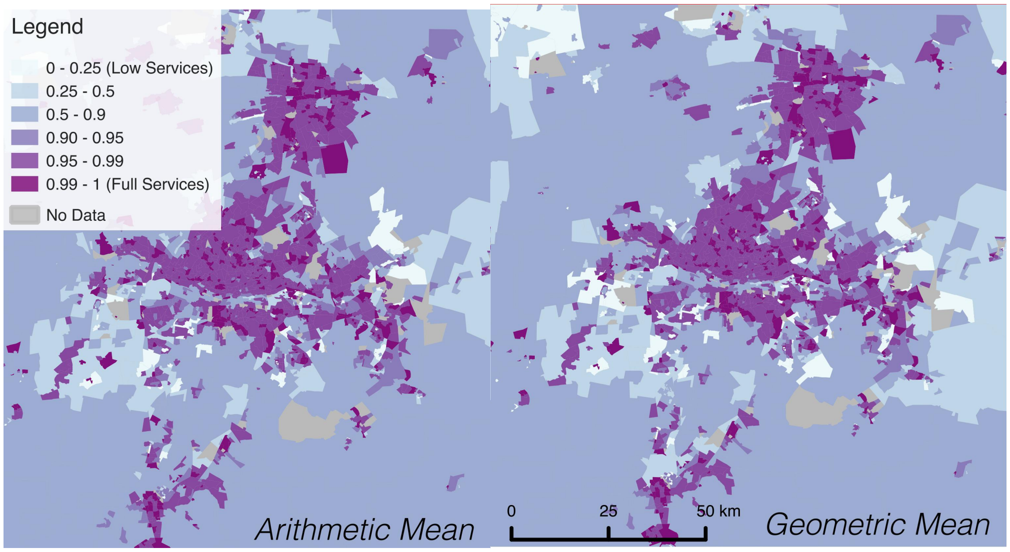


Figure S15: Map comparison between multiplicative and additive forms o the Sustainability Index, X in South Africa. These maps show the combined City of Johannesburg, City of Tshwane Metro, and Ekurhuleni Metro areas. Panel A shows the arithmetic mean of the four components of the Sustainable Development Index. Panel B shows the geometric mean of the same data.

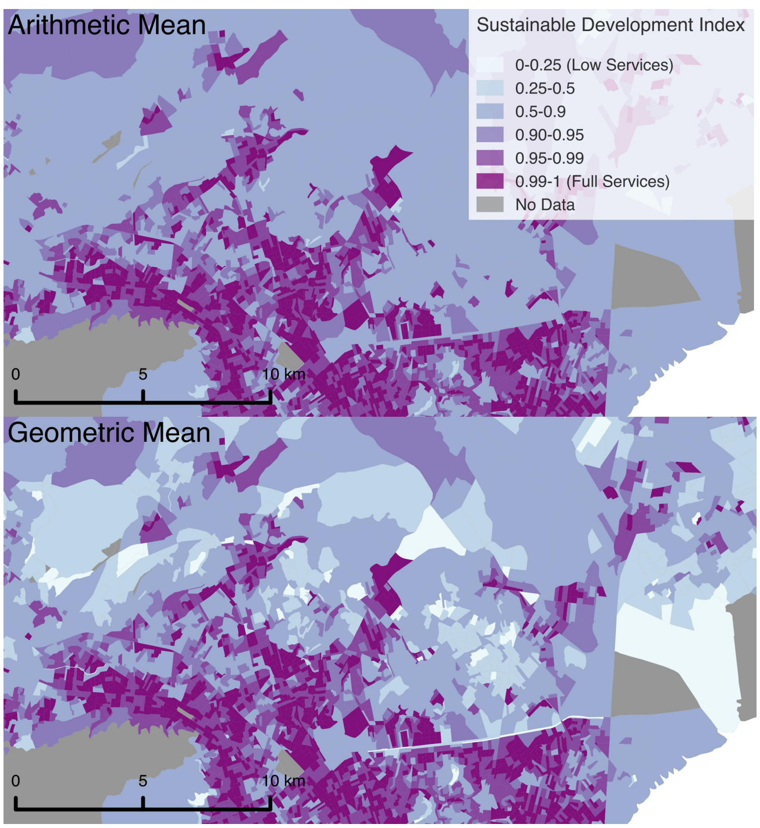


Figure S16: Map comparison between multiplicative and additive forms o the Sustainability Index, X in Brazil. These maps show a small, northern part of the city of Rio de Janeiro. Panel A shows the arithmetic mean of the four components of the Sustainable Development Index. Panel B shows the geometric mean of the same data.

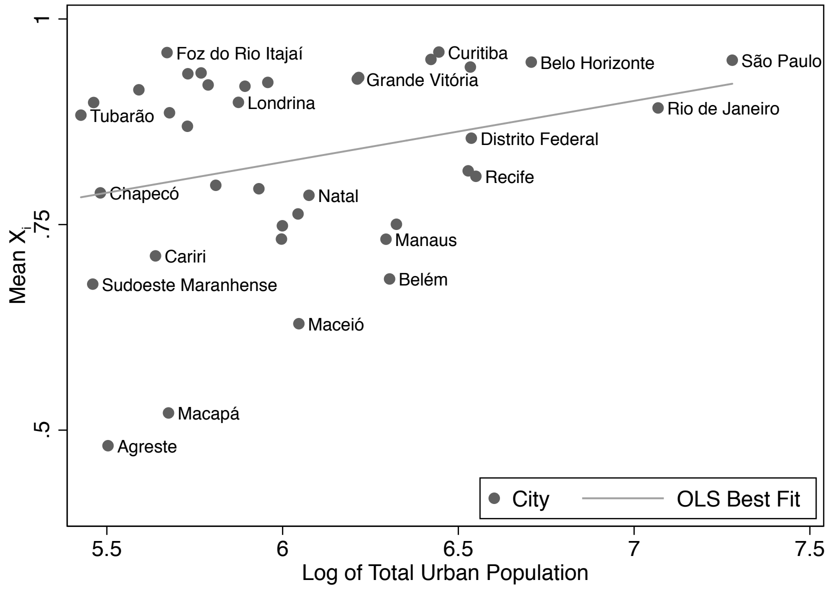


Figure S17: The mean sustainability Index, *X_i* versus total metropolitan population for Brazilian Metropolitan Areas. There is a slight correlation (slope= 0.075, R^2 =0.051) indicating that larger cities tend to provide greater access to services to their residents. Importantly some smaller cities in Brazil's richest regions are performing well in service provision, such as Curitiba, Tubarão or Londrina.

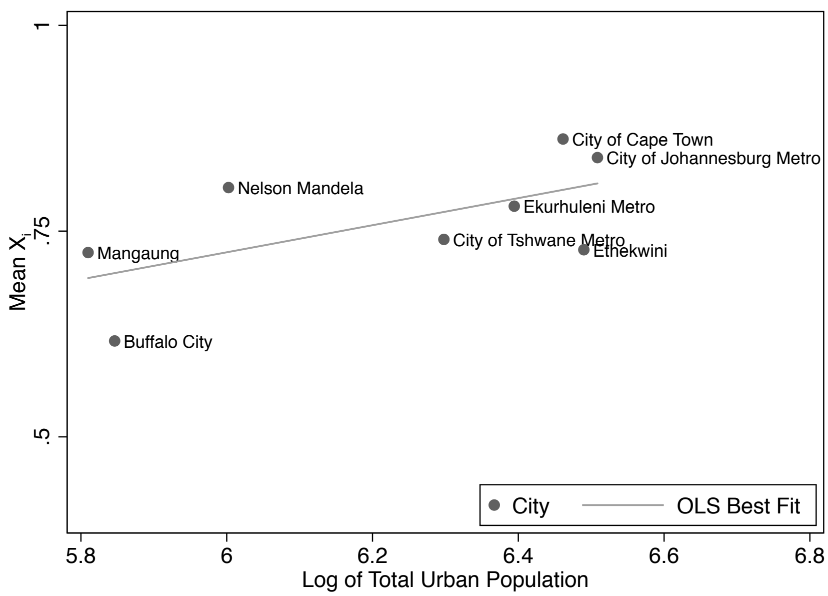


Figure S18: The mean sustainability Index, X_i versus total metropolitan population for South African Metropolitan Municipalities. The line indicates a significant correlation between city size and improved service provision (slope=0.164, , R^2 =0.29).

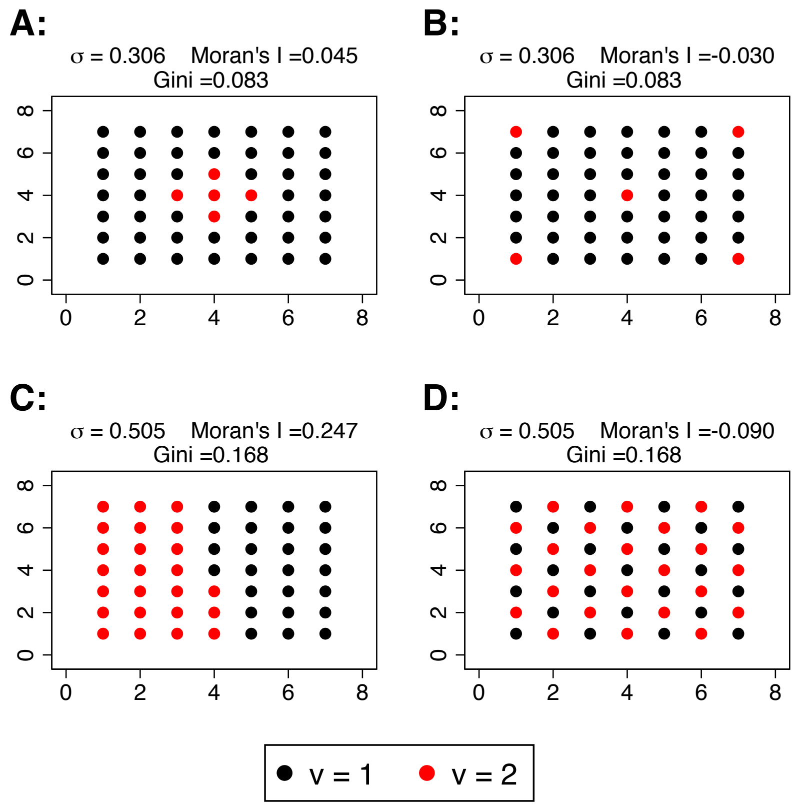


Figure S19: Simple schematic situations illustrating the relationships between the standard deviation, the Gini coefficient and Moran's I. Only Moran's I is sensitive to the spatial configuration of different colors, while the other quantities express how much mixing there is overall. Note that σ and Moran's I are unchanged by linear transformations of the quantities of red and black dots, but the Gini coefficient is not. For example, using the same spatial layout as panel D; with black = 100 and red = 101 yields σ = 0.505; Moran's I = -0.090 and Gini =0.002.

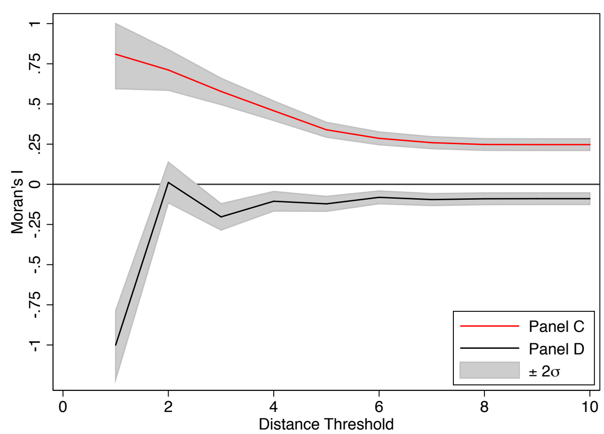


Figure S20: The estimated Moran's I value for illustrative spatial arrangements. The curves correspond to the values of Moran's I, similar to the inset in Fig 2D and Fig S22, for the spatial arrangements shown in Panel C and D of Fig. S15.

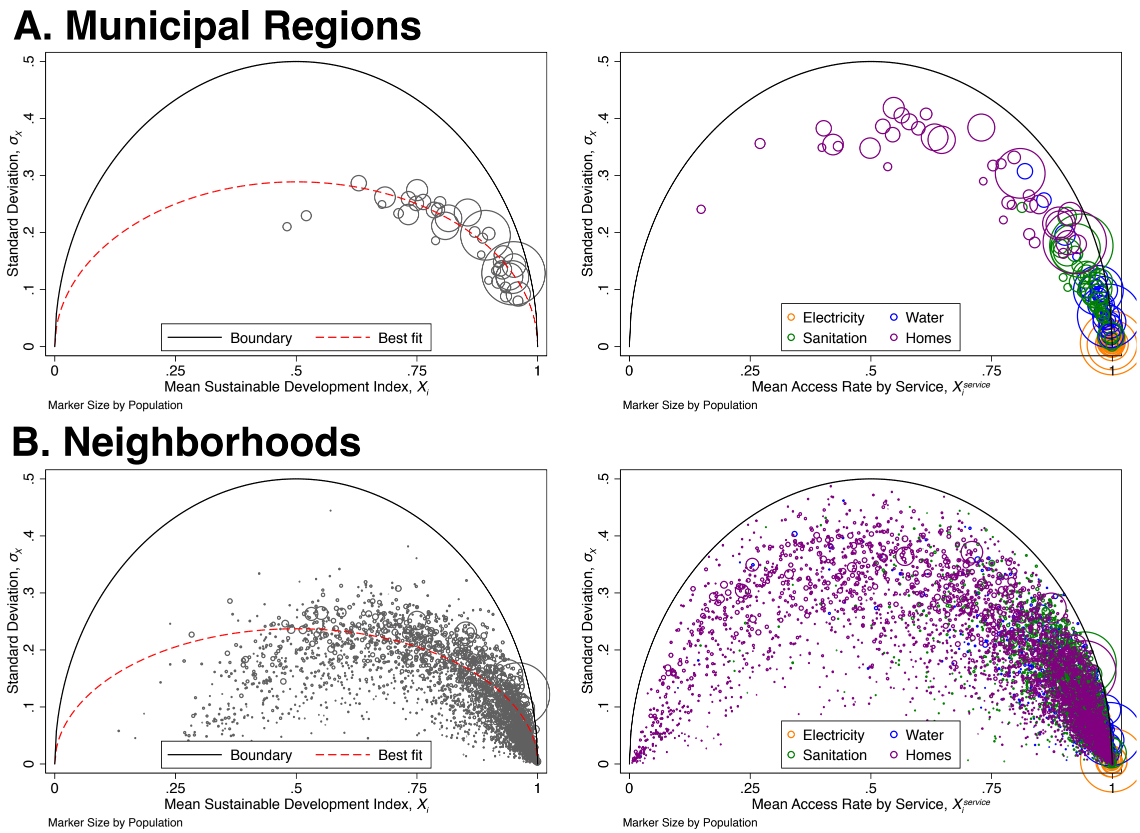


Figure S21: Infrastructure Access rates and inequality in Brazil. Panel A shows the mean and standard deviation of *X* for the 38 Metropolitan Areas in Brazil. These values are estimated using X_i for all urban *setor*s in each city. The colors show how permanent housing remains a greater challenge in these cities, followed by issues of water and sanitation. Access to electricity is comparatively a solved problem. Panel B shows the same estimates, but aggregated at the neighborhood level rather than the city level. The right column in both panels shows the four individual components of X_i: $X_i^{electricity}$, X_i^{water}, $X_i^{sanitation}$, and X_i^{homes} against their standard deviation.

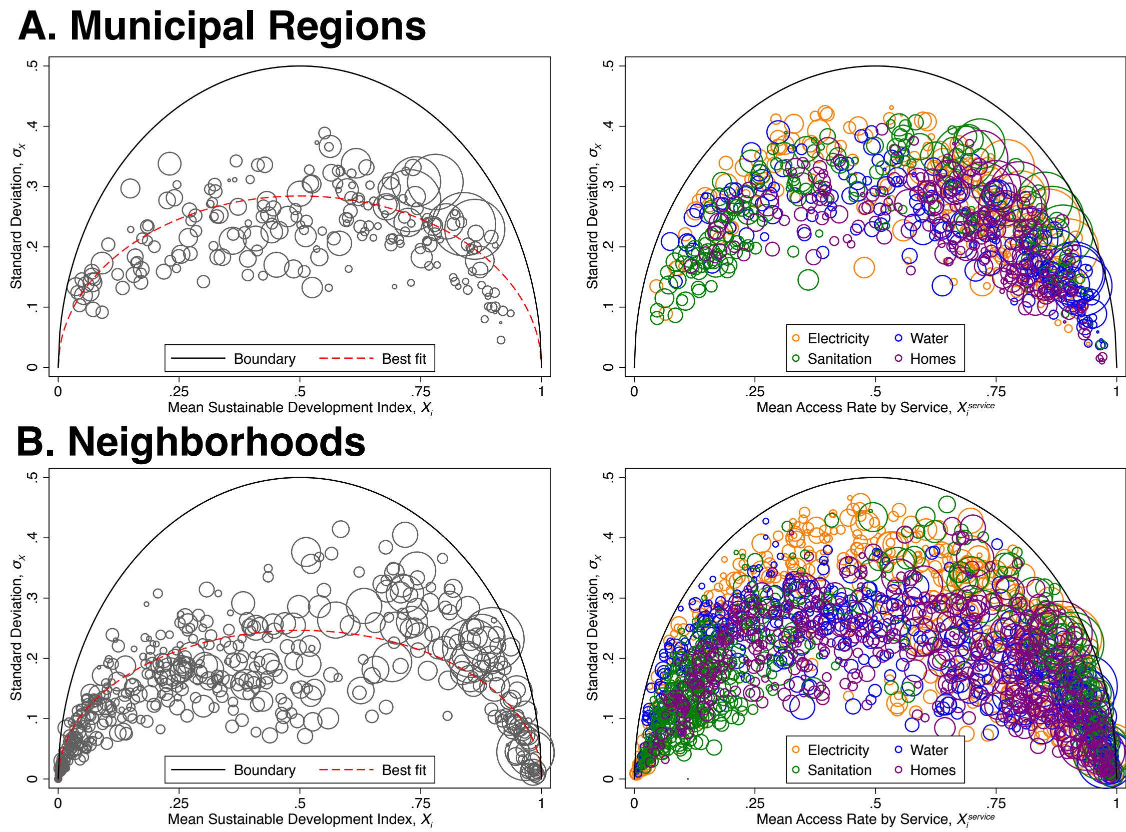


Figure S22: Infrastructure access rates and inequality in South Africa. Panel A shows the mean versus standard deviation of the sustainable development, *X,* for each of the 248 municipalities (metropolitan and not) in South Africa. These values are estimated using X_i for all sub-places in each unit. Issues of sanitation (green) tend to be the most difficult and of water (blue) and housing (purple) less so, but there is also a considerable mix of issues across municipalities. Panel B shows the same estimates, but aggregated at the main-place level rather than the municipal level. The right column in both panels shows the four individual components of X_i: $X_i^{electricity}$, X_i^{water}, $X_i^{sanitation}$, and X_i^{homes} against the standard deviation of each component.

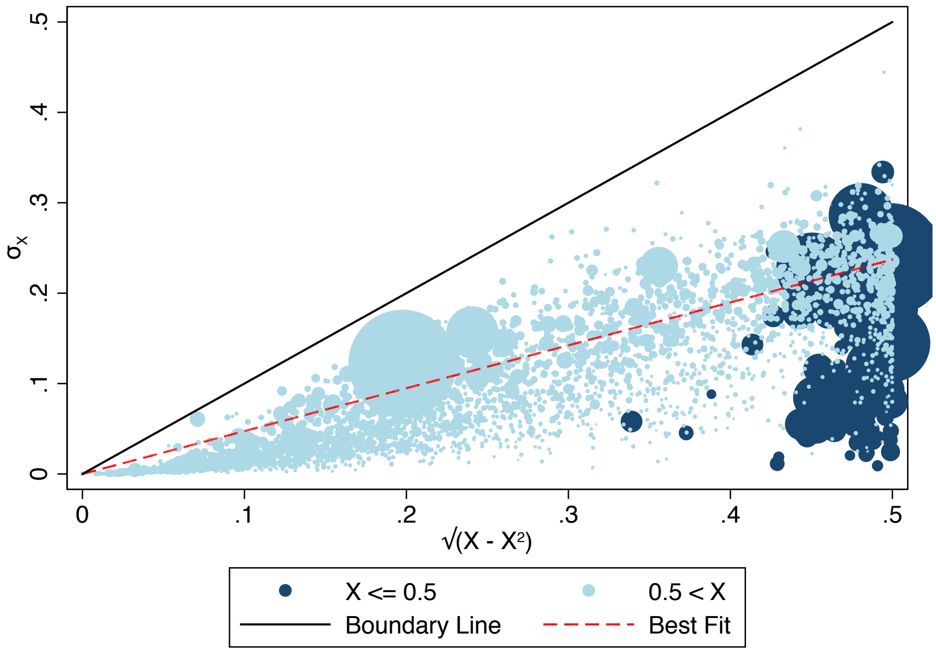


Figure S23: Estimating of the heterogeneity index, *b*, for neighborhood in Brazil. Dark blue denotes places with $X \leq 0.5$, and light blue denotes $X \geq 0.5$, and both sets of X values are plotted at their position under the transformation $\sqrt{(1-X)X}$ to generate a linear dependence on this variable of the standard deviation, with slope *b*. The black boundary line shows the maximum possible σ_X for each X value, while the dashed red line shows the OLS best fit line for $\sigma_X = b\sqrt{(1-X)X}$. We estimate *b* using a standard population weighted OLS regression on the transformed data with White standard errors to account for heteroskedasticity in the errors.

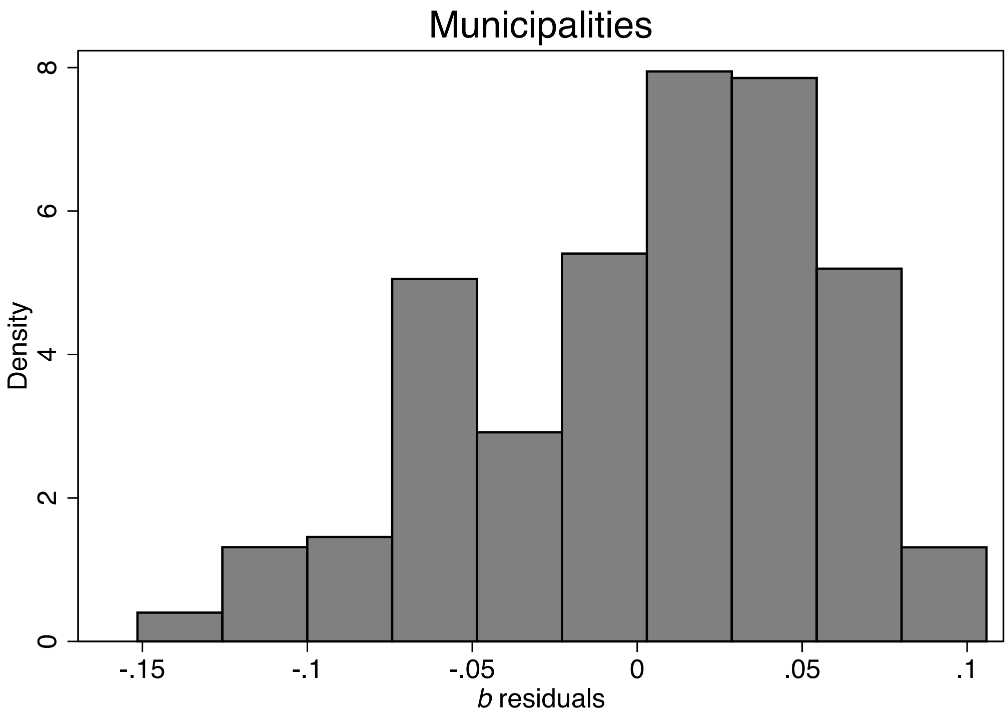


Figure S24: The residuals of the heterogeneity index, *b,* for Brazil's 38 Metropolitan Areas. We see that these values have a small dispersion around the mean, and that their values are somewhat left skewed, so that in some cases considerably less unequal outcomes are possible.

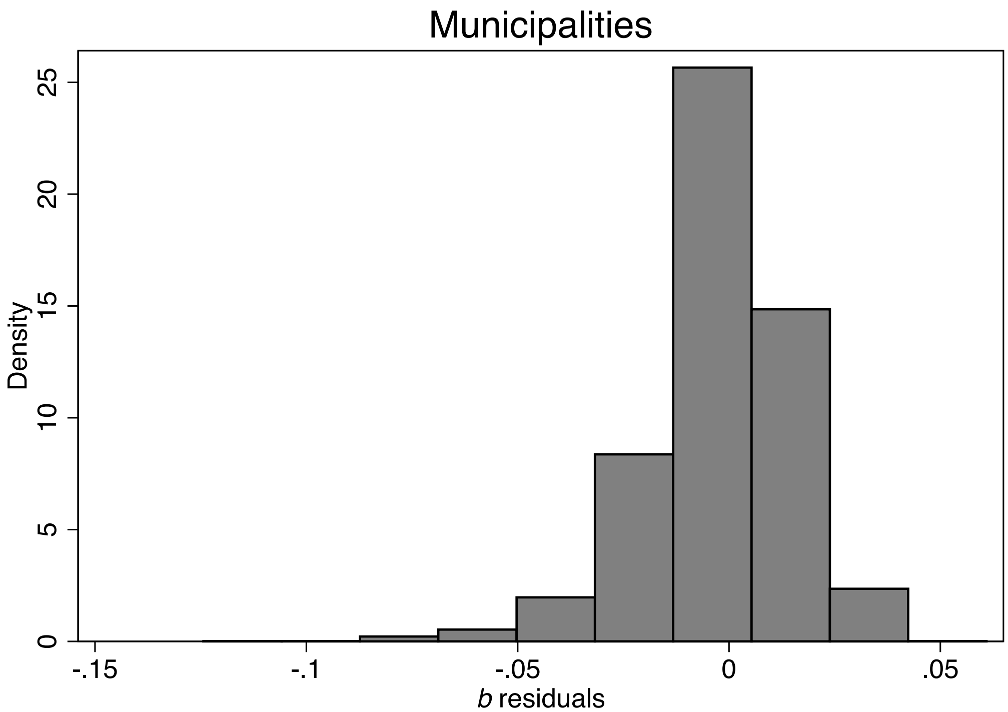


Figure S25: The residuals of the heterogeneity index, *b,* for all of South Africa's municipalities (N=248). Analogously to Brazil, Fig. S24, the distribution is relatively narrow and left skewed, meaning that development trajectories can be characterized by lower heterogeneity than observed on average.

Moran's I Sensitivity Analysis to distance threshold

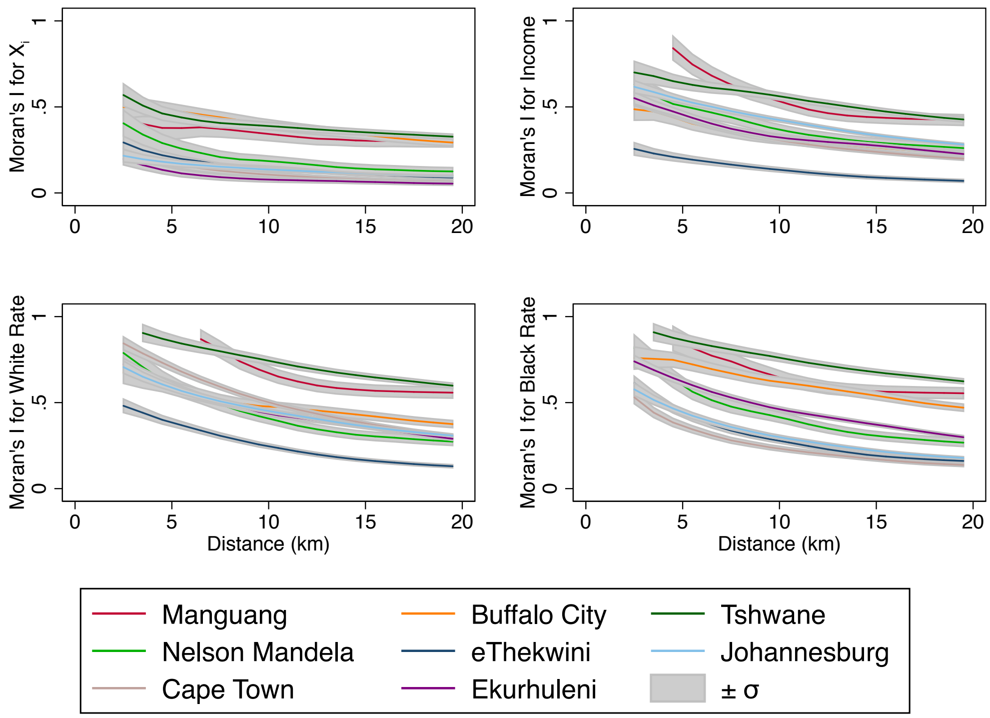


Figure S26: The normalized spatial correlation between neighborhoods in South Africa as a function of the distance threshold, see main text**.** Different panels show distinct quantities, specifically A. The Sustainability Index, *X*, B. Personal Income, C. Percent White Population (race), D. Percent Black population (race). Different metropolitan regions are shown in different colors.

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