Urbanization and child growth failure in Sub-Saharan Africa: a geographical analysis

Yating Ru¹ · Beliyou Haile² · John I. Carruthers¹

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Abstract
This paper raises a fundamental question about Sub-Saharan Africa: has urbanization there been accompanied by improvements in personal wellbeing? It then proceeds to open an investigation focused on child health—in the form of child growth failure, including (i) stunting; (ii) wasting; and (iii) underweight—that addresses the question. The main contribution of the work is to reconcile an array of data, collected across different spatial scales and over different timeframes, in a manner that enables some preliminary insight into the relationships explored. Evidence derived from the analysis suggests that the wave of urbanization breaking across Sub-Saharan Africa is associated with improvements in wellbeing, a finding that is qualified by need for further research.

Keywords Economic growth · Development economics · Time geography · Nutrition · Sub-Saharan Africa

JEL Classification C21 · I15 · O12 · O18 · R12

“I don’t mind stealing bread from the mouths of decadents, but I can’t feed on the powerless when my cup’s already overfilled …”

~Chris Cornell, Hunger Strike (1991)
1 Introduction

Since 1971, the United Nations (UN) has actively monitored a number of Least Developed Countries (LDCs), or countries having structural frailties that make them especially susceptible to economic downturns, natural disasters, human conflicts, contagious diseases, and other existential threats. As a set, LDCs represent the poorest of the world’s poor, with more than 75% of their people living in poverty and bearing all the deprivation and other cruelties that poverty inflicts. While countries worldwide face challenges, a combination of three factors formally defines LDCs: (i) per capita gross national income (GNI), composed of the gross national product adjusted for the value of investment needed to maintain a constant level of production, measuring prosperity; (ii) a human assessment index (HAI), composed of health and education indicators measuring human capital; and (iii) an economic vulnerability index (EVI), composed of exposure and shock indicators, measuring economic risk. The current list of LDCs has 46 countries—with a combined population of about 12% of the world’s 7.8 billion—33 of which are located in Sub-Saharan Africa.

This concentration of poverty is so entrenched that it is understood as common knowledge. Less understood, is the geography of the toll that Sub-Saharan poverty takes on the people caught up in it—and, even less, how this geography has shifted relative to the massive changes in settlement that have reshaped Africa over the past few decades. (Examples of recent progress on this front include Jean et al. 2016, Xie et al. 2016, and Osgood-Zimmerman et al. 2018). As shown in Table 1, which lists data from the last 20 years summarizing the world at large, the 46 LDCs, and the whole of Sub-Saharan Africa, the rate of urbanization across these groups registered annual averages of 2.15%, 4.08%, and 4.12%, respectively. A closer look is provided in Table 2, which ranks the top 20 countries in the world by their urbanization rates in 2000, 2005, 2010, 2015, and 2019. At the beginning of the timeframe, countries located in Sub-Saharan Africa accounted for 11 of the top 20—by the end, they accounted for 17 of the top 20. In all cases shown on the table, the annual rate of urbanization exceeds 4.00%, a pace that yields a doubling in under two decades. Though Africa is the least urbanized of the settled continents, it is experiencing the greatest urban growth of all—mostly in its Sub-Saharan countries, where 15.75% of the region’s 1.1 billion people now live in agglomerations of a million or more (World Bank and World Development Indicators 2020).

The rapid transformation of Africa raises a fundamental question, which this paper begins to investigate: has urbanization there been accompanied by improvements in personal wellbeing? While economists, geographers, regional scientists, and others have good reason to think that that urbanization, a process having both

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1 For details, see: https://www.un.org/ohrlls/content/ldc-category.
Urbanization and child growth failure in Sub-Saharan Africa: spatial and temporal dimensions, makes people in the developing world better off, evidence remains sparse (Glaeser 2013; Young 2012; Glaeser and Ghani 2015; Bryan et al. 2020; OECD 2020). This paper addresses the gap by examining the relationship between urbanization and a key dimension of wellbeing across Sub-Saharan Africa: child growth failure, including (i) stunting; (ii) wasting; and (iii) underweight (Osgood-Zimmerman et al. 2018). Child growth failure is a fundamental indicator of wellbeing because, globally, about 45% of deaths among children under the age of five are associated with malnutrition and most of this death occurs in the LDCs of Africa and Asia (WHO 2021).

Like all projects focused on Sub-Saharan Africa, this one faces a tall barrier: namely, that quality data on urbanization and people there is extremely limited, a problem compounded by the fact that what data does exist comes from a variety of sources and was never meant to work together. A main contribution, therefore, is to reconcile an array of data—collected for different purposes, across different spatial scales, and over different timeframes—in a manner that enables some insight into the question set out above. Specifically, the paper combines remotely sensed data on urbanization, collected at continuous time intervals, with microdata on the health of people, collected at discrete time intervals, in a way that enables exploration of the relationship between the two. This reconciliation yields a rich database, covering all of Sub-Saharan Africa, that is used to estimate a series of econometric models.

| Table 1 | Annual rate of urbanization, 2000–2019 |
|---------|-------------------------------------|
| Year    | World  | LDCs   | SSA    |
| 2000    | 2.16%  | 3.91%  | 3.84%  |
| 2001    | 2.27%  | 4.13%  | 4.05%  |
| 2002    | 2.35%  | 4.23%  | 4.07%  |
| 2003    | 2.33%  | 4.25%  | 4.08%  |
| 2004    | 2.32%  | 4.20%  | 4.09%  |
| 2005    | 2.31%  | 4.17%  | 4.14%  |
| 2006    | 2.28%  | 4.07%  | 4.13%  |
| 2007    | 2.24%  | 3.84%  | 4.00%  |
| 2008    | 2.26%  | 4.13%  | 4.26%  |
| 2009    | 2.22%  | 4.13%  | 4.27%  |
| 2010    | 2.19%  | 4.14%  | 4.27%  |
| 2011    | 2.07%  | 4.15%  | 4.26%  |
| 2012    | 2.06%  | 4.09%  | 4.21%  |
| 2013    | 2.05%  | 4.08%  | 4.18%  |
| 2014    | 2.04%  | 4.07%  | 4.17%  |
| 2015    | 2.03%  | 4.05%  | 4.14%  |
| 2016    | 2.02%  | 4.03%  | 4.12%  |
| 2017    | 1.98%  | 4.02%  | 4.09%  |
| 2018    | 1.93%  | 4.00%  | 4.06%  |
| 2019    | 1.89%  | 3.98%  | 4.02%  |
| Averages| 2.15%  | 4.08%  | 4.12%  |

Source: World Bank, World Development Indicators
| Rank | 2000: 11/20 | 2005: 11/20 | 2010: 13/20 | 2015: 14/20 | 2019: 17/20 |
|------|-------------|-------------|-------------|-------------|-------------|
| 1    | Rwanda 11.55% | Qatar 14.18% | Qatar 11.65% | Oman 7.28% | Uganda 5.99% |
| 2    | Guinea 7.72% | UAE 12.50% | UAE 8.10% | Uganda 6.05% | Burundi 5.66% |
| 3    | Burkina Faso 6.72% | Guinea 7.45% | Somalia 7.07% | Burundi 5.69% | Tanzania 5.07% |
| 4    | TCI 6.62% | Bahrain 6.93% | Guinea 6.99% | Maldives 5.58% | Burkina Faso 4.94% |
| 5    | Bhutan 6.41% | Eritrea 6.91% | Jordan 6.56% | Tanzania 5.28% | Mali 4.82% |
| 6    | Laos 6.26% | Burkina Faso 6.65% | Oman 6.30% | Burkina Faso 5.13% | Ethiopia 4.78% |
| 7    | Liberia 6.14% | Maldives 6.45% | Kuwait 5.88% | Nauru 5.11% | Bahrain 4.59% |
| 8    | UAE 6.04% | TCI 6.03% | Uganda 5.83% | Ethiopia 4.99% | Congo 4.50% |
| 9    | Nepal 5.93% | Uganda 5.88% | Burundi 5.79% | Mali 4.94% | Solomon Is 4.49% |
| 10   | Uganda 5.79% | Burundi 5.77% | Mali 5.40% | Guinea 4.80% | Madagascar 4.44% |
| 11   | Eritrea 5.69% | Angola 5.65% | Tanzania 5.34% | Solomon Is 4.79% | Mozambique 4.40% |
| 12   | Angola 5.68% | Mali 5.63% | Burkina Faso 5.29% | Mauritania 4.64% | Niger 4.35% |
| 13   | Mali 5.35% | Tanzania 5.36% | Ethiopia 5.17% | Congo 4.62% | Mauritania 4.29% |
| 14   | S. Sudan 5.16% | Bhutan 5.26% | Angola 4.93% | Madagascar 4.58% | Angola 4.25% |
| 15   | Kiribati 5.06% | Somalia 5.25% | Mauritania 4.88% | Angola 4.57% | Guinea 4.20% |
| 16   | Gambia 5.04% | South Sudan 5.14% | S. Sudan 4.82% | Nigeria 4.45% | Nigeria 4.17% |
| 17   | Yemen 4.82% | Laos 5.10% | Madagascar 4.81% | Lebanon 4.41% | Zambia 4.15% |
| 18   | Kuwait 4.82% | Madagascar 5.07% | Solomon Is 4.75% | Mozambique 4.36% | Somalia 4.14% |
| 19   | Somalia 4.77% | Mauritania 4.97% | Nigeria 4.74% | Yemen 4.35% | Oman 4.03% |
| 20   | Solomon Is 4.75% | Solomon Is 4.83% | Bahrain 4.66% | Zambia 4.33% | Malawi 4.03% |

Source: World Bank, World Development Indicators; data on Eritrea not available after 2010.
including spatial autoregressive specifications, that systematically connect the large-scale process of urbanization to the small-scale experience of child health outcomes. By estimating models at multiple spatial scales, the analysis is able to evaluate both the compatibility of the data involved and the stability of the relationships it uncovers. Overall, the results suggest that the wave of urbanization breaking across Sub-Saharan Africa is likely to the benefit of its people—but clearly indicate the need for further geographical research.

2 Theory and stylized facts

The first organizing idea of this work is that urbanization makes people better off, so much so that it matters to economic growth at the country level. This idea is converted into a stylized fact by formally testing it via a model of convergence in per capita gross domestic product (GDP) within a panel of countries from all around the world. The results are presented in Table 9, in the appendix; further discussion of the model is beyond the scope of this paper, but details are available from the authors upon request. The model contains two variables on urbanization—the percent of total population living in agglomerations of greater than one million and urban population growth—both of which positively influence economic growth. The second organizing idea of this work is that urbanization rearranges not only people but, also, the conditions impacting them—meaning that the deprivations of poverty move along with people and may be mediated, for better or for worse, by new locational circumstances. Moreover, urbanization follows the arrow of time so the urbanization happening throughout Sub-Saharan Africa is reconfiguring the population in a way that is more-or-less permanent, or at least not likely to reverse. This permanence—or irreversibility, regardless of the scale from which it is viewed (Hopkins 2001; Lai 2021)—brings further weight to the question of personal well-being that motivates this work.

Putting these two ideas together, the lens of time geography is helpful because it exposes what Hägerstrand (1989) called the bare skeleton that connects the large-scale outcomes of urbanization to the small-scale experiences of individuals. In a nutshell, time geography is concerned with the movement of people through space under constraints tied to location that wax and wane with the passage of time.

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2 The idiom stylized fact is a term of art widely used in economics to denote empirical regularities that are generally taken to be true, though they may not hold up in all instances. It was coined by Kaldor (1961) in an early essay on economic growth.

3 See Barro (1991, 1997) Barro and Sala-i-Martin (1992, 2005) and Sala-i-Martin (1997), plus Durlauf et al. (2009a, 2009b).

4 These benefits must be qualified by acknowledging that they do not occur in a vacuum—in the absence of industrialization, urbanization may be more detrimental than helpful to economic growth (Duranton 2014; Glaeser and Ghani 2015; Glaeser and Xiong 2017; Henderson and Turner 2020).

5 Hägerstrand was a geographer whose bare skeleton is analogous to what the economist Kaldor (1961) labeled stylized facts—both are about the starting point for building theory used to predict behavior and/or outcomes within human systems.
It is common in neoclassical economics to assume that relocation decisions are rational and based on complete information; time geography holds that, these assumptions notwithstanding, the wellbeing of individuals is inextricably tied to place, plus the circumstances of the moment. What’s past is past, no matter its bearing on the future, and constraints on the human condition—so-called *capability, coupling, and authority constraints*—tighten and relax accordingly. This lens is useful for understanding the behavioral relationships of geographic systems across multiple spatial scales because it explicitly connects the spatial behavior of people to their environment (Golledge and Stimson 1997; Miller 2017). Not only that, the constraints-oriented approach of time geography squares neatly with Sen’s (1985, 1999) capability approach to development economics, which has been translated directly into standards for urban planning in developing countries throughout the world (Frediani and Hansen 2015).

Urbanization presents in time geography because of how it restructures capability constraints and coupling constraints: in terms of the former, people are better able to care for themselves and their dependents; in terms of the latter, people are brought into contact with organizations, including markets, medical facilities, social networks, and more, that may enhance their wellbeing. This is explained by the fact that cities serve as both centers of production, offering increased opportunity, and centers of consumption, offering increased access to goods and services—meaning that moves to them hold the possibility of welfare gains in both dimensions. The idea of the *consumer city* was popularized in an eponymous paper by Glaeser et al. (2001) but was first used by Weber (1921) in a taxonomy that distinguished between consumer and producer cities by economic base (Batty 2018); decades ago, Harris and Ullman (1945) and Ullman (1962) explored similar themes from the perspective of urban geography. Even earlier, location theorists identified cities as being, above all else, market centers that serve as focal points for the trade of agricultural commodities and other products—among them rare and specialized services like medical care (von Thünen 1826; Christaller 1933; Lösch 1938). The present analysis works from the premise that cities are beneficial to people, even as it acknowledges that there is much to learn about cities in LDCs, in general, and those in Sub-Saharan Africa, in particular (Ashraf et al. 2016; Glaeser and Ghani 2015; Gollin et al. 2017; Glaeser 2014, 2020; Bryan et al. 2020). For example, sanitation is a critical public good without which urbanization can be dangerous (Glaeser 2013).

The discussion now turns to stylized facts, which are two: *urbanization promotes economic growth*; and, *as Sub-Saharan Africa has urbanized over the past decades, child growth failure has moderated*. As discussed, the first of these is established by helpful pair of hypothesis tests in a macroeconomic model of convergence that is contained in the appendix. The second of these is documented in Table 3, which reports on urbanization and child growth failure by country. By both measures—impervious surface area and light intensity—urbanization has increased regionwide (Cameroon being the exception) between the two years of observation, $t$– and $t$. At the same time, in most cases, the measures of child growth failure, expressed as

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6 Authority constraints may also be relevant, but they are not addressed here.
### Table 3  Urbanization and child health metrics in Sub-Saharan Africa

| Urbanization outcomes | Child growth failure: z-scores |
|-----------------------|-------------------------------|
| Impervious area | Light intensity |
| $t$ | $t$ | $t$ | $t$ | $t$ | $t$ | $t$ | $t$ |
| Benin | 373,799 | 1,272,096 | 47 | 88 | -1.405 | -1.445 | -1.247 | -1.065 | -0.654 | -0.312 |
| Burkina Faso | 1,600,501 | 2,982,240 | 181 | 227 | -1.133 | -1.160 | -1.269 | -1.146 | -0.909 | -0.642 |
| Burundi | 564,115 | 669,817 | 38 | 20 | -2.079 | -2.058 | -1.344 | -1.383 | -0.202 | -0.276 |
| Cameroon | 1,224,621 | 1,501,161 | 88 | 113 | -1.334 | -1.041 | -0.603 | -0.297 | 0.254 | 0.435 |
| Congo | 1,574,588 | 1,692,766 | 89 | 117 | -1.603 | -1.531 | -1.018 | -0.987 | -0.110 | -0.142 |
| Cote d’Ivoire | 740,631 | 3,086,548 | 121 | 249 | -1.268 | -1.082 | -1.007 | -0.756 | -0.422 | -0.192 |
| Ethiopia | 493,922 | 640,031 | 47 | 68 | -2.038 | -1.343 | -1.674 | -1.069 | -0.686 | -0.431 |
| Ghana | 821,310 | 2,750,517 | 112 | 214 | -1.285 | -0.910 | -1.134 | -0.662 | -0.571 | -0.208 |
| Guinea | 760,849 | 1,839,048 | 77 | 128 | -1.233 | -1.076 | -0.920 | -0.746 | -0.297 | -0.196 |
| Kenya | 610,060 | 777,365 | 111 | 131 | -1.287 | -1.081 | -0.774 | -0.580 | -0.067 | 0.037 |
| Lesotho | 372,606 | 436,327 | 41 | 55 | -1.692 | -1.543 | -0.857 | -0.626 | 0.158 | 0.34 |
| Liberia | 1,538,970 | 1,601,922 | 43 | 64 | -1.439 | -1.176 | -0.941 | -0.754 | -0.143 | -0.135 |
| Madagascar | 650,738 | 814,288 | 76 | 83 | -2.014 | -1.713 | -1.479 | -0.001 | -0.432 | 0 |
| Malawi | 417,566 | 642,274 | 52 | 67 | -1.958 | -1.508 | -1.023 | -0.791 | 0.216 | 0.11 |
| Mali | 466,830 | 1,464,276 | 65 | 159 | -1.330 | -1.024 | -1.627 | -0.955 | -1.206 | -0.524 |
| Namibia | 249,543 | 388,387 | 142 | 172 | -1.079 | -0.85 | -0.908 | -0.578 | -0.418 | -0.125 |
| Nigeria | 1,439,577 | 4,546,656 | 338 | 356 | -1.811 | -1.405 | -1.346 | -1.031 | -0.371 | -0.294 |
| Senegal | 2,666,388 | 3,118,815 | 170 | 360 | -1.479 | -0.851 | -1.100 | -0.788 | -0.331 | -0.456 |
| Sierra Leone | 826,724 | 1,231,732 | 32 | 48 | -1.208 | -1.237 | -0.663 | -0.747 | -0.030 | -0.030 |
| Tanzania | 870,846 | 1,184,234 | 88 | 91 | -1.835 | -1.330 | -1.143 | -0.796 | -0.100 | -0.075 |
| Togo | 405,375 | 1,543,347 | 67 | 97 | -1.212 | -1.259 | -1.152 | -0.948 | -0.636 | -0.326 |
| Uganda | 493,322 | 631,679 | 39 | 62 | -1.692 | -1.312 | -0.868 | -0.643 | 0.144 | 0.138 |
| Zambia | 939,278 | 1,244,513 | 127 | 222 | -1.645 | -1.458 | -0.797 | -0.743 | 0.189 | 0.129 |
The lower (i.e.: more negative, in most cases) the $z$-score, the worse the child growth failure; m = meters, DN=Digital Number. Times $t$– and $t$ are: Benin = 1996, 2018; Burkina Faso = 1993, 2010; Burundi = 2010, 2017; Cameroon = 2004, 2019; Congo = 2007, 2014; Cote d’Ivoire = 1994, 2010; Ethiopia = 2000, 2016; Ghana = 1993, 2014; Guinea = 1999, 2018; Kenya = 2003, 2014; Lesotho = 2004, 2014; Liberia = 2007, 2013; Madagascar = 1997, 2009; Malawi = 2000, 2016; Mali = 1996, 2018; Namibia = 2000, 2013; Nigeria = 1990, 2018; Senegal = 1993, 2019; Sierra Leone = 2008, 2019; Tanzania = 1999, 2016; Togo = 1998, 2014; Uganda = 2001, 2016; Zambia = 2007, 2019; and Zimbabwe = 1999, 2015

| Urbanization outcomes | Child growth failure: $z$-scores |
|-----------------------|---------------------------------|
| Impervious area       | Stunting | Wasting | Underweight |
| Light intensity       | $t$–      | $t$     | $t$–       | $t$     | $t$–   | $t$     |
|                       | $t$       |         | $t$–       | $t$     | $t$–   | $t$     |
| Zimbabwe              | 593,554   | 885,692 | 135        | 113     | −1.155 | −1.216  |
|                       |           |         |            |         | −0.577 | −0.544  | 0.100   | 0.206   |
z-scores, have also registered improvements, moving closer to the mean (zero) from their negative starting levels. Note here that, as footnoted in the table, time $t$ and time $t_d$ differ by country, due to when the rounds of survey data on child growth failure were conducted; impervious surface area and light intensity are collected continuously from space and are keyed in time to the survey data. It is readily apparent from the table that, as urbanization has increased, child growth failure has moderated—but appearances are not evidence, so the question remains: has urbanization in Sub-Saharan Africa been accompanied by improvements in personal wellbeing?

Words convey the cruelties of poverty far better than $z$-scores. A stunted child has a height-for-age $z$-score below minus two standard deviations from the median of the reference population. Stunted children, who are too short for their age, often suffer from cognitive and physical impairment, leading to poor educational performance and productivity, plus higher risk of various forms of mortality and morbidity. A wasted child has a weight-for-height $z$-score that is below minus two standard deviations from the median of the reference population. While wasting is less prevalent than stunting, it is more severe in the sense that wasted children are more likely to die than stunted children (Black et al. 2008). Wasted children, who are too thin for their height, suffer acutely due to recent and drastic weight loss. Wasting results from a sudden reduction in food intake and/or frequent or prolonged illness in the absence of medical care. Last, an underweight child has a weight-for-age $z$-score that is below minus two standard deviations from the median of the reference population. Underweight children, who are too light for their age, may also be wasted and/or stunted (Dop 2016; Goudet et al. 2015). Worldwide, about 20.3% and 6.9% of children under the age of five years old were, respectively, stunted and wasted in 2019 (UNICEF, WHO, World Bank 2020). The upcoming sections on database development and econometric analysis provide a closer look.

3 Data and geospatial methodology

The data at the core of this analysis is of two different forms: (i) data on urbanization collected at continuous time intervals via satellites; and (ii) microdata on the health of children collected at discrete time intervals via USAID’s Demographic and Health Surveys (DHS) and harmonized by the Advancing Research on Nutrition and Agriculture (AReNA) project (IFPRI 2020). The following paragraphs describe the data and explain how it has been reconciled for the purpose at hand. The centerpiece of the discussion is a spatial sampling strategy that enables the DHS survey data, collected on different individuals across different timeframes, to be used in an econometric analysis to examine change over time.

Getting consistent statistical data on urbanization, measured via developed land, across multiple countries over long intervals anywhere in the world is difficult. The DHS data utilized here does contain urban/rural information, but the definition of an urban location is country-specific and differs across countries. For example: some countries define urban areas based on population; others define urban areas based on administrative boundaries; and still others define urban areas based on combination of the two (United Nations 2019). For that reason, this analysis turns to two remotely
sensed databases, briefly introduced in Table 3, that cover continent-spanning areas longitudinally.

The first of these is a land cover measure of impermeable surface area, a key indicator of urban land use, obtained from the *Global Artificial Impervious Areas (GAIA)* 1985–2018 database created by Gong et al. (2020). The GAIA database is derived from Landsat imagery at a 30 m × 30 m resolution and is capable of capturing even subtle changes over its 33-year-long timeframe. The accuracy of GAIA at the global scale is 90%, based on tests done for the years 1985, 1990, 1995, 2000, 2005, 2010, and 2015. The second of these is a luminosity measure of nightlights—a key indicator of human settlements (Doll et al. 2006; Li and Zhou 2017; Pinkovskyi 2017; Düben and Krause 2021) and, as well, economic activity (Henderson and Storygard (2012)—developed by Li et al. (2020). This harmonized global nighttime light database consists of luminosity data from the *Defense Meteorological Satellite Program / Operational Linescan System*, from 1992–2013, and the *Visible Infrared Imaging Radiometer Suite*, from 2012–2018. It has been radiometrically corrected to remove light from the aurora borealis, wildfires, and other noise and it enables consistent monitoring of nightlights at a 1 km × 1 km resolution over its 27-year timeframe. Unlike the GAIA data, there is no measure of accuracy for the luminosity data, because Li et al. (2020) do not have a comprehensive means of ground-truthing.

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**Fig. 1** Step-by-step geoprocessing

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The two remotely sensed databases complement each other and, together, form a portrait of urbanization across Sub-Saharan Africa. The DHS data covers Sub-Saharan Africa over a 30-year timeframe, but it presents challenges when compiling it for a cross-sectional, longitudinal analysis. In particular, the data is collected over multiple rounds at different times in different countries—see time $t_1$ and time $t_2$ as identified at the bottom of Table 3—with each round surveying different households. So, while the DHS data is exceptionally rich, the challenge is to use it longitudinally because it is not a panel survey. Given the
structure of the DHS, the goal here is to turn its information into an approximation of a panel survey through a spatial sampling strategy and combine it with the data on landcover and nighttime light. This process involves four steps, which are illustrated in Fig. 1 using the case of Uganda:

- In the first step, illustrated in Fig. 1a, child-level $z$-scores were assigned to their geocoded households; points were offset randomly in the DHS (by up to two kilometers in urban areas and by up to five kilometers in rural areas) to preserve

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Fig. 3 Spatial sampling in Namibia
the privacy of respondents. The points in the map are colored by the rounds in which the DHS was conducted and, as noted Table 3, in the case of Uganda, time $t = 2001$ and time $t = 2016$. The silhouettes, used to characterize child growth failure, follow those commonly used by UNICEF and are reprinted from Osgood-Zimmerman et al. (2018).

- In the second step, illustrated in Fig. 1b, the three $z$-scores were interpolated from the locations where they were recorded into a $1 \text{ km} \times 1 \text{ km}$ grid using an empirical Bayesian kriging (EBK) approach developed by Krivoruchko (2012).
and Gribov and Krivoruchko (2020). Kriging is a theoretically sound approach that yields errors as part of its output (Longley et al. 2015) and the resulting trend surfaces seamlessly cover all of Sub-Saharan Africa. In each country, the earliest survey round is used to construct the base-line trend surface, and the latest round is used to construct the end-line trend surface. As shown below, it does not matter to the analysis that the earliest and latest rounds are in different years across different countries, because first-year effects are controlled for in...
the econometric models. The EBK approach was selected for this step because it integrates Bayesian probabilities that account for the uncertainties in choosing parameters to build variograms. It automatically subsets data and builds localized semi-variograms through iterative simulations; in this way, it yields more accurate estimates of standard errors than other forms of kriging.7

• In the third step, illustrated in Fig. 1c, a 10 km × 10 km hexagonal grid, composed of hexagons, denoted \( \eta \), was created and placed over the trend surfaces of the three measures of child growth failure. The 10-km size was selected because it best captures the DHS sample points and reconciles well with the 1 km × 1 km grids of the urbanization and child growth failure variables. Zone-level mean values were then calculated for the hexagons and assigned to first-round households depending on their location within the grid. In this way, the trend surfaces, which cover the entirety of all surveyed countries, act as proxies that enable measurement between time \( t^- \) and time \( t \). A hexagonal grid was adopted instead of a square grid because hexagons have more locational precision (Birch et al. 2007). This is what enables change over time, measured as the difference between the average value within the hexagons at time \( t \) and the average value at time \( t^- \), to be regressed on child-level data from time \( t^- \).

• In the fourth step, illustrated in Fig. 1d, the urbanization indicators were calculated by creating buffer zones around households and summing up the values within those buffer zones using Google Earth Engine. The buffer radius is two kilometers for households in urban clusters and five kilometers in rural clusters, corresponding to the GPS offsets used by DHS to protect the privacy of respondents.

The steps just outlined form a straightforward—and easily replicable—spatial sampling approach that enables data on different individuals collected across different timeframes to be used to approximate change over time. Although admittedly subject to a degree of imprecision, introduced by privacy-preserving offsets in geocoding and the use of the two survey rounds, it yields a spatially and temporally reconciled database (from sources never meant to work together) covering all of Sub-Saharan Africa.

Maps speak volumes to spatial scientists—economists, geographers, and regional scientists alike—so the analytical results of the process just described are summarized in Figs. 2, 3, 4, 5, which display Ethiopia, Namibia, Nigeria, and Zambia, respectively. In each figure: (a), (b), and (c) cover stunting at time \( t^- \), time \( t \), and \( t \) minus \( t^- \); (d), (e), and (f) cover wasting at time \( t^- \), time \( t \), and \( t \) minus \( t^- \); and (g), (h), and (i) cover underweight at time \( t^- \), time \( t \), and \( t \) minus \( t^- \). Note that the color ramps flip in the last map in each row—i.e.: the column containing (c), (f), and (i)—because those maps register change in, not levels of, child growth failure. In all

7 In fact, EBK was chosen after comparing it to local polynomial interpolation (LPI) and universal kriging (UK) approaches on the basis of it having smaller values of the root mean square error and the average standard error, which signal better model performance. Test statistics and variograms are available from the authors upon request.
cases, red represents worse, or worsening, conditions, as measured by the $z$-scores and changes in the $z$-scores. To be clear, the difference is the average value within a given hexagon, $\eta$, at time $t$ minus the average value at time $t–$ (that is: $\eta_t – \eta_{t–}$) and these values are used as dependent variables in the child-level regressions below; the independent variables include urbanization, as calculated in the last step of the geoprocessing procedure, plus micro data captured by the initial DHS round. The strength of this methodology lies in the fact that it is straightforward: it relies on tried and true tools of cartography, quantitative geography, and geographic information science (Fotheringham et al. 2000; Longley et al. 2015); is easily replicable; and computationally inexpensive. The result is a database that covers all of Sub-Saharan Africa and includes over 105,000 observations at the child level.

## 4 Econometric analysis

As stated in the introduction, the models estimated in this section systematically connect the large-scale process of urbanization to the small-scale experience of child health outcomes. They do this by progressively narrowing in terms of spatial scale and expanding in terms of complexity. At this stage, the analysis makes no claim to precision, but it does, broadly, establish the relationship it set out to explore.

The DHS is conducted in multiple rounds across Sub-Saharan Africa, meaning that the county- and region-level models can be estimated as unbalanced panels, leveraging all rounds of the survey data to expand the sample size. Additional control variables at these levels come from the World Bank’s World Development Indicators (WDI) database. At the child level, the models account for the error introduced via the kriging process—maps of the EBK errors are available from the authors upon request—and spatial dependence is addressed via an autoregressive specification (see Anselin 1988). Across all scales, the dependent variables are the three forms of child growth failure: (i) stunting; (ii) wasting; and (iii) underweight. Each of these is initially measured in the form of $z$-scores, but they are operationalized somewhat differently at different spatial scales. Specifically, the dependent variables are expressed as prevalence in the country-level models; levels in the region-level models; and changes within 10 km $\times$ 10 km hexagons in the child-level models. Descriptive statistics for all variables engaged in the analysis are provided in Table 4 and variable descriptions are provided in Tables 10 and 11, in the appendix.

To start, the country- and region-level models take the general form of:

$$\zeta = (\zeta^s_i, \zeta^w_i, \zeta^u_i) = f(u_i, x_i, \phi),$$

where the $\zetas$ $[\zeta^s_i, \zeta^w_i, \zeta^u_i] \in \zeta$ represent values derived from the $z$-scores for stunting, wasting, and underweight in country/region $i$ at time $t$; $u_i$ represents the two urbanization variables; $x_i$ represents a vector of explanatory variables measuring economic conditions; and $\phi$ represents a vector of locational (country- or region-level) fixed effects. In these models, child growth failure is a function of the

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8 See: https://datatopics.worldbank.org/world-development-indicators/.
### Table 4  Summary statistics

|                          | n   | Mean    | SD     | Min    | Max    |
|--------------------------|-----|---------|--------|--------|--------|
| **Country-level data**   |     |         |        |        |        |
| Prevalence of stunting (% of children under 5) | 233 | 38.40   | 10.20  | 15.50  | 66.9   |
| Prevalence of underweight (% of children under 5) | 233 | 20.70   | 8.00   | 5.90   | 46.9   |
| Prevalence of wasting (% of children under 5) | 233 | 8.20    | 4.20   | 1.30   | 24.4   |
| Sum of artificial impervious area (km²) | 233 | 685.00  | 1,608.00 | 0.00 | 10,470 |
| Sum of luminosity (DN) | 233 | 74,780.00 | 200,149.00 | 0.00 | 1,382,270 |
| GDP per capita (constant 2010 US$) | 233 | 1,165.00 | 1,460.00 | 164.00 | 10,170 |
| Women business and the law index score (scale 1–100) | 233 | 62.09  | 13.43  | 25.60  | 88.10  |
| **Child-level and region-level data** |     |         |        |        |        |
| Change in height-for-age z-score (HAZ) | 105,547 | 0.29 | 0.37 | -1.65 | 2.04 |
| Change in weight-for-age z-score (WAZ) | 105,547 | 0.29 | 0.36 | -1.25 | 1.97 |
| Change in weight-for-height z-score (WHZ) | 105,547 | 0.11 | 0.32 | -1.27 | 1.77 |
| HAZ in t– | 105,547 | -1.57 | 0.46 | -3.40 | 0.14 |
| WAZ in t– | 105,547 | -1.10 | 0.42 | -2.35 | 0.73 |
| WHZ in t– | 105,547 | -0.26 | 0.45 | -1.96 | 1.44 |
| Standard error for HAZ in t– | 105,547 | 0.31 | 0.11 | 0.14 | 0.90 |
| Standard error for WAZ in t– | 105,547 | 0.25 | 0.08 | 0.11 | 0.68 |
| Standard error for WHZ in t– | 105,547 | 0.23 | 0.10 | 0.10 | 0.83 |
| Standard error for HAZ in t | 105,547 | 0.29 | 0.11 | 0.11 | 1.10 |
| Standard error for WAZ in t | 105,547 | 0.21 | 0.09 | 0.00 | 0.64 |
| Standard error for WHZ in t | 105,547 | 0.20 | 0.09 | 0.00 | 0.63 |
| Change of average luminosity (DN/km²) | 105,547 | 0.02 | 0.06 | -0.34 | 0.47 |
| Change of impervious area percentage point (%) | 105,547 | 4.14 | 12.63 | 0.00 | 95.73 |
| Year, t– | 105,547 | 2000.00 | 5.00 | 1990.00 | 2010.00 |
| **Years between t– and t** |       |         |        |        |        |
| 105,547 | 16.00 | 6.00 | 6.00 | 28.00 |
| **Women’s education in t– (years)** |       |         |        |        |        |
| 105,547 | 3.00 | 4.00 | 0.00 | 22.00 |
| **Middle class households** |       |         |        |        |        |
| 105,547 | 0.35 | 0.48 | 0.00 | 1.00 |
| **Top class households** |       |         |        |        |        |
| 105,547 | 0.24 | 0.42 | 0.00 | 1.00 |
urbanization hypothesized to impact it and basic economic controls obtained from the WDI database. Equation (1) is implemented as:

\[ \zeta = \beta_0 + \beta_1 \cdot u_{it} + \beta_2 \cdot x_{it} + \phi + \epsilon_{it}. \]  

Here, \( i \) indexes the country (\( n = 33 \)) or region (\( n = 257 \)), as the case may be; the vector of dependent variables, \( \zeta \), is used to indicate that the specifications are identical across \( \zeta_{it}^u, \zeta_{it}^w, \), and \( \zeta_{it}^u \); and the index \( t \) indicates that all variables are measured contemporaneously. The \( \beta \)'s are estimable parameters expressed in single and vector (bold) form and \( \epsilon_{it} \sim N (0, \sigma^2) \) is the stochastic error term. This basic set-up extends to the individual level:

\[ \Delta \zeta_{it}^u = \beta_0 + \beta_1 \cdot u_{it-1} + \beta_2 \cdot x_{it-1} + \beta_3 \cdot \kappa_i + \beta_4 \cdot \tau_{it-1} + \phi + \epsilon_i. \]

In Eq. (3), \( \Delta \zeta_{it}^u \) is change in child growth failure, as captured by differencing mean z-scores in hexagons \( \eta \) at time \( t \) and time \( t-1 \), where the years, \( t \) and \( t-1 \), are as recorded in Table 3; \( \eta \) indexes unique hexagons (\( n = 4,626 \)) in the sampling net and \( i \) (\( n = 105,467 \)) indexes individual children. (Although a 10 km \( \times \) 10 km sampling net may seem large, it is not given that the net covers all of Sub-Saharan Africa: on average, each hexagon captures 21 children.) At this level, the vector \( x_{it-1} \) contains household conditions related to women’s education and standing, plus household assets. As additional controls, given the exploratory nature of the analysis, the equation contains: \( \kappa_i \), a location-specific measurement error from the EBK procedure at both the beginning and end of the time period, and, \( \tau_{it-1} \), a set of time controls that captures the base year and number of years elapsed between \( t \) and \( t-1 \).

Finally, spatial autoregressive specifications of (3) are implemented by introducing a spatial lag of the dependent variables. The spatial lags were created using an \( n \times n \) (\( 105,467 \times 105,467 \)) row-standardized spatial weights matrix (\( W_{ij}, \forall i \neq j \)) where neighboring observations \( i \) and \( j \) are defined as children living in households located within 15 km of each other. The lag is then calculated by multiplying the three dependent variables by this weights matrix. The spatial lag complicates estimation because it is endogenous: surrounding values depend on each other, so the model can no longer be properly estimated via ordinary least squares, or OLS. Among the many possible interventions available to correct for the problem is Kelejian and Prucha’s (1998) spatial two-stage least squares (S2SLS) strategy, which provides a solution that yields unbiased and efficient estimates, even if spatial error dependence persists (Das et al. 2003). This is a mildly intervention that relies on a set of instrumental variables composed of all explanatory variables plus spatial lags of those same variables. It is a least squares estimator plenty appropriate for this stage of an analysis, when the focus is on establishing broad relationships. The resulting model is as follows:

\[ \Delta \zeta_{it}^u = \beta_0 + \lambda \cdot W_{ij} \cdot \Delta \zeta_{it}^u + \beta_1 \cdot u_{it-1} + \beta_2 \cdot x_{it-1} + \beta_3 \cdot \kappa_i + \beta_4 \cdot \tau_{it-1} + \phi + \epsilon_i, \]

where \( W_{ij} \cdot \Delta \zeta_{it}^u \) is the endogenous spatial lag and \( \lambda \) is the autoregressive parameter measuring spatial dependence.

The OLS estimation results are reported in Tables 5, 6, 7 for the country-, region-, and child-level models, respectively, and the (child-level) S2SLS estimates.
are reported in Table 8; all fixed effects have been suppressed in order to conserve space, but are available upon request. To be clear, at in child-level models, the dependent variable is the difference in the average value of hexagon \( \eta \) between time \( t \) and time \( t-1 \) where the child is located, so it is a proxy for individual change—taking on one of 4,626 possible values—but the explanatory variables are all child specific and vary accordingly across the 105,467 observations. These models progressively increase the set of control variables listed above to check the sensitivity of the urbanization parameter estimates. For each nutrition indicator, three model specifications are estimated in the country and region-level analyses and four model specifications are estimated in the child-level analysis, for both aspatial (OLS) and spatial (S2SLS) cases. For ease of reference, the equations are numbered, including all specifications, from (1) to (42). The next paragraphs summarize the estimation results, which, together, validate the data processing methodology detailed above and form a holistic picture of the relationship between urbanization and personal wellbeing in Sub-Saharan Africa.

The summary—which focuses on the urbanization variables and only touches on the controls—begins with the sets of country and region-level estimates. The country-level models, reported in Table 5, which take the prevalence of stunting, wasting, and underweight (measured as national percentages) as their dependent variables, show consistent evidence of a negative relationship between urbanization and child growth failure. Importantly, these models are panels, so they account for the evolution of urbanization, measured via impervious surface area and luminosity, over time. The exception is luminosity in the three wasting models: (4), (5), and (6). These results are consistent, as registered by the estimated parameters, \( \hat{\beta} \), and robust, as shown by the \( t \)-statistics, across the various specifications, which introduce the two economic indicators one-by-one. As expected, higher GDP per capita and a business climate that is friendly to women also reduce the prevalence of child growth failure. Next, the region-level models, reported in Table 6, which take of levels of stunting, wasting, and underweight (measured as regional mean values of \( z \)-scores) as their dependent variables, show additional evidence that, overall, urbanization reduces child growth failure. These models are also panels, so they, too, account for the evolution of urbanization. Note that the relationships here are positive, not negative, because negative \( z \)-scores indicate growth failure—the more negative the worse. The impervious surface area variable comes in insignificant in just one stunting equation, (12) when both economic indicators are introduced and, like the national-level models, luminosity does not register in the wasting equations, (13), (14), and (15), or in the final equation, (18). Also like the national models, the estimated influence of urbanization is consistent and holds across specifications. In models (11) and (12) women's education and the asset-based wealth index have a positive influence. These country and region-level models begin suggest that urbanization does matter to personal wellbeing.

Moving on, the child-level models, reported in Tables 7 and 8, which take change in child growth failure, captured by differencing mean \( z \)-scores in hexagons \( \eta \) at time \( t \) and time \( t-1 \), as their dependent variables, deliver direct evidence of a relationship between urbanization, \( u_{it-1} \), and child growth failure. Table 8 also shows consistent evidence of spatial dependence in the models, and should be considered the more accurate of the two sets. In these models, all of the explanatory variables are initial conditions—that is, measured at time \( t-1 \), as listed in the footnote of the table—and most are measured at the
Table 5 OLS estimates of country-level models

| Stunting equations | Wasting equations | Underweight equations |
|--------------------|------------------|---------------------|
|                    | (1)              | (2)                | (3)              | (4)           | (5)           | (6)           | (7)           | (8)           | (9)           |
| ln (Impervious area) | –5.664*** | –4.355*** | –2.383* | –3.973*** | –3.737*** | –2.941*** | –5.665*** | –4.869*** | –3.384*** |
|                    | (–4.926) | (–3.793) | (–1.913) | (–6.431) | (–5.834) | (–4.166) | (–6.971) | (–5.933) | (–3.813) |
| ln (Luminosity)    | –3.550*** | –2.978*** | –2.438*** | –0.482 | –0.379 | –0.161 | –2.353*** | –2.005*** | –1.598*** |
|                    | (–5.581) | (–4.756) | (–3.888) | (–1.410) | (–1.084) | (–0.453) | (–5.234) | (–4.479) | (–3.578) |
| Real GDP per capita | –0.006*** | –0.004*** | –0.001 | –0.001 | –0.001 | –0.003*** | –0.003** | –0.003** | –0.003** |
|                    | (–4.188) | (–3.241) | (–1.348) | (–0.663) | (–0.663) | (–3.561) | (–2.578) | (–2.578) |
| Women in business  | –0.159*** | –0.064** | –0.120*** | –0.159*** | –0.064** | –0.120*** | –0.159*** | –0.064** | –0.120*** |
|                    | (–3.553) | (–2.534) | (–3.553) | | (–2.534) | | | |
| Constant           | 103.398*** | 97.378*** | 89.872*** | 34.519*** | 33.437*** | 30.404*** | 74.189*** | 70.530*** | 64.876*** |
|                    | (17.604) | (16.723) | (14.879) | (10.941) | (10.291) | (8.886) | (17.875) | (16.946) | (15.081) |
| n                  | 233       | 233       | 233       | 233       | 233       | 233       | 233       | 233       | 233       |
| Adjusted $R^2$     | 0.278     | 0.333     | 0.371     | 0.155     | 0.159     | 0.181     | 0.364     | 0.400     | 0.437     |

All hypothesis tests are two-tailed: 99% ***; 95% **; 90% *; t-statistics are listed in parentheses under the coefficients; the dependent variables are stunting prevalence, wasting prevalence, and underweight prevalence, respectively. 
### Table 6  OLS estimates of region–level models

|               | Stunting equations | Wasting equations | Underweight equations |
|---------------|-------------------|------------------|----------------------|
|               | (10)              | (11)             | (12)                 | (13) | (14) | (15) | (16) | (17) | (18) |
| **ln (Impervious area)** | 0.102*** | 0.008 | −0.029 | 0.167*** | 0.175*** | 0.199*** | 0.183*** | 0.133*** | 0.132*** |
|               | (3.560)           | (0.275)          | (−0.835)            | (7.360) | (7.070) | (6.280) | (8.770) | (6.068) | (4.932) |
| **ln (Luminosity)** | 0.026*** | 0.020*** | 0.003 | −0.000 | 0.000 | 0.004 | 0.018*** | 0.014*** | 0.007 |
|               | (3.891)           | (3.176)          | (0.373)             | (−0.049) | (0.043) | (0.450) | (3.556) | (2.972) | (1.005) |
| Woman’s education | 0.126*** | 0.129*** | −0.010 | −0.014 | 0.067*** | 0.067*** | 0.067*** |
|               | (8.205)           | (6.314)          | (−0.782)            | (−0.754) | (5.787) | (4.218) |
| Wealth index   | 0.044*            |                  |                     | −0.000 |                  |                     | 0.025 |
|               | (1.941)           |                  |                     | (−0.015) |                  |                     | (1.369) |
| Constant       | −1.878***         | −2.119***        | −1.948***           | −0.693*** | −0.673*** | −0.746*** | −1.604*** | −1.731*** | −1.698*** |
|               | (−23.490)         | (−26.396)        | (−15.750)           | (−10.905) | (−9.865) | (−6.539) | (−27.440) | (−28.566) | (−17.633) |
| \( \hat{n} \)   | 673               | 673              | 491                 | 667       | 667       | 485       | 667       | 667       | 485       |
| \( R^2 \)       | 0.085             | 0.023            | 0.159               | 0.120     | 0.121     | 0.137     | 0.219     | 0.273     | 0.215     |

All hypothesis tests are two-tailed; 99% ***; 95% **; 90% *; \( t \)-statistics are listed in parentheses under the coefficients; the dependent variables are height-for-age \( z \)-score/stunting, weight-for-height \( z \)-score/wasting, and weight-for-age \( z \)-score/underweight, respectively.
|                | Stunting equations |                       | Wasting equations |                       | Underweight equations |                       |
|----------------|--------------------|-----------------------|-------------------|-----------------------|-----------------------|-----------------------|
|                | (19)               | (20)                  | (21)              | (22)                  | (23)                  | (24)                  | (25)              | (26)                  | (27)                  | (28)                  | (29)                  | (30)                  |
| Change of impervious area percentage point (%) | 0.003***            | 0.003***              | 0.003***          | 0.006***              | −0.000                | −0.001***             | −0.001***          | −0.001***             | 0.001***              | 0.000                  | 0.000                  | 0.002***              |
|                | (12.306)            | (11.251)              | (10.942)          | (20.056)              | (−0.159)             | (−3.130)              | (−3.977)           | (−3.159)              | (2.780)               | (0.904)               | (0.333)               | (10.684)             |
| Change of average luminosity (DN/km²) | 0.368***            | 0.376***              | 0.349***          | 0.29                  | 0.188***             | 0.170***             | 0.138***          | 0.242***              | 0.320***              | 0.337***              | 0.308***              | 0.198***             |
|                | (5.875)             | (6.050)               | (5.999)           | (0.451)              | (3.599)              | (3.392)              | (2.760)           | (5.200)              | (6.321)              | (6.816)               | (6.238)               | (3.864)             |
| Years between t− and t | 0.009***            | 0.009***              | 0.009***          | −0.007                | −0.002                | −0.000               | −0.001           | −0.018***             | −0.024***             | −0.023***             | −0.023***             | −0.126***            |
|                | (4.724)             | (5.139)               | (4.769)           | (−1.476)              | (−1.625)             | (−0.321)             | (−0.681)          | (−8.460)              | (−10.090)             | (−9.483)              | (−9.835)              | (−37.475)            |
| Year, t− | −0.004***  | −0.005***              | −0.006***          | −0.002                | 0.002                 | 0.003**              | 0.002           | −0.030***             | −0.033***             | −0.032***             | −0.033***             | −0.154***            |
|                | (−2.284)            | (−2.640)              | (−3.363)          | (−0.600)              | (1.447)              | (2.088)              | (1.466)           | (−18.866)             | (−12.384)             | (−12.430)             | (−13.062)             | (−60.938)            |
| HAZ, WHZ, OR WAZ in t− | −0.451***  | −0.462***              | −0.464***          | −0.518***             | −0.452***             | −0.490***             | −0.498***         | −0.594***             | −0.419***             | −0.466***             | −0.474***             | −0.453***            |
|                | (−38.652)           | (−39.548)             | (−39.891)         | (−40.940)             | (−58.386)            | (−62.351)            | (−63.478)        | (−47.432)             | (−38.284)             | (−39.189)             | (−41.008)             | (−34.124)            |
| Women’s educ. in t− | 0.007***  | 0.006***              | 0.010***          | 0.013***              | 0.013***             | 0.012***             | 0.005***         | 0.013***             | 0.013***             | 0.013***             | 0.007***              |                     |
|                | (9.777)             | (8.347)               | (15.350)          | (21.167)              | (20.640)             | (10.514)             | (19.227)         | (18.909)              | (15.440)              |                     |                     |                     |
| Female head in t− | 0.031***  | 0.030***              | 0.009***          | 0.013***              | 0.012***             | 0.003               | 0.014***        | 0.014***             | 0.007***              |                     |                     |                     |
|                | (7.509)             | (7.385)               | (2.702)           | (3.442)               | (3.367)              | (0.924)              | (3.426)          | (3.422)               | (2.576)               |                     |                     |                     |
| Middle wealth, t− | 0.041***  | 0.013***              | 0.011***          | 0.053***              | 0.033***             | 0.056***             | 0.066***        | 0.028***             | 0.013*                |                     |                     |                     |
|                | (5.362)             | (2.035)               | (4.156)           | (2.781)               | (8.843)              | (6.932)              | (9.732)         | (5.970)               | (6.653)               |                     |                     |                     |
| Top wealth, t− | 0.035***  | 0.019***              | 0.023***          | 0.023***              | 0.045***             | 0.013***             | 0.036***       | 0.036***             | 0.036***             |                     |                     |                     |
|                | (4.156)             | (2.781)               | (3.582)           | (8.352)               | (3.582)              | (1.819)              | (1.819)        | (1.819)               | (1.819)               |                     |                     |                     |
| Standard error, t− | 0.518***  | −0.016***             | −0.193***         | (11.860)              | −0.314***             | −0.307***             | −0.307***     | −0.307***             | −0.307***             |                     |                     |                     |
|                | (−2.896)            | (−6.900)              | (−3.304)          | (−2.896)              | (−6.900)             | (−3.304)             | (−6.900)       | (−3.304)              | (−3.304)              |                     |                     |                     |
| Constant | 7.686**  | 8.885**              | 11.591***         | 4.080                | −4.910                | −7.014**             | −4.886         | 60.580***            | 65.711***            | 64.209***            | 67.031***            | 309.486***          |
Table 7 (continued)

| Stunting equations | Wasting equations | Underweight equations |
|--------------------|-------------------|-----------------------|
| (19) 105,547       | (23) 105,547      | (27) 105,547          |
| (20) 105,467       | (24) 105,467      | (28) 105,467          |
| (21) 105,467       | (25) 105,467      | (29) 105,467          |
| (22) 105,467       | (26) 105,467      | (30) 105,467          |
| Adjusted R²        |                   |                       |
| 0.322              | 0.390             | 0.342                 |
| 0.327              | 0.410             | 0.358                 |
| 0.330              | 0.415             | 0.364                 |
| 0.512              | 0.570             | 0.680                 |

All hypothesis tests are two-tailed; 99% ***; 95% **; 90% *. t-statistics are listed in parentheses under the coefficients. The dependent variables are change in height-for-age z-score/stunting, change in weight-for-height z-score/wasting, and change in weight-for-age z-score/underweight, respectively. "Columns 4, 8, and 12 control for country fixed effects (not shown)"; Times t– and t represent, respectively, the first and last years of available DHS data (see Appendix Table A1).
Table 8  S2SLS estimates of child-level models, spatial

|                                | Stunting equations | Wasting equations | Underweight equations |
|--------------------------------|--------------------|-------------------|-----------------------|
|                                | (31)               | (32)              | (33)                  |
|                                | (34)               | (35)              | (36)                  |
|                                | (37)               | (38)              | (39)                  |
|                                | (40)               | (41)              | (42)                  |
| Spatial lag                    | 0.494***           | –1.029***         | –0.032                |
|                                | (8.745)            | (–3.383)          | (–0.223)              |
|                                | 0.724***           | 0.790***          | 0.864***              |
|                                | (29.697)           | (44.883)          | (73.096)              |
|                                | 0.722***           | 0.999***          | 0.886***              |
|                                | (29.910)           | (48.600)          | (86.380)              |
|                                | 0.723***           | 0.786***          | 0.882***              |
|                                | (30.286)           | (44.759)          | (90.649)              |
| Change of impervious area      | 0.002***           | –0.000            | 0.001***              |
| percentage point (%)           | (8.458)            | (–0.200)          | (2.653)               |
|                                | 0.001***           | –0.000            | 0.000                 |
|                                | (8.351)            | (–1.621)          | (1.637)               |
|                                | 0.001***           | –0.000*           | 0.000*                |
|                                | (8.263)            | (–1.950)          | (1.317)               |
| Change of average luminosity  | 0.180***           | 0.385***          | 0.331***              |
| (DN/\text{km}^2)              | (4.526)            | (0.33)            | (4.693)               |
|                                | 0.094***           | 0.033             | 0.042***              |
|                                | (4.084)            | (1.170)           | (2.798)               |
|                                | 0.087***           | 0.024             | 0.030***              |
|                                | (3.776)            | (0.903)           | (2.150)               |
|                                | 0.090***           | 0.019             | 0.022                 |
|                                | (3.882)            |                   |                       |
| Year, \( t – t_0 \)           | –0.002**           | 0.004             | –0.034***             |
|                                | (–2.000)           | (1.273)           | (–6.922)              |
|                                | –0.001**           | 0.001***          | –0.004***             |
|                                | (–1.974)           | (2.727)           | (–6.966)              |
|                                | –0.002**           | 0.001***          | –0.003***             |
|                                | (–2.628)           | (2.212)           | (–8.650)              |
|                                | –0.135***          | –0.114***         | –0.002***             |
| Year, \( t – t_0 \)           | (–9.466)           | (–6.172)          | (–4.886)              |
|                                | –0.136***          | –0.111***         |                       |
| HAZ, WHZ, or WAZ in \( t – t_0 \) | –0.233***          | –0.117***         |                       |
|                                | (–11.764)          | (–12.270)         |                       |
|                                | –0.137***          | –0.117***         |                       |
|                                | (–11.891)          | (–12.380)         |                       |
| Women's education in \( t – t_0 \) | 0.002***           | 0.003***          | 0.002***              |
|                                | (7.909)            | (0.003)           | (0.002)               |
|                                | 0.002***           | 0.003***          | 0.002***              |
|                                | (6.733)            | (11.697)          | (0.002)               |
| Female head in \( t – t_0 \)  | 0.009***           | 0.003***          | 0.002***              |
|                                | (6.424)            | (2.424)           | (0.002)               |
|                                | 0.009***           | 0.003***          | 0.004***              |
|                                | (6.340)            | (2.424)           | (2.574)               |
| Middle wealth tercile in \( t – t_0 \) | 0.012***           | 0.012***          | 0.009***              |
|                                | (4.967)            | (6.987)           | (4.816)               |
|                                | 0.012***           | 0.013***          |                       |
|                                | (4.926)            | (7.135)           |                       |
| Top wealth tercile in \( t – t_0 \) | 0.011***           | 0.005**           | 0.002                 |
|                                | (3.823)            | (2.288)           | (1.401)               |
|                                | 0.010***           | 0.006***          | 0.001                 |
|                                | (3.567)            | (2.727)           | (0.531)               |
| Standard error for HAZ, WHZ,   | 0.048***           | 0.033***          | 0.032***              |
| or WAZ in \( t – t_0 \)       | (3.364)            | (3.136)           | (2.837)               |
| Standard error for HAZ, WHZ,   | –0.048***          | –0.059***         | –0.129***             |
| or WAZ in \( t \)             | (–2.870)           | (–4.495)          | (–9.949)              |
| Constant                      | 3.661*             | –8.832            | 67.865***             |
|                                | (1.844)            | (–2.412)          | (7.747)               |
|                                | 2.154*             | –1.878            | 6.765***              |
|                                | (1.810)            | (–2.711)          | (4.535)               |
|                                | 2.994**            | –2.711***         |                       |
|                                | (2.464)            | (–3.035)          |                       |
|                                | 4.804***           | (6.185)           |                       |
|                                | (3.699)            | (6.929)           |                       |
|                                | –8.322             | (6.809)           |                       |
|                                | (–1.257)           | (5.423)           |                       |
Table 8 (continued)

| Stunting equations | Wasting equations | Underweight equations |
|--------------------|-------------------|-----------------------|
| (31)               | (32)              | (33)                  |
| (34)               | (35)              | (36)                  |
| (37)               | (38)              | (39)                  |
| (40)               | (41)              | (42)                  |
| $n$                | 105,547           | 105,467               |
|                   | 105,467           | 105,467               |
|                   | 105,467           | 105,467               |
|                   | 105,467           | 105,467               |
|                   | 105,467           | 105,467               |
|                   | 105,467           | 105,467               |
| Adjusted $R^2$     | 0.807             | 0.923                 |
|                   | 0.923             | 0.923                 |
|                   | 0.923             | 0.923                 |
|                   | 0.937             | 0.939                 |
|                   | 0.936             | 0.936                 |
|                   | 0.300             | 0.966                 |
|                   | 0.970             | 0.970                 |

All hypothesis tests are two-tailed; 99% ***; 95% **; 90% *; $t$-statistics are listed in parentheses under the coefficients. The dependent variables are change in height-for-age $z$-score/stunting, change in weight-for-height $z$-score/wasting, and change in weight-for-age $z$-score/underweight, respectively; Times $t$– and $t$ represent, respectively, the first and last years of available DHS data (see Appendix Table A1).
level of the child or household that the child belongs to. (Note that all models control for error introduced by the interpolation / kriging process at both time $t$ and time $t-$ but that, as measurement error, there is to particular expectation for these variables.) Impervious surface area and luminosity, measured as change at the child’s location, are statistically significant and positive, meaning that they are associated with improvement, in virtually all cases—in both the spatial and aspatial models. In the OLS estimates, impervious surface area is statistically significant in 12/16 equations and luminosity is significant in 15/16 equations. In the S2SLS estimates, impervious surface area is statistically significant in 13/16 equations and luminosity is significant in 12/16 equations. While not perfectly consistent, these results meet the broad expectation that urbanization matters to personal wellbeing. Looking past the urbanization variables, household characteristics also matter: years of women’s education, a female head of household, and indicator variables (medium and high tercile) derived from the asset-based wealth index, are all positive and, for the most part, statistically significant. The initial levels of the models’ own variables, lagged to time $t-$, are consistently significant and negative, meaning that poor starting levels of stunting, wasting, and underweight lead to worsening of those maladies over time. The outstanding elements of the models, $\kappa$, $\tau$, and $\phi$, are, respectively, the measurement errors from kriging; temporal effects tracing the timing of the DHS survey; and country fixed effects. All are included as controls due to the exploratory nature of the models and have no direct interpretation.

What can be said, based on these regressions, exploratory as they are, is that urbanization matters to wellbeing: children living in urbanized areas are less likely to be stunted, wasted, and/or underweight. The modeling results connect the stylized facts, as set out above, but more refined econometric analysis is needed to say anything with precision—or about cause and effect (Angrist and Pischke 2015).

5 Summary and conclusion

This paper opened by explaining that Sub-Saharan Africa, home to 33 of the 46 UN-designated LDCs, is experiencing the greatest urban growth in the world and posed a question fundamental to the region: has urbanization there been accompanied by improvements in personal wellbeing? While a decisive answer to this question is not available, the investigation opened here suggests a reason for optimism: urbanization, measured across spatial scales and over time, is associated with reduced child growth failure, in the form of stunting, wasting, and underweight. This signals that the wave of urbanization breaking across Sub-Saharan Africa is likely to the benefit of its people. The few remaining comments are general observations derived from the evidence and implications for further research.

The two organizing ideas behind this work—that urbanization: (i) makes people better off; and (ii) is a spatial process that rearranges not only people but, also, the conditions impacting them—appear to hold up under empirical scrutiny. The constraints-oriented approach of time geography adopted as a theoretical lens is helpful because it exposes the behavioral relationships of geographic systems across multiple spatial scales. And, it squares neatly with the capability approach to development economics. Future work on this project will look further into these dynamics,
particularly by exploring opportunities for policy intervention. Such interventions may come in a variety of forms, including aid from the international community focused on enhancing the benefits of urbanization, plus technical and/or financial assistance with industrial reorganization. For example, a key element of the urbanization process is an economic reorientation, away from agriculture toward industry. United Nations designated LDC status brings, among other things, benefits related to development financing, including eligibility for special grants and loans from donor countries and financial institutions; multilateral trading, including preferential market access and favorable terms of trade; and, importantly, assistance, including access to the Enhanced Integrated Framework, a program supported by 24 countries and eight international agencies. Clearly, given the trajectory of Sub-Saharan Africa, to be successful, these programs should be implemented with cities and their powerful agglomeration economies in mind.

From a policy perspective, it is important to understand not just relationships, as explored here, but also the various pathways through which urbanization contributes to improvements in personal wellbeing. Moreover, while child growth failure is a critical measure, it is but one among many dimensions of health. It is a measure that can be built upon through the monitoring of indicators, especially incidence of communicable disease and other problems that manifest through the density of cities. To this point, wellbeing implies a holistic view of quality of life—and quality of life in cities can readily be enhanced by paying careful attention to the negative externalities of urbanization in the urban planning process. Finally, it must be acknowledged that the findings presented here are the preliminary results of a larger process of compiling and reconciling remotely sensed and DHS data across the entirety of Sub-Saharan Africa; the purpose of this particular paper has been to document the methodology involved. The empirical findings, while sound, are only preliminary. They are findings that must be refined via further development of the data, plus more precisely tuned econometric models. Like many projects, this one concludes by qualifying its findings and noting the need for not only more, but more expansive research. The matter is one of critical importance, given the sheer number of lives being transformed by urbanization in Sub-Saharan Africa and all of the complexity involved in the transition. The futures of many people, including generations to come, depend on making the transition successfully.

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9 These are: Australia; Belgium; Canada; Denmark; Estonia; the European Commission; Finland; France; Germany; Hungary; Iceland; Ireland; Japan; Korea; Luxembourg; the Netherlands; Norway; Saudi Arabia; Spain; Sweden; Switzerland; Turkey; the United Kingdom; and the United States of America.

10 These are: the World Tourism Organization (UNWTO); the United Nations Industrial Development Organization (UNIDO); the World Trade Organization (WTO); the World Bank Group (WB); the United Nations Development Program (UNDP); the United Nations Conference on Trade and Development (UNCTAD); the International Trade Centre (ITC); and the International Monetary Fund (IMF).
Appendix

See Tables 9, 10, 11.

Table 9  GLS Estimates of convergence

|                          | Est      | t-value |
|--------------------------|----------|---------|
| Constant                 | 0.1312   | n/s     |
| ln (GDP)                 | −0.0734  | ***     |
| Life expectancy          | 0.0050   | ***     |
| Primary education        | 0.0542   | ***     |
| Dependency ratio         | −0.1744  | ***     |
| Natural resource rents   | 0.4220   | ***     |
| Women in business        | 0.0010   | **      |
| Population in agglomerations > 1 million | 0.1050 | **   |
| Annualized population growth | 0.0121 | ***   |
| Adjusted $R^2$           |          |         |
| $n$                      |          | 563     |

All hypothesis tests are one-tailed; *** and ** indicate significant at 99% and 95% confidence intervals, respectively; n/s indicates not significant; all data comes from the World Bank’s WDI Database; due to missing data on Primary Education, two observations, from Sudan in 1990 and 1995, are dropped so the sample size is 563 instead of 565; GDP is measured in real (2010) dollars; Life Expectancy is measured as average number of years at birth; Primary Education is measured in years; Dependency Ratio is measured as the number of children and elderly as a percent of the working-aged population; Natural Resource Rents is measured as the sum of oil rents, natural gas rents, coal rents, mineral rents, and forest rents as a percentage of GDP; Women is Business is measured as a composite index of women’s economic opportunity; Population in Agglomerations is measured as the percent of total population living in agglomerations of one million or more; and Annualized Population Growth is measured as the number of people, in millions, moving to urbanized areas in the preceding year. GLS estimates produced using the xtreg command in Stata, with country-specific random effects.
Table 10  National- and regional-level variables

| Variable               | Unit       | Measure                                                                 | Source                  |
|------------------------|------------|-------------------------------------------------------------------------|-------------------------|
| National-level         |            |                                                                         |                         |
| shgststng              | %          | Percentage of under-5 children who are stunted—HAZ below 2 standard deviations of the WHO standard | WDI                     |
| shstmalz               | %          | Percentage of under-5 children who are underweight—WAZ below 2 standard deviations of the WHO standard | WDI                     |
| shstawastz             | %          | Percentage of under-5 children who are wasted—WHZ below 2 standard deviations of the WHO standard | WDI                     |
| gaia_area_log          | km²        | Sum of artificial impervious area within the country boundary           | Gong et al. (2020)      |
| light_int_log          | DN value   | Sum of light intensity within the country boundary                      | Li et al. (2020)        |
| ngdppcapkd             | constant 2010 US$ | Gross Domestic Product per capita                                   | WDI                     |
| sglawindx              | scale 1–100 | A composite index indicating how laws and regulations affect women’s economic opportunity | WDI                     |
| Regional-level         |            |                                                                         |                         |
| ch_haz                 | z score    | Calculated from children’s height and age within the region            | DHS                     |
| ch_waz                 | z score    | Calculated from children’s weight and age within the region            | DHS                     |
| ch_whz                 | z score    | Calculated from children’s weight and height within the region         | DHS                     |
| gaia_area_log          | m²         | Sum of artificial impervious area within the region                    | Gong et al. (2020)      |
| light_int_log          | DN value   | Sum of light intensity within the region                                | Li et al. (2020)        |
| wom_educ               | years      | Average of women’s education within the region                          | DHS                     |
| wealthcommon           | scale      | Average of asset-based household wealth index within the region        | DHS                     |
| Variable          | Measure                                                                 | Unit | Source                                                                                           |
|-------------------|------------------------------------------------------------------------|------|--------------------------------------------------------------------------------------------------|
| haz_first         | HAZ for the child in the first survey                                   | z score | Calculated from children’s height and age information DHS                                        |
| haz_last          | HAZ for the child in the last survey                                    | z score | Calculated from children’s height and age information DHS                                        |
| haz_change        | Change of HAZ between first and last surveys                           | z score | Calculated from children’s height and age information DHS                                        |
| waz_first         | WAZ for the child in the first survey                                   | z score | Calculated from children’s weight and age information DHS                                        |
| waz_last          | WAZ for the child in the last survey                                    | z score | Calculated from children’s weight and age information DHS                                        |
| waz_change        | Change of WAZ between first and last surveys                           | z score | Calculated from children’s weight and age information DHS                                        |
| whz_first         | WHZ for the child in the first survey                                   | z score | Calculated from children’s weight and height information DHS                                     |
| whz_last          | WHZ for the child in the last survey                                    | z score | Calculated from children’s weight and height information DHS                                     |
| whz_change        | Change of WHZ between first and last surveys                           | z score | Calculated from children’s weight and height information DHS                                     |
| gaia_area_f_log   | Log of impervious area in the first survey year                         | m²    | Sum of impervious area within a buffer zone centered on households (The radius is 5 km for rural and 2 km for urban) | Gong et al. (2020) |
| gaia_area_l_log   | Log of change of impervious area between first and last surveys         | m²    | gaia_area_l_log—gaia_area_f_log                                                                  | Li et al. (2020) |
| light_int_f_log   | Log of light intensity in the first survey year                        | DN value | Sum of light intensity within a buffer zone centered on households (The radius is 5 km for rural and 2 km for urban) | Li et al. (2020) |
| light_int_ch_log  | Log of change of light intensity between first and last surveys         | DN value | light_int_f_log—gaia_area_f_log                                                                  | Li et al. (2020) |
| year_first        | Year of the first survey                                              | Year   | Year of the first survey, different for children in different countries                           | DHS |
| anysickness       | Whether children had sickness in the last two weeks                     | 1 for yes, 0 for no | Children who had diarrhea, cough, or fever in the last two weeks are recorded 1, otherwise 0 | DHS |
| wom_educ          | Women’s education years                                                | Years  | Women’s education in single years                                                                 | DHS |
| female_head       | Female headed household                                                | 1 for yes, 0 for no | Whether the head of the household is female or not                                               | DHS |
| wealthcommon      | Asset-based wealth index scale                                         | Scale  | A composite wealth index calculated based on types of drink, water, toilet, and floor owned by households | DHS |
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