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Linking Food Security, Urbanization, and Climate Change in Africa

A dissertation submitted in partial satisfaction of the

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in Geography

by

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Linking Food Security, Urbanization, and Climate Change in Africa

Cascade P. Tuholske

ABSTRACT

Africa's urban population will increase from 600 million people today to nearly 1.5 billion in 2050. The vast majority of new urban residents will be poor and will face a host of challenges that are amplified by climate change. Chief among them is how to reduce urban poverty and ensure food security. Yet, due to a persistent lack of data, the feedbacks among food security, urbanization, and climate change in Africa have not been explored. This knowledge gap directly impedes progress to achieve the United Nations Sustainable Development Goals 1, 2, and 11—ending poverty, zero hunger, and ensuring sustainable and equitable cities.

This dissertation takes a step towards linking these themes. First, using original data collected in Accra, Ghana, I examine urban food security measurement. I find that while poverty is generally correlated with households' experiences with food insecurity, traditional dietary-recall metrics may not be appropriate measures of household food security in African cities. Next, I integrate OpenStreetMap data and gridded population datasets to map the populations of 4,500 urban settlements in Africa. This approach fills a crucial void in our capacity to measure urban population dynamics across the continent. Finally, I document how urban exposure to extreme heat changed from 1983 - 2016 not just in Africa, but across 13,000 towns and cities globally. This is the first fine-resolution, global synthesis of urban population exposure to extreme heat. I argue that mitigating exposure to extreme heat is key to reducing urban poverty and thus ensuring food security. But mitigation efforts must be tailored to local

contexts. In sum, the results of this dissertation call into question the sustainable and equitable development of Africa’s ever-expanding urban areas.

CHAPTER I – Introduction

The confluence of climate change and urbanization pose significant and unique challenges for Africa's development prospects. While urban populations are expected to increase from nearly 600 million in 2014 to nearly 1.5 billion by 2050 [1], much of Africa has urbanized without concurrent economic growth [2,3]. As a consequence, the majority of urban dwellers live in poverty today [4]. Climate change is intensifying water stress, decreasing crop productivity, increasing aridity and extreme heat, burdening livelihoods, amplifying rural-to-urban migration, and elevating concerns of both rural and urban food security [5–12]. Troubling research from South Asia suggests that some African cities may become inhospitable as climate change produces more frequent extreme temperatures in mid-latitude regions [13]. Such rapid urban growth presents a host of challenges for the continent's development prospects. Yet, because of a persistent lack of data, few empirical studies have examined food security, urbanization, and climate change in tandem and at fine-spatial scales. This body of work fills this crucial knowledge gap.

First, using original household data from Accra, Ghana, I compare how different measures of household-level food security relate to urban poverty. I find that while poverty is generally correlated with households' experiences with food insecurity, traditional dietary-recall metrics may not be appropriate measures of household-food security in large Africa cities. Rather, I advocate for a new food security paradigm that properly accounts for the growing food security needs of the urban poor.

Next, I use a new methodology to estimate the population of 4,750 individual urban settlements across Africa. By integrating data from OpenStreetMap and gridded population rasters, I measure and map the populations of more than 4,500 urban settlements across Africa.

My results reveal that 77%–85% of urban settlements in Africa have fewer than 100,000 people and that at least 50% of Africa's urban population live in urban settlements with fewer than 1 million residents. Across almost all African countries, the distribution of urban population shifted towards larger cities between 2000 and 2015. However, in arid regions, small- and medium-sized urban settlements may be absorbing a greater share of urban population growth compared to large urban settlements.

Finally, I zoom out to the global scale to build the first global synthesis of urban exposure to extreme heat. Using new fine-resolution data, I find that urban population exposure to extreme heat more than doubled from 1983 – 2016 globally. Urban warming explains 26% of the annual exposure increase. In Africa, urban population exposure to extreme heat increased nearly 250% from 1983 - 2016, with urban warming contributing to more than 17% of the increase in exposure. Like much of the planet's urban areas, urban population exposure to urban extreme heat in Africa is highly spatially heterogeneous. Accordingly, adaptation and mitigation strategies will require locally appropriate approaches framed within broader regional and global context.

Across all three themes, the results showcased here call into question the future sustainability and equitability for many of Africa's ever-expanding urban areas. Ensuring urban food security depends on decreasing urban poverty; Poverty reduction in urban areas ultimately hinges on increasing labor productivity. Yet exposure to extreme heat not only harms human health and risks increased mortality [14], but it also crucially limits economic output and productivity [15] . Accordingly, the increased rates of urban exposure to extreme heat across Africa documented here may crucially limit the urban poor's ability to realize the economic gains associated with urbanization. And, in turn, urban food security is threatened.

Given that climate change is increasing the frequency, duration, and magnitude of extreme heat across Africa [16–20], without targeted adaptation and mitigation strategies reducing poverty and ensuring urban food security remains a challenge. This has alarming implications for achieving the United Nations Sustainable Development Goals 1, 2 and 11—ending poverty, zero hunger, and ensuring sustainable and equitable cities.

CHAPTER II - COMPARING MEASURES OF URBAN FOOD SECURITY IN ACCRA, GHANA[1]

1. Introduction

The urban population in Sub-Saharan Africa (SSA) is projected to balloon from 376 million in 2015 to over 1.25 billion people by 2050 [1]. How this rapid urban transition is affecting urban food security, and how it is reverberating into broader food systems, is unclear. Most food security studies across the region have concentrated on rural areas and the few case studies that have examined urban food security in SSA have depended on metrics designed to study rural food security [21–26]. Achieving the United Nations (UN) Sustainable Development Goals (SDGs) 2 and 11—zero hunger and the development of sustainable cities––requires accurate and consistent tools that capture the multidimensionality of household-level food security in SSA's rapidly growing cities [11]. But no studies have explored the relationship among established household-level food security metrics in the SSA urban context in a multivariate framework. As such, how urban household demographic, socioeconomic, environmental, and spatial characteristics may vary across established household-level food security metrics is unknown.

Food security is a theoretical construct predicated on complex, multiscale spatiotemporal processes that encompass a broad range of human and environmental variables [24,27]. It cannot be measured by a single metric. While orthodox methodologies break food security into manageable components, household-level food security measurement remains rooted in rural-centric conceptualizations of food security [23,26]. Furthermore, some

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development agencies still advocate for policies centered on rural food security, encouraging approaches that use the urban transition as a lynchpin to buttress rural producers. For example, in the 2017 State of Food and Agriculture Report, FAO advocates that growing demand from urban consumers can be a major force for rural inclusion and bolster rural food security but makes no mention of urban food security [28]. Such rural-centric paradigms not only fail to account for the food security needs among the growing number urban poor, but also ignore the fact that we currently lack tools specifically designed to measure food security in the urban context.

Indeed, the nascent body of urban food security research from SSA illuminate how the region's rapid urban transition is presenting new challenges for food systems and requires new, urban-oriented approaches to measure household-level food security [26]. For example, evidence indicates that the urban poor in SSA rely on purchased food for 90% of their calories and spend up to 70% of their income on food [21,29,30]. This suggests that local price stability is a key component to urban food security. Urban food prices face greater exposure to external market forces and commodity price shocks can increase food insecurity among urban households while at the same time boosting prices and increasing food security among rural producers. During the 2007/8 global commodity price shock urban households across SSA reported being less food secure, whereas food security among rural households improved [31]. With urban household's food security dependent on price, food security metric designed to capture caloric intake or dietary diversity among rural households may not accurately measure food security among urban households [26].

Food preferences and retailing options are also different for urban consumers compared to rural households across SAA. Changes in diet and lifestyle historically associated with urbanization are burdening health systems by creating a dual burden of disease of both over- and undernourished poor households [32,33]. In some cases, shifting food preferences among urban consumers can transform rural production toward large-scale agribusiness in SSA countries, which can be detrimental to smallholders [28]. Finally, the urban transition is also transmogrifying food retail systems, specifically leading to an increase in the number of supermarket retail outlets [34,35]. It is unclear, however, how this shift in diets and food retailing affects food security among the urban poor, nor how if this shift is accurately captured by current food security metrics [11,26].

In summation, understanding urban food security in SSA requires tools that measure economic access, nutrition, and urban food retailing, as well as municipal-level limitation such as water and sanitation, governance, and road infrastructure [26]. To this end, this paper has four aims: (i) we compare the food security status of households from nine low- and middle-income residential areas in Accra across three established food security metrics; (ii) we identify where households source food; (iii) we explore the household-level demographic, socioeconomic, environmental, and spatial predictors of urban food security; and (iv) we examine how these predictors vary across three indicators of household food security. With an ever-increasing number of Africans poised to live in cities, and, given that many of these new residents will be poor, understanding *who* is food (in)secure in cities, *where* food (in)security exists, *why* diets may be changing, and *how* urban food security will affect broader food systems, is paramount for countries across SSA to accurately measure their progress toward achieving UN SDGs 2 and 11.

2. Measuring food security in urban households

The most direct measurement of household-level food security that captures caloric and nutritional intake are either anthropometry measurements or detailed, multi-visit household expenditure or dietary recall logs [24]. But acquiring accurate data through such methods is time-intensive, invasive, and expensive. Instead, household food security is generally assessed via proxy metrics derived from questions concerning one of three broad categories: (1) single-visit dietary recalls; (2) coping strategies; and (3) psychosocial and physical experience-based [26]. All three categories stem from a historical rural-centric bias and, if used individually fail to capture the multidimensionality of household food security [22,24,26,36]. Indeed, aggregate pairwise comparison of 8,000 - 30,000 households from a wide range of developing countries showed that established dietary recall metrics have weak correlation with coping strategies and experience-based food security metrics [27]. As such, using a single metric focused on dietary diversity may show that a household is food secure in terms of diversity of food consumed, but does not capture a household's ability to cope with food insecurity. What is more, unless collected over time, all these metrics fail to capture any temporal changes in household food security.

The few existing household-level urban food security assessments are largely from Southern African cities and have measured food security according to two interrelated experience-based metrics, the household food insecurity access scale (HFIAS) and household food insecurity access prevalence (HFIAP). The data were collected from sub-populations of urban dwellers and tend not to be representative of the city's population. Nonetheless, all of these case studies suggest that low-income households regularly experience instances of food insecurity across a range of African cities. Surveys conducted by the African Food Security

Network (AFSUN) in low-income areas of 11 Southern African cities found that household-level food insecurity measured by the HFIAP range from 56% to 98% of sampled households and that poverty significantly correlated with food insecurity [30]. A different survey from Tshwane, South Africa, found lower levels of food urban insecurity, with 61.3% of 507 sampled households characterized as food secure by HFIAP [37]. In Nairobi, Kenya's capital, 85% of households in two major slums reported being food insecure according to HFIAP [38]. During the 2007/8 global commodity price spike, food insecurity measured among over 3,000 randomly selected households in Ouagadougou, Burkina Faso, increased from 66.7% to 78.0% [39], indicating that rising global commodity prices can affect local prices and increase household-level food insecurity in SSA cities. Last, also using HFIAP, a recent survey of households in two medium-sized cities in Northern Ghana found over half of households were food insecure [40].

The AFSUN dataset offers insights into dietary diversity, provisioning, socioeconomic, and demographic associations with levels of household food security characterized by HFIAP [30]. But AFSUN's published data does not compare how dietary diversity correlates with food security measured by HFIAP, nor does it employ multivariate statistical models to assess demographic, socioeconomic, dwelling, and spatial predictors household-level food security. To date, only one case study from Sub-Saharan Africa has compared proxy measures of household food security in the urban context. A sample of over 3,000 households in Ouagadougou found that both HFIAS and the index-member's dietary diversity score (IDDS) were significantly associated with household-level dietary and nutritional intake calculated from multiple visit full dietary recalls that weighted and measured of food portions and ingredients [41]. However, the Ouagadougou study, like the AFSUN dataset, did not assess how demographic, socioeconomic, environmental, and spatial characteristics relate across these measures of household-level food security.

In this study we employ three measures of household food security: HFIAS; HFIAP; and the food consumption score (FCS). The HFIAS was designed to produce a simple single statistical tool to monitor and evaluate food security that has been empirically validated for both population and individual level estimates of food security [24]. Adopted from a set of questions used to estimate prevalence of food insecurity in the United States, HFIAS produces a numeric score derived from nine subjective yes/no questions [42]. The subjective questions gauge respondents' behaviors and attitudes related to household food security, including anxiety related to household food insecurity, perceptions of insufficient quality or variety of food, and reduction of food intake and subsequent physical consequences. If the respondent replies in the affirmative to any question, the enumerator asks about the frequency of occurrence. For example, if the respondent replies yes to "Did you or any household member go to sleep at night hungry because there was not enough food?", the respondent is then asked the frequency to which this occurred: rarely (1-2 in the past four weeks) scored as 1, sometimes (3-10 times in the past for weeks) scored as 2, or often (>10 times in the past four weeks) scored as 3. The HFIAS score is the summation of the frequency of occurrence of each question with a range of 0-27.

The HFIAS can be used to calculate the HFIAP, a categorical variable that employs a logic tree from the frequency responses to HFIAS questions. Households are labeled food secure or mild, moderate, or severe food insecure. It is important to highlight that HFIAS and HFIAP are used to measure access to food as a dimension of food security. But they are not intended to assess the causes of food insecurity, understanding coping strategies, cultural appropriateness, or nutritional knowledge or uptake.

The FCS is a composite score that uses a seven-day dietary recall that measures dietary diversity, food frequency and sourcing, and relative nutritional importance [43]. Respondents report the number of days out of the last seven days their respective household members have consumed locally appropriate food items. The items are grouped into overarching food groups, which are weighted based on the caloric values of those foods. The weighted values are then summed together to produce the FCS. A threshold is applied to determine if a household's food security situation based on consumption is poor (FCS of 0-21), borderline (FCS between 21.5 – 35), or acceptable (FCS greater than 35) food security. The FCS has been shown to correlate with per capita calorie consumption across divergent geographical and cultural contexts [44].

3. Materials and Methods

3.1 Study Site

Ghana has experienced rapid urbanization seen in developing and emerging economies over the past few decades across Asia, Latin America, and now increasingly in SSA. In developing economies, the change from a rural agrarian economy to an economy less dependent on agriculture often includes migration out of rural areas into secondary and primary cities. Ghana has been no different. While the urban share of the population was 36 percent in 1990, by 2014 the share had climbed to 54%, and is projected to reach 70% by 2050 [1]. This situation is somewhat unique among countries in SSA. According to the UN, the region is only 38.8% urban [1]. However, cross-country comparisons of urbanization rates must account for the different definitions of what counts as urban in each country [45]. For example, in Ghana, towns with populations greater than 5,000 are considered urban (Ghana Statistical Service

2012). This threshold may account for at least part of the difference between Ghana and other African countries.

That notwithstanding, urbanization is still a clear manifestation of Ghana's economic and demographic transition, especially when the populations of the largest cities are closely examined. Ghana's labor has moved out of agriculture to an economy dominated by services [46], and this shift has been accompanied by rural-urban migration since Ghana's independence. But this trend may be changing. Nationally representative data from 2014 shows that urban-to-rural migration and urban-to-urban migration exceeds rural-to-urban migration [47].

In tandem with urbanization, Ghana is currently undergoing the nutritional transition [32], with under-nutrition rates dropping and over-nutrition increasing. Nationally, obesity rates are increasing across rural and urban populations [48]. Among women 14 – 49, nearly 50% of urban women and 30% of rural women are obese, compared to 23% and 8% of urban and rural men, respectively [48]. Child undernutrition levels have decreased at the national level, though rural areas still have higher rates of stunting and wasting compared to urban areas. For example, in 2014, 22% of rural and 15% of urban children under were two standard deviations below recommended height-for-age ratio [48].

Accra has been recognized as one of Africa's emerging mega-cities. The capital is growing faster compared to the country as a whole—the national population growth rate between 2000 and 2010 was 2.5%, the Accra region, which includes Ghana's capital, recorded a growth rate of 3.1% [49]. The city had an official population of 2.6 million in the last national census (2010). Over half of Accra's residents are migrants [47], showing that much of this growth is not a result of natural increase within the city. Over 80% of migrants to Accra came from other urban areas [47]. Although Ghana's main industrial activities are clustered in Accra, the services sector employs the lion's share of Accra's labor force. This includes formal sector activities like education and health, but also many informal activities such as trading, catering, manual labor, and transportation. According to UN-Habitat, 38.4% Accra's residents live in neighborhoods characterized as slums, where urban poverty might be expected to be endemic [47]. However, household-level socioeconomic conditions and health status in the city's slums tend to be highly spatially heterogeneous [50–52] and the official poverty rate, determined by the consumption threshold of US$1.83 per day, is quite low at 2.2 percent in 2012/13.

Accra's retail food system is diverse. Along with a myriad of roadside shops and individual street hawkers, over 30 open-air markets serve the city [53]. But like other major cities in SSA [11], food retailing is evolving in Accra. From a baseline of only three supermarkets before 2005, Accra now boasts 37 large-format supermarkets according to an unpublished 2017 survey by International Food Policy Research Institute [54]. If supermarkets capture part of the market share from local retailers, then this shift in food retailing may have negative consequences for the urban poor who may not be able to afford the larger unit sizes of staples at supermarkets or access supermarkets at often distant locations [11].

A wide-variety of food products produced from Ghana's rural areas are sold across all retail locations. Traditional staples such as cassava, plantains and maize, and dried and frozen fish, fruits and vegetables are readily available. Like most West African countries, imports of rice and other commodities play a major role in food consumption. Meat—especially chicken and fish—and processed foods, are increasingly consumed in Accra, and convenience meals away from home are a major food source [55].

3.2 Data and Analysis

The 2017 Accra Urban Food Security Survey, collected over a three-week period in July/August, surveyed 677 households in 9 long-established, low- and middle-income residential areas throughout Accra. Structured-area sampling was employed [56]. Residential areas were chosen based on UN Habitat slum maps [57] and vernacular neighborhood maps that showcase finer-scale (census enumeration area) socioeconomic characteristics provided by San Diego State University [50,51]. We note that our sample should not be considered representative of all low- and middle-income households in Accra, as we did not survey informal or squatter low-income areas due to safety concerns. Local enumerators surveyed households at approximately even spatial intervals according to the density of houses to achieve complete spatial coverage of each residential area. The survey included question blocks related to household demographic, dwelling, labor, income, socioeconomic characteristics, food expenditures, and market preference as well as FCS, HFIAS, and HFIAP questions. Enumerators surveyed one consenting adult per household with knowledge of the household finances and food procurement. However, enumerators collected demographic information for the entire household, as well as labor characteristics for up to five household members. Data was collected using Qualtrics mobile data collection platform on iPad tablets.

Four models were generated using 668 complete cases to assess how household demographic, socioeconomic, environmental, and spatial characteristics relate to the three household food security metrics, as well as how such predictors may vary across the three food security metrics. While the FCS is a bounded integer variable that can only take on values between 0 and 112, here FCS distribution is normal and thus an ordinary least squares (OLS) regression was performed for the FCS. In OLS regression, the estimate effect size linearly correlates with the dependent variable. For example, if the household size effect is estimated to be 1 and statistically significant, then an increase of one person in a household is associated with FCS increasing by 1, all else being equal.

The HFIAS is treated as a count variable because it is the summation of the frequency of occurrences in response to categorical questions. The number of zeros is inflated (Fig 2b). Households who answer no to all HFIAS questions are categorized as food secure and receive a score of zero. But because the zeros are not assumed to be a result of a different underlying process, a negative binomial model is appropriate rather than a zero-inflated poisson regression [58]. A second logistic regression was performed on a binary HFIAS variable that categorized households HFIAS scores as <0 or 0 [39]. In negative binomial model and logit models, statistically significant effects of an independent variable are associated with an increase in the log counts of the dependent variable. The larger the effect size, the greater the increase in log counts of the dependent variable.

Marginal effects ordinal logistic regression was performed on HFIAP. Results from a marginal effects model indicate the probability of a household switching from a given HFIAP food security category given a change in predictor variable, holding all else held equal. For example, if the marginal effect for households with no school is -0.15, all else equal, household without any educated adult are 15% less likely to be in the secure category. All analysis and plots were performed in RStudio (version 1.1.143, RStudio Inc.). Maps were generated with QIS (version 2.18.20, QGIS Development Team).

Both categorical and continuous independent variables were selected to account for the range of demographic, socioeconomic, environmental, and spatial characteristics pertinent to households in our sample. We controlled for the possibility of free meals consumed by household members at work or school, as well as meals given away to non-household members, household language, and residential area of the household. We employed a slum index to characterize a wide-range of dwelling characteristics found in highly spatially heterogeneity low- and middle-income residential areas of Accra [51]. UN-Habitat designates a household as a slum if it lacks one or more of the five following characteristics: durable housing; sufficient living space; access to safe water; access to adequate sanitation; and secure land tenure [4]. The slum index is calculated by summing the number slum indicators a household is lacking and dividing it by five, whereby households with high slum index scores exhibit more slum-like conditions based on the household UN slum definition.

While the household survey attempted to gather monthly household income, we did not include this data in our models because of the high number of missing values and the known biases and unreliability of self-reported income. Alternatively, we constructed an asset index using similar procedures designed by the Demographic and Health Surveys Program to approximate household wealth [59]. After normalizing the raw data, principal components analysis (PCA) was performed on a list of common household assets [60]. To produce a continuous measurement of asset ownership by each individual household, PCA assigns each household a factor score by multiplying the first principle component of each asset by the household's normalized count of that asset and then summing the total across all assets owned by a household. Missing values for total household monthly food expenditures and distance traveled to primary food purchase location were imputed by bootstrapping random values from a Monte Carlo simulation based on the cumulative density function related to the distribution of two variables, respectively. Finally, because only one household in our sample reported ever shopping at a modern supermarket, we did not include the primary locations of food purchases. All other sampled households sourced food from local markets, neighborhood shops and

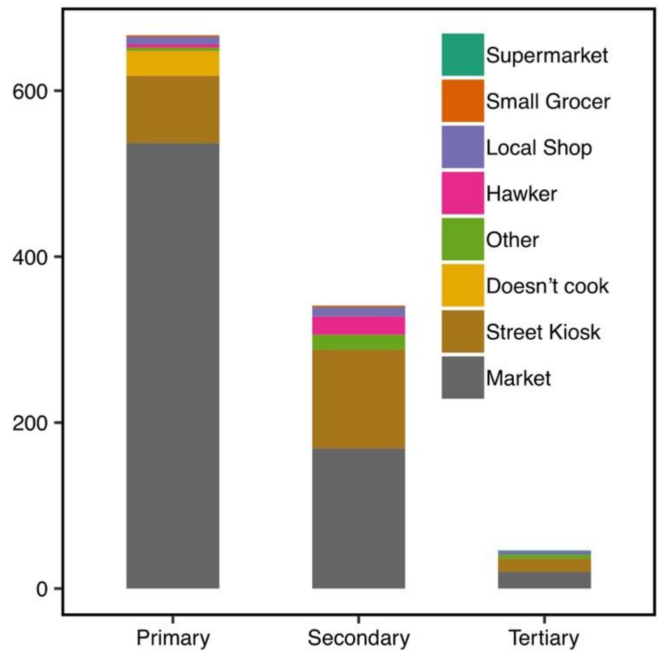

Figure 1 Primary, secondary, and tertiary sources where sampled households purchase food. Only one household reported ever going to a supermarket (tertiary source) and fewer than 3% of households reported sourcing food from gardening, fishing, or farming. Households that that reported 'doesn't cook' purchase prepared meals from street venders, kiosks, and restaurants.

kiosks, street vendors, or hawkers (Fig. 1). Likewise, we did not include self-production as independent variables because fewer than 3% of households reported gardening, fishing or farming from own consumption.

3.3 Descriptive Statistics

Just over 50 percent of the 668 households in our analytical sample were headed by a male (Table 1). The average household consisted of four members. The mean age of the household head was 47 years. On average, 56 percent of household members were employed. Self-employment was the most common form of employment—on average, households had at least one self-employed adult. Both regular and casual wage employment are considerably rarer—one member out of every three surveyed households has regular wage employment and one member out of every six surveyed households has casual employment. Although not reported in Table 1, from the 424 households that provided complete income information, the average monthly income from employment was 890 Ghana cedis (~4 Ghana cedis equaled 1 US dollar at the time of the survey).[2]

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[2] The exchange rate to the US dollar at the time of the survey was about 4 Ghana cedis.

Table 1 Descriptive Statistics of Household Characteristics (n=668)

	Mean or Count	Standard Deviation or Percent	Min	Max
Age of household head, years*	46.87	14.27	17	95
Household size	4.01	2.03	1	13
Male head of household, 0/1	361	54.0%		
Asset Index	0.00	1.61	-2.34	9.47
Received remittances, 0/1	193	28.5%		
Slum Index	0.09	0.117	0	0.6
No school, 0/1†	36	5.4%		
Primary school, 0/1†	223	33.4%		
Secondary school, 0/1†	253	37.9%		
Tertiary school, 0/1†	156	23.3%		
Household members employed, percent	56	0.27	0.11	1
Self-employed, number	1.02	0.81	0	5
Casually employed, number	0.16	0.43	0	4
Regularly employed, number	0.33	0.60	0	3
Travel time to market, minutes	15.0	15.9	0	180
Free meals at school or work, 0/1	0.17	0.36	0	3
Meals given to non-household members	1.61	5.35	0	70
Daily Street food expenses, cedi	11.67	14.22	0	150
Total monthly food expenses, cedi	555.01	376.69	2	3,000

* Four households recorded an average age below 5 and were omitted from summary statistics but were retained for modeling.
† The highest education attained by any working household member.
Note: Asset index normalizes the count data for each asset. Thus, the counts are centered at a mean of zero.

One-third of all households had at least one adult who had attended or completed primary education. Nearly 40 percent of households had an adult that had attended or completed secondary education, and more than 20 percent of households had an adult who had received some form of post-secondary education. Only 5 percent of households had no adult with any formal education.

Our sample reflected the ethnic diversity of Accra. Asante Twi, originating from central Ghana, was the dominant language for 30 percent of our sample, but languages originating from northern Ghana were predominantly spoken in about 21 percent of the households. Ewe, the main language for people from the Volta region east of Accra, was the main language in 9 percent of the households. The second most common language spoken was Ga (29 percent), the language for the Ga tribe which is indigenous to Accra. Only 2 percent of households spoke English as their primary language.

In terms of food consumption, expenditure on prepared food away from home was nearly 12 Ghana cedi per household per day (~3 USD). This compares to an average monthly total household food expenditure of 555 Ghana cedi (~139 USD). Household members received on average 0.17 meals per capita at school or work per day. This may include public food assistance. For example, Ghana has a School Feeding Program that provides meals to children in selected public schools, and currently reaches a third of school children in Ghana [61].

4. Results

4.1 Comparing measures of food security

Based on HFIAP, nearly 70 percent of households sampled are categorized as mildly to severely food insecure (Fig. 2a). Over the previous month, these households experienced anxiety related to food insecurity or were unable to access sufficient or preferred foods. But few households characterized as food insecure by HFIAP have high HFIAS scores (Fig. 2b). Those who answered "yes" to any of the nine HFIAS questions did not experience the problem frequently. Thus, our results indicate prevalent but low frequency of anxiety and experiences related to food insecurity among low- and middle-income households in Accra. In contrast, only 14 of the 668 households in the survey sample can be characterized as borderline or food

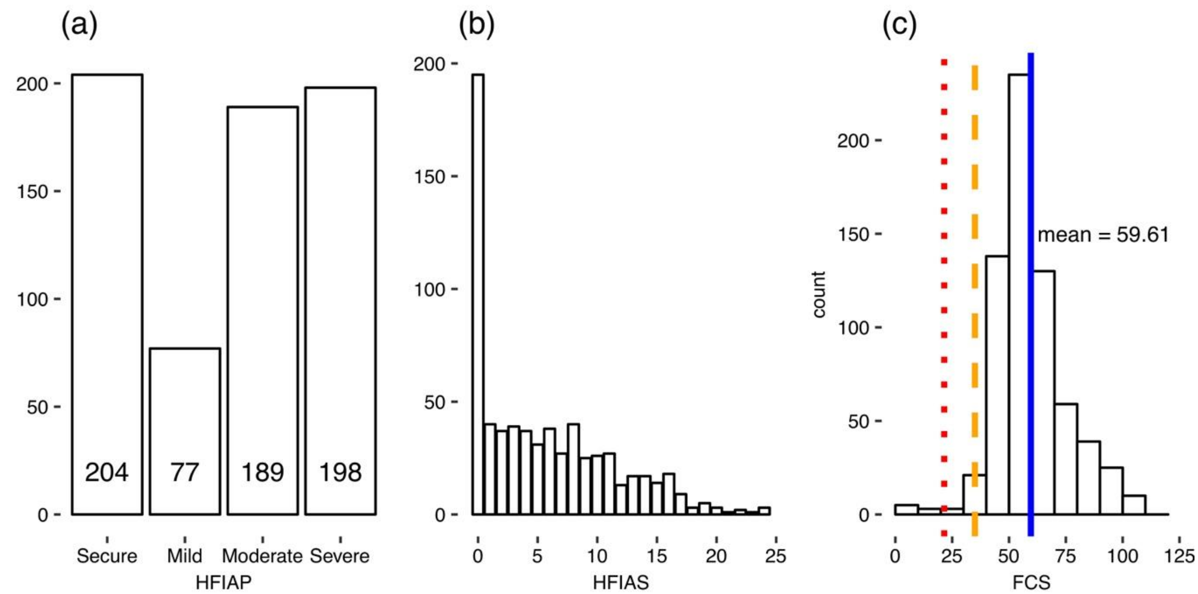

Figure 2 Distribution of the FCS (a), HFIAS (b), and HFIAP counts (c). Households below the red dotted line dotted line in panel A are food insecure (FCS < 21.5) and below the orange line are borderline food insecure (FCS < 35).

insecure (FCS < 35) according to the FCS (Fig 2c). This signals that households within our sample consumed sufficient calories over the previous seven days.

There is no correlation between FCS and HFIAS (Fig 3a) or between FCS and HFIAP (3b). In contrast, HFIAS and HFIAP are more closely correlated, with each being computed from the same information (3c). The increase in variance in HFIAS scores as HFIAP categories moves from secure to severe suggests that some sample households may not have answered "yes" to less serious HFIAS questions. For example, such households may have responded 'no' to the question "Did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food", but responded 'yes' to the question about a more serious situation, "Did you or any household member go to sleep at night hungry

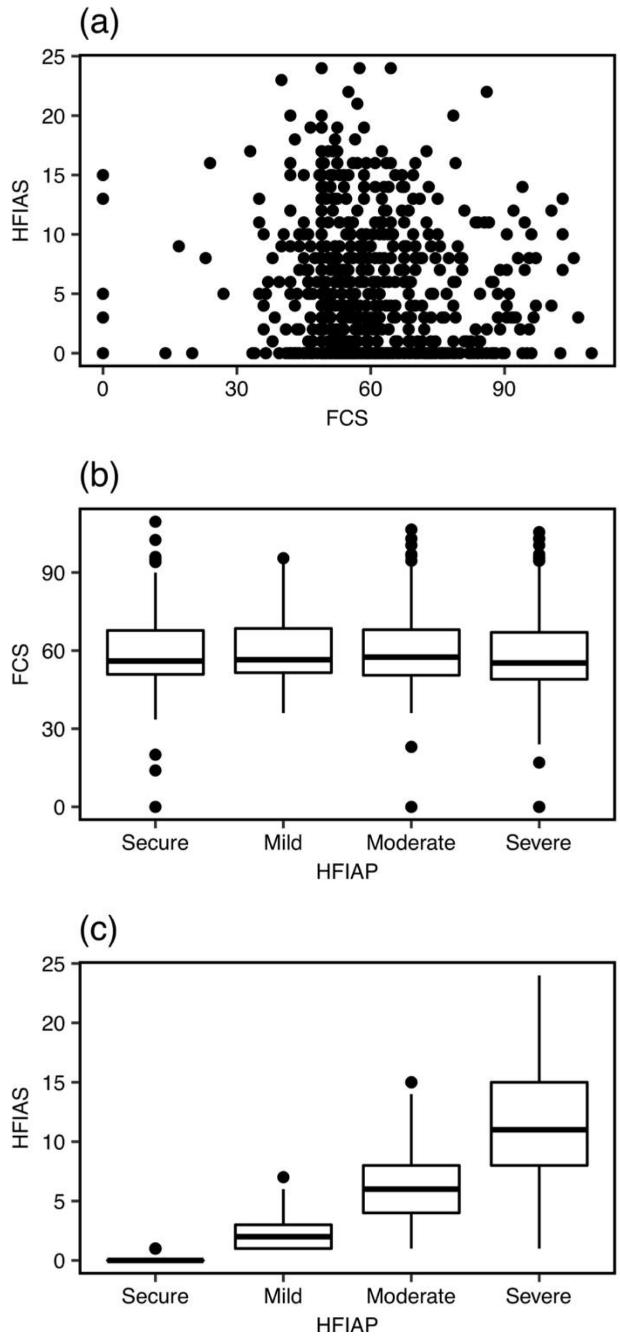

Figure 3 Household FCS plotted against HFIAS (a), as well as boxplots of FCS and HFIAP (b) and HFIAS and HFIAP (c). There is no correlation between the FCS and the HFIAS (a), nor HFIAP (b). There is greater variance in HFIAS scores among more food insecure HFIAP categories (c).

because there was not enough food?" Affirmative responses to questions such as these would place the respondent in the severe HFIAP category.

Across all three food security metrics, we find high spatial heterogeneity (Fig. 4). While cluster analysis was not performed due to the spatially discontinuous sampling between residential areas, no clear spatial pattern is visually evident in the point maps of all three measures of household-level food security. Overall, residential areas can be characterized as having a wide range of household-level food security outcomes across all three household-level food security metrics.

4.2 Drivers of Food Insecurity in Accra

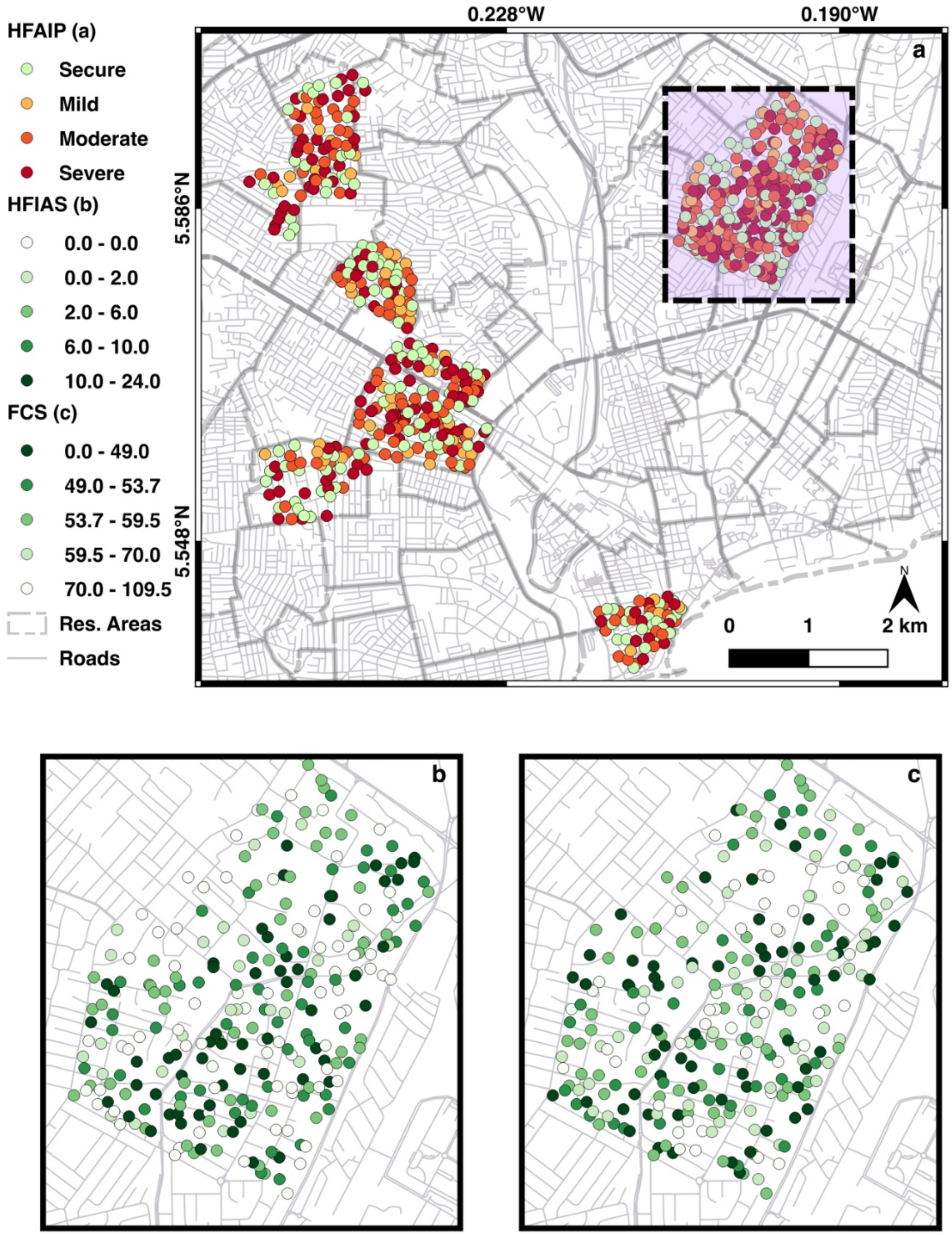

Figure 4 Spatial distribution of food security measured by the HFIAP for all sampled households (a). Household food security measured by the HFIAS (b) and FCS (c) also exhibited spatial heterogeneity as evident from zoomed in areas around Nima residential area of Accra. For the HFIAS and FCS intervals are derived from sample quintiles. Five households are excluded due to inaccurate GPS coordinates.

The estimates across the suite of linear models are largely consistent for HFIAS and HFIAP, but differ for FCS. Household demographic composition plays an important role in determining food security outcomes measured by HFIAS and HFIAP (Table 2, Table 3). Across HFIAP categories, smaller households have a greater likelihood of being food secure. But the size of the household has no significant effect on FCS. The HFIAS logit model suggests that larger households tend to have a greater likelihood of food insecurity. Though the effect size is near zero, households with an older head have a greater likelihood of being food secure according to HFAIP. The slum index has no significant effect across all four models, nor does the sex of the household head. The lack of a significant relationship between household demographics, household composition, and slum conditions with FCS suggests that household diet and food consumption is sufficient across all households no matter the composition or quality of housing.

Table 2 Predictors of household Food Consumption Score (FCS) and Household Food Insecurity Access Scale (HFIAS).

	Food Consumption Score (FCS)		**Household Food Insecurity Access Scale (HFIAS)**		**Household Food Insecurity Access Scale (HFIAS)**	
	ordinary least squares model		**negative binomial model**		**logit model**	
	Estimate	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
Age of household head, years	-0.078	0.043	0.637	0.004	-0.014	0.007
Household size	-0.087	0.543	0.007	0.046	0.308**	0.100
Male head of household, 0/1	1.876	1.260	0.100	0.106	-0.260	0.220
Asset Index	0.637	0.408	0.000	0.037	-0.406***	0.075
Receives remittances, 0/1	4.289**	1.307	0.735	0.110	0.063	0.228
Slum Index	2.704	5.200	0.228	0.438	1.054	0.935
No school, 0/1†	-0.835	2.962	0.006	0.244	1.153	0.594
Primary school, 0/1†	-1.305	1.759	0.594	0.149	0.583	0.298
Secondary school, 0/1†	-0.681	1.609	0.298	0.137	0.224	0.264
Household members employed, percent	0.816	0.747	0.220	0.063	-0.197	0.133
Self-employed, number	0.960	1.018	0.264	0.086	-0.096	0.178
Casually employed, number	0.752	1.512	0.178	0.125	0.310	0.299
Regularly employed, number	0.676	1.227	0.299	0.104	-0.161	0.209
Travel time to market, minutes	0.092*	0.036	0.935	0.003	-0.006	0.006

Free meals at school or work, 0/1	-1.056	1.620	0.209	0.135	-0.259	0.267
Meals given to non-household members	0.356***	0.106	0.267	0.009	0.000	0.020
Street food expenses, cedis	0.088*	0.041	0.020	0.003	0.031***	0.009
Total food expenses, cedis	0.005**	0.002	0.430	0.000	0.000	0.000
Control for language	Yes	Yes	Yes	Yes	Yes	Yes
Control for residential area	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	57.409***	3.643	0	0.306	0.954	0.637
Adjusted R-squared	0.181					

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ †Tertiary education is the reference category

While the highest educational attainment of any member within a household is not a significant predictor of FCS, higher education significantly increases household food security measured by HFIAS and HFIAP (Table 2, Table 3). Households that have members who attended or completed tertiary education (23.3 percent of our sample) have a greater likelihood of being in the food secure HFIAP category. This is especially evident between households with no adult members who received schooling and those households with members who have some tertiary education, with the greatest effect size among severely food insecure households with no education in the HFIAP ordered logit marginal probabilities model. In contrast, educational attainment was not significantly correlated to a households' FCS.

Table 3 Ordered logit marginal probabilities of a household being in a specific Household Food Insecurity Access Prevalence (HFIAP) food security category

	Secure		Mild		Moderate		Severe	
	Marginal Effect	Standard Error	Marginal Effect	Standard Error	Marginal Effect	Standard Error	Marginal Effect	Standard Error
Age of household head, yrs	0.003*	0.001	0.001*	0.000	-0.001*	0.000	-0.003*	0.001
Household size	-0.040**	0.015	-0.008*	0.003	0.010*	0.004	0.039**	0.014
Male head of household, 0/1	0.060	0.033	0.013	0.007	-0.014	0.008	-0.059	0.033
Asset Index	0.061***	0.012	0.013***	0.003	-0.015**	0.005	-0.059***	0.012
Receives remittances, 0/1	-0.033	0.034	-0.007	0.008	0.007	0.007	0.033	0.035
Slum Index	-0.213	0.137	-0.045	0.030	0.051	0.035	0.206	0.133
No school, 0/1†	-0.171***	0.045	-0.058*	0.023	-0.025	0.037	0.254*	0.102
Primary school, 0/1†	-0.099*	0.043	-0.023*	0.012	0.018*	0.008	0.104*	0.049
Secondary school, 0/1†	-0.062	0.042	-0.014	0.010	0.013	0.009	0.063	0.043
Household members employed, percent	0.030	0.020	0.006	0.004	-0.007	0.005	-0.029	0.019
Self-employed, number	0.013	0.027	0.003	0.006	-0.003	0.006	-0.012	0.026
Casually employed, number	-0.077	0.042	-0.016	0.009	0.018	0.011	0.075	0.041
Regularly employed, number	0.032	0.032	0.007	0.007	-0.008	0.008	-0.031	0.031
Travel time to market, mins	0.003**	0.001	0.001*	0.000	-0.001*	0.000	-0.003**	0.001
Free meals at school or work, 0/1	0.039	0.043	0.008	0.009	-0.009	0.010	-0.038	0.041
Meals given to non-household members	-0.001	0.003	0.000	0.001	0.000	0.001	0.001	0.003
Street food expenses, cedis	-0.004***	0.001	-0.001**	0.000	0.001**	0.000	0.004***	0.001
Total food expenses, cedis	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*	0.000
Control for language	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for residential area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ †Tertiary education is the reference category

A greater household asset index increases the likelihood of a household being food secure based on HFIAS and HFIAP (Table 2, Table 3), suggesting that household wealth is associated with household food security. However, the asset index is not significantly associated with FCS. Furthermore, household labor does not appear to play a role in determining the level of household food security. Both the labor type and the share of the household engaged in employment does not significantly affect food security across all four models.

Annual remittances are significantly associated with a higher FCS. Receiving remittances, all else equal, increases the FCS for a household by four score points. This highlights the potential for remittances and gifts as a mechanism to increase the quantity and diversity of a household's diet by raising disposable income to purchase higher-calorie foods or more diverse food types. Higher total monthly food expenditures also are associated with a higher FCS and with improved food security outcomes based on HFIAP. But the effect size is nearly zero. Total monthly food expenditures are not significantly associated with HFIAS.

Giving free meals to non-household members are significantly associated with a higher FCS. However, these variables are not significant determinants of HFIAS or HFIAP (Table 2, Table 3). The ability to give away meals may imply that those households have excess food. Longer travel times to markets are significant predictors of a higher FCS, as well as better HFIAP outcomes. We reason that household wealth may be the underlying driver here, suggesting that some households have the luxury of time to travel to more distant locations and thus have better food security outcomes. But the effect size of market distance measured in minutes is nearly zero. Finally, increased daily expenditures on prepared food purchased away from home from street food vendors, fast food outlets, or restaurants is significantly correlated with higher FCS, but also a greater likelihood of food insecurity based on HFIAS and HFIAP models. However, the effect size is nearly zero across all models.

5. Discussion and Conclusion

Low- and middle-income households in Accra may not suffer from insufficient calories according to dietary recalls such as FCS. The majority do, however, experience regular inability to access "sufficient, safe, and nutritious food to maintain a healthy and active life to access food to achieve", per FAO's definition of food security [62]. With 70% of our sample characterized by HFIAP as mildly to severely food insecure, it is clear that households regularly worry about having enough food and, at times, cannot access sufficient food to meet their needs. By this measure, our results agree with the handful of similar case studies from cities in SSA that have also shown high levels of food insecurity among low-income residents measured with HFAIS and HFIAP [30,37–40].

As previously stated, our sample is not representative of all low- and middle-income households in Accra. We did not survey households in informal settlements and less than five percent of sampled household heads had lived in Accra for fewer than five years. This in itself is striking. Even though these often-vulnerable groups—recent migrants and residents of informal settlements—were not included in the sample, the results show high levels of food insecurity. As such, severity of food insecurity measured by HFIAP is likely higher among Accra's newest and poorest residents. Furthermore, the extreme spatial heterogeneity of household food security measured by all three indicators—FCS, HFIAS, and HFIAP—reveal that low- or middle-income residential areas have a broad underlying distribution of household-level food security outcomes (Fig. 4). Because cities like Accra are changing so rapidly, some households may be achieving economic and educational advancements ahead of their neighbors. As noted by studies of socioeconomic and health status in Accra [50,51] , blanket terms that characterize residential as slums can be misleading. Interventions should account for the distribution of food security situations within low- and middle-income residential areas.

The HFIAS and HFIAP model results show that educational attainment, household assets, and the demographics of a household all associate with how households perceive their ability to access food. As sampled households primarily rely on purchased food to meet their needs—fewer than 3% of households source food from farming, gardening, or fishing—the ability to afford food ultimately underpins household-level food security in our sample. And while our results do not reveal the exact mechanisms in which these variables directly lead to higher or lower levels of experiences related to food security, higher educational levels, in case studies from around the world [63–65], have been shown to strongly correlate with decreased levels of poverty. Thus, vis-à-vis educational attainment, greater wealth increases a household's economic access to food, decreases anxiety related to procuring food, and may increase resiliency should prices increase.

Due to the poor correlation and model agreement between the HFIAS/HFIAP and FCS, we echo recent calls to develop multifaceted metrics specifically designed to measure food security in the urban context of SSA [11,26]. This is the first study to empirically confirm a weak correlation between dietary recalls, such as FCS, and experience-based metrics like the HFIAS and HFIAP, in the urban African context. These results do, however, parallel the results of Vaitla *et al.* (2017) in their much larger aggregate study that do not separate urban from rural households. Given the association between educational attainment and household wealth and HFIAS and HFAIP outcomes, our results indicate that the HFAIS and HFIAP do accurately capture, at least in part, household-level urban food insecurity related to ability access food. Poorer, less educated households may meet baseline caloric requirements measured by the FCS. But such households regularly experience situations and anxieties related to the inability to access food. Should food prices increase, all else being equal, these households' food security situation will likely worsen.

The HFIAS and HFIAP do have limitations when used alone. These metrics do not provide insights into how sourcing of food nor seasonality may play a role in decision making related to food security in cities. The HFIAS and HFIAP also do not explain the range of households' dietary preferences. One possible approach would be to capture multiple metrics that cover different aspects of household food security—e.g. dietary diversity, experiences, coping, and poverty—for each household and combine them into a single food security index, such as the World Food Program's Consolidated Approach to Reporting Indicators of Food Security [66]. But even metrics designed to specifically measure household-level food security in urban areas may not shed light on the broader urban food system, including infrastructure challenges, travel, food safety, and market governance [26].

Our results further buttress the need for a greater understanding of how the food security challenges of the urban growing poor will cascade into broader food systems and affect governance [22,25,26]. In spite of the growing importance of ensuring urban food security, development organizations are advocating for approaches geared toward enhancing rural livelihoods through off-farm employment as a means to stem the influx of migrants to cities while, at the same time, improving local agricultural output and sustainability[28]. This rural-centric focus neglects to fully account for the food security challenges of the growing urban poor [23]. Indeed, recent study conducted by the World Bank and FAO shows that on a global scale 50% of urban households can be characterized as food insecure while only 46% of rural households fit that criteria using an experience-based metric similar to the HFIAS and HFIAP [11].

Local governments do have options to shore up household urban food security. Our results showcase that ensuring access to high-quality education opportunities for all urban dwellers may strengthen food security in the long-term, as the results from the HFIAP models show that higher level of education are associated with fewer experiences food insecurity. But proven overarching urban policies—such as transportation and water and sanitation infrastructure improvements—in the medium term can reduce poverty-levels and disease-risk and may reduce vulnerability to food insecurity among low- and middle-income households. As our results suggest that household wealth correlates with higher levels of food security, local governments can also strengthen household food security directly by reducing the economic burden of procuring food. For example, expanding free school lunch programs for children may reduce the overall costs of purchasing food, especially for large households who have a greater likelihood of being food insecure based on our results.

Finally, governance plays an important role in the creation and structure of food systems within urban areas [11]. Both informal and formal governance arrangements of food retailing influence household food purchases and food security [67]. Tackling the problems of diverse governance requires a nuanced approach that balances the modernization of food retailing with the needs of low-income consumers and local vendors. Only one household within our sample reported ever purchasing food from supermarkets, despite the substantial influx of modern grocery stores. Thus, local governments should support policies that do not limit a household's access to traditional markets, street vendors and hawkers, and prepared street food to keep costs as low as possible for consumers [11]. This can include infrastructure improvements for local markets and vendors, as well as avoiding incentivization of multinational supermarkets over local retailers.

Ghana's urban transition has outpaced its neighbors, and, despite economic growth, our results add to the growing body of research indicating that many low- and middle-income urban households regularly experience instances of food insecurity. Policymakers across SSA should heed notice. International policy resonates with national leaders and thus initiatives such as the sustainable development goals often set national policy objectives and donor funding. The SDGs, notably, do not interlink the Goals 1 and 2—zero hunger and zero poverty—with the Goal 11, the development of sustainable cities [68]. This is despite the fact that the planet is now more urban than rural, and that urban poverty and economic inequality are at record highs. Our paper showcases that tracking SDGs 2 and 11 requires employing consistent and accurate tools to measure food security in urban areas.

Sustainable cities in SSA will depend on ensuring that the ever-expanding urban poor are food secure, at all times. Reports of widespread hunger stemming from the ongoing economic crisis in Venezuela, a country that is 88.2% urban, highlight the potential dire consequence of not ensuring stable economic access to food for all urban dwellers [1,69]. If the future of Sub-Saharan Africa lies primarily within cities, then to feed the future, policy and research agendas that focus on ensuring urban food security must be pursued.

CHAPTER II: VARIABILITY IN URBAN POPULATION DISTRIBUTIONS ACROSS AFRICA[3]

1. Introduction

Africa is projected to add 1 billion urban residents over the next thirty years, ballooning from 491 million in 2015 to nearly 1.5 billion by 2050 [1]. Such rapid urban growth presents a host of challenges for the continent's development prospects. Urbanization, the shift in the proportion of population from rural to urban areas, has not led to concurrent economic growth [2,3] nor equitable economic gain for the majority of Africa's urban dwellers. UN-Habitat states that over 50% of urban Africans live in slums today [4]. The development of basic services within cities—including water and sanitation, education, infrastructure, and public health—has not kept pace with the rapid increase in urban population [70]. Urban food security is a chief concern [11,30]. Numerous case studies have shown that most poor urban Africans regularly experience food insecurity [71]. Troubling research from South Asia suggests that some African cities may become inhospitable as climate change produces more frequent extreme temperatures in mid-latitude regions [13]. Together these mounting challenges raise concerns for Africa's ability to achieve United Nations Sustainable Development Goal 11 to "Make cities and human settlements inclusive, safe, resilient and sustainable" [72].

Our ability to understand the drivers of urban population growth and develop sustainable solutions to tackle the challenges Africa's urban settlements face is stymied by a lack of municipality-level population data for Africa. It is unclear how many people live in many of Africa's cities and towns, especially those with fewer than 1 million residents [73–75]. For many countries, censuses are infrequently conducted, can be unreliable [76], and most

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do not provide geo-located municipality-level population counts. At present, United Nations Population Division data is widely used to track urbanization across the continent. But UN urban growth projections often over-emphasize primary cities and have been shown to be previously incorrect [74,75,77–79]. UN data is only provided at the national-level and for select municipalities with populations greater than 300,000 residents [1], even though the UN estimated that in 2015 49% of Africans live in urban settlements with fewer than 300,000 people. Similarly, alternative census databases do not provide municipality-level data [80] nor geographic information that can be incorporated with other geo-referenced datasets [81].

Despite such data inadequacies, a diverse body of research has attempted to identify drivers of urban population growth in Africa [2,3,10,79,82–85]. Early work argued that Africa uniquely urbanized without concurrent economic growth [3], though this conclusion may be over generalized [2,82,83]. More recent research suggests that climate change may be amplifying urban population growth in drying regions across Africa [10,84,85]. While the drivers of urban growth are complex, climate change is already negatively affecting rural livelihoods [12,86–88], migration is a well-established response to environmental change [89], and rural-to-urban migration has been thought to be the predominate driver of urban population growth across the region [90]. Others suggests that, at least at the national-level, natural increase among urban populations may be contributing more to urban population growth than rural-to-urban migration [91]. Nonetheless, all of these studies either rely on UN national-level urban population estimates [2,82,83] or employ imprecise definitions of urban settlements [10]. Without geolocated population estimates for individual urban settlements delineated with contestant criteria in Africa, we cannot accurately assess the drivers of urban population growth, much less gauge how the distribution of Africa's urban population is changing within and between countries or across climatological zones.

Since the 1990s, researchers have generated synthetic gridded population datasets to overcome the lack fine-scale population data across the planet. These data sets are available at the continental scale at 1-km spatial resolution and are produced using geospatial modeling techniques that assigns individual pixels a population value based on spatial covariates derived from remote sensed imagery and/or auxiliary GIS data [76]. It is not possible to directly estimate the population of individual urban settlements with these data sets alone. The data are available in raster format, providing a continuous plane of population counts that do not delineate political boundaries or labels. Furthermore, the methodologies and input data used to generate gridded population data sets vary. To date, no study has compared urban settlement population estimates across gridded population data sets using a consistent methodology.

Our objectives are twofold. First, we develop comparative measures of how the Africa's urban population is currently distributed among over 4,750 individual labeled urban settlements across Africa. To accomplish this, we intersect volunteered geographic information (VGI) data from OpenStreetMap (OSM) with five gridded population datasets: WorldPop 2015; LandScan 2015; Global Human Settlement Layer Population Grid (GHS-Pop) 2000 and 2015; and the World Population Estimate (WPE) 2016. We delineate urban settlement extent with a standard population density threshold. Second, we assess how the distribution of Africa's urban population among small and medium-sized urban settlements (those with fewer than 5 million people) is changing within and between countries and across climate gradients using GHS-Pop 2000 and 2015 datasets. We employ two methods to evaluate changes in urban population distributions. First, we construct Lorenz curves and urban settlement Gini coefficients using GHS-Pop 2000 and 2015. Second, we examine urban settlement size distributions using the more traditional city rank size power law distribution exhibited by Zipf's law. This research showcases a novel methodology to measure individual urban settlement populations to highlight what urban growth trajectories may occur across Africa in light of broader environmental and economic challenges.

2. Data

2.1 Synthetic Gridded Population Data

The PopGrid Data Collaborative provides detailed information on publicly available gridded population datasets [92]. We use five datasets from four providers: WorldPop 2015 by the University of Southampton [93]; LandScan 2015 from Oak Ridge National Lab [94]; WPE 2016 by Esri Inc. [95]; and GHS-Pop 2000 and 2015, produced by the European Union Joint Research Center [96]. All datasets are available at 1-km grid cell, but the methodologies and input data vary [76]. WorldPop establishes spatial weights between area features and census population estimates by applying a random forest algorithm to a suite of remote-sensed derived land cover classes and GIS layers, such as distance to roads, and environmental data, including elevation and mean temperature, to estimate population counts [97]. In this study we use WorldPop data that is adjusted to United Nations national population estimates.

WPE couples remote-sensed derived land cover classes and GIS data, to develop weights for individual grid cells based on the likelihood that a given cell contains a human settlement. Finest-scale census data are then divided and apportioned to individual grid cells based on the likelihood weights. WPE validates their data by ensuring that populations for all countries total to national population estimates [95]. LandScan uses a dasymetric spatial model that relies on smart interpolation [98]. This approach proportionally allocates finest-scale available census data to each cell within a given census unit with model weights derived from remote sensed satellite imagery and GIS data [94].

GHS-Pop integrates the Gridded Population of the World version 4 (GPWv4) with the Global Human Settlement Layer Built-Up Grid (GHS-Built). GWPv4 apportions the finest scale census data available equally across grid cells within a given census boundary and does not use auxiliary remote sensing or GIS. The GHSL-Built grid is derived from a supervised learning land cover classification of LandSat imagery at 38 m spatial resolution. To produce GHS-Pop, GWPv4 is proportionally allocated to GHS-Built cells based on built-area density [99]. While WorldPop provides gridded population at five-year intervals from 2000 to 2020, GHS-Pop datasets are independently produced for each time point. GHSL-Built is constructed using Landsat mosaics at each time step (e.g. the GHS-Built 2000 uses images from 2000, while GHS-Built 2015 uses images from 2015) and GWPv4 derives population counts for target years by using a simple growth rate equation between two censuses [100,101].

2.2 OpenStreetMap

OpenStreetMap is a global collaboration to map the planet with VGI from anonymous contributors curated by the OpenStreetMap Foundation. All data are free to download and is continuously updated. Within the OSM typology, ‘places’ are known population settlements from which an urban hierarchy labels individual point locations, or “nodes”, as either a ‘city’, ‘town’, or ‘village. In this study, we use OSM point data for 950 cities and 8,863 towns in Africa. OSM defines cities as the largest urban settlement within a bounded political territory and towns as “An important urban centre, between a village and a city in size.” To our knowledge no study has combined OSM data with continental-scale gridded population datasets to identify individual urban settlements, though OSM roads are used as input data for WPE 2016 [95].

2.3 Moisture Zones

To demonstrate how our mythology can be used to advance our knowledge of how urban population distributions are changing across climate zones in Africa [10,85,89], we group our estimates of urban settlements according to moisture zones identified in HarvestChoice's 2009 agro-ecological zones (AEZ) map for Sub-Saharan Africa [102]. The AEZ map classifies moisture zones by using the length of growing period (LGP) based on moisture and temperature conducive to crop growth. LGP are estimated by the number of days where average temperature exceeds 5 degrees Celsius and precipitation plus soil moisture exceeds half the potential evapotranspiration. Arid zones have fewer than 70-day LGP, semi-arid 70- to 180-day LGP, sub-humid 180- to 270-day LGP and humid have over 270-day LGP. The AEZ is produced at approximately 10-km grid cells, though the final product is available at 1-km spatial resolution.

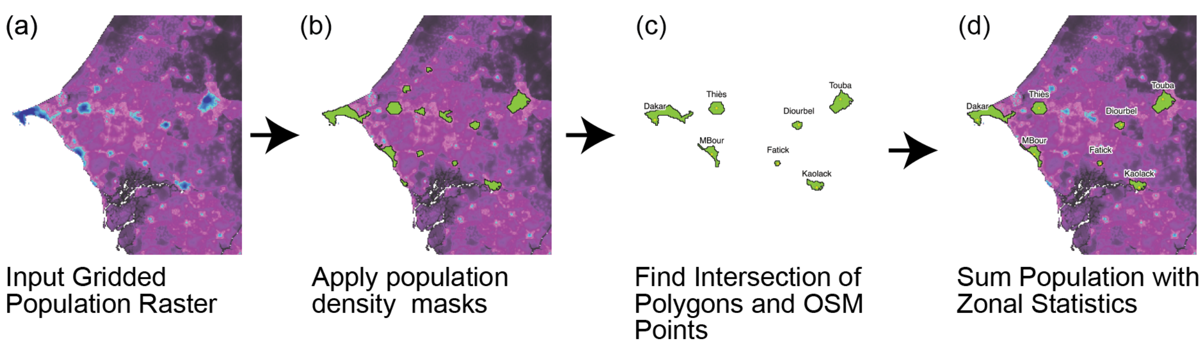

Figure 1 Workflow of method to intersect urban settlement 1,500-300 persons per km^2 density mask from gridded population raster dataset with associated labeled OSM urban point data to estimate the population of individual urban settlements in Africa.

3. Methods

3.1 Measuring Population of Individual Urban Settlements

We first clip gridded population datasets to an Africa continental GIS basemap available from Esri Inc. that was manually buffered to prevent coastal pixels from being dropped (Fig. 1a). Then we use a density threshold to identify urban vs. non-urban locations.

Strict population density thresholds are not necessarily the only criteria that identify urban settlements versus rural, nor do settlements necessarily follow a strict urban-rural dichotomy [103,104]. However, few alternatives exist for delineating labeled urban settlements from raster data without GIS jurisdictional boundaries. We use the European Union degree of urbanization (DEGURBA) classification [105] for high-density urban areas (cities) and lower-density urban clusters (towns and suburbs). First, we first mask pixels that contain at least 1,500 persons per km^2. Then we apply a second mask that includes pixels with at least 300 persons per km^2 that are connected to the urban cores identified with the first mask. We set all other pixels to zero, leaving the pixels containing the urban cores and extended suburban areas identified with the 1,500-300 persons per km^2 double density masks, which we transform into vector polygons (Fig. 1b). We recognize population density thresholds have limitations for application in Africa [73,79], but provide a consistent basis to evaluate differences across the gridded population datasets evaluated in this analysis.

Next, we find the spatial intersection between the urban settlement polygons delineated in each gridded population raster with the OSM city and town points (Fig. 1c). OSM points are buffered by ~250m to ensure that individual points do not fall just outside the bounds of the polygons. At the time of download, OSM listed 950 cities and 8,863 towns in Africa. Intersecting OSM urbans settlement points with the polygons derived from the destiny masks in the gridded population data sets provides an independent method to cross validate the location of urban settlements.

Table 1 Spatial agreement/disagreement OSM urban settlement point locations with masked 1500-300 persons / km2 urban settlement polygons isolated in gridded population datasets.

	GHS-Pop 2000	GHS-Pop 2015	WorldPop 2015	LandScan 2015	WPE 2016
Masked 1500-300 persons / km^2 urban settlement polygons	45,303	46,100	12,453	28,663	30,532
OSM "towns" that do not intersect with masked 1500-300 persons / km^2 urban settlement polygons out of 8,863 total OSM "towns"	3,441	3,025	5,612	3,704	3,692
OSM "cities" that do not intersect with masked 1500-300 persons / km^2 urban settlement polygons out of 950 total OSM "cities"	119	104	197	45	92
Masked 1500-300 persons / km^2 urban settlement polygons that intersect with one or more OSM urban settlement points and have >5,000 people*	4,486	4,784	2,536	4,045	4,167

* Retained for our analysis

We retain all urban settlement polygons that spatially intersect with one or more OSM city or town point. All else are dropped (Table 1). The retained urban settlement polygons are then overlaid on the original raster. We calculate the total population for each labeled urban settlement polygon using zonal statistics (Fig. 1d). Then each urban settlement is assigned to a moisture zone based on AEZ classification and grouped by country. Settlements that span international borders are clipped and allocated to their respective countries. Finally, we remove urban settlements with fewer than 5,000 people per DEGURBA criteria.

3.2 Estimating Change in the Distribution of Urban Population 2000 - 2015

We employ two approaches to estimate the change in the distribution of urban population for Africa, within and between select countries, and across moisture zones using GHS-Pop 2000 and 2015. First, we plot points along Lorenz curves and calculate urban settlement Gini coefficients. Lorenz curves and Gini coefficient can be used to quantify inequality, or size hierarchy, within a series [106,107]. Countries with Gini coefficients closer to zero have a larger share of the total urban population distributed among smaller and medium sized cities. Third, we assess the rank size distribution across all African countries following Zipf's Law for city size distribution [108]. For urban hierarchies in agreement with Zipf's Law, the second largest city has half the population of the largest, and the third largest city has a third of the population of the largest and so forth. This is expressed as:

$$R = KP^{-\alpha} \quad (1)$$

where R is a given city's rank, P is a city's population and K and α are constants. Here we estimate α by fitting using ordinary least squares (OLS) loglinear models.

As a focus of this paper is to examine how urban populations are changing among small- and medium-sized urban settlements, we remove settlements with greater than 5 million people from our distribution change analysis (Table 2). So called mega-cities [109,110] have received a disproportionate amount of attention from urban scholars [111] and have long been tracked with UN data. Furthermore, several urban settlements in our analysis exceed the largest urban mega agglomerations on the planet [1] and overly skew our ability to identity changes in urban population distribution among small and medium-sized urban settlements. For example, two polygons from Egypt in 2000 contain 33.20 million and 11.81 million people, respectively. By 2015 they merge together to form a single continuous urban plain with 83.46 million people that spans the entire Nile River Basin and houses nearly 90% of Egypt's population (Table 2).

Table 2 Urban Agglomerations with at least 5 million residents for GHS-Pop 2000 and 2015.

Country(s)	Agglomeration Name	Pop. 2000 (Millions)	Pop. 2015 (Millions)
Egypt	Cairo (Northern Nile Basin)	33.20	83.46
Nigeria	Lagos	9.66	13.73
Nigeria	Onitsha (Niger Delta)	4.95	9.35
South Africa	Johannesburg	5.43	8.26
Sudan	Khartoum-Omdurman	4.70	7.64
Angola	Luanda	0.47	7.22

Algeria	Algiers	3.87	6.55
Nigeria	Kano	2.88	5.95
DRC	Kinshasa	6.47	5.79
Tanzania	Dar es Salaam	2.26	5.78
Kenya	Nairobi	2.60	5.12
Egypt	Al-Minya (Southern Nile Basin)	11.815	Joined to Cairo Agglomeration

4. Results

4.1 Comparative Estimates of Africa's Urban Population by Settlement Size

The total number of Africans estimated to be living in urban settlements ranges from 479.15 for WorldPop 2015 to 608.89 million for WPE 2016. UN estimated that 491.53 million people lived in urban areas in 2015 [1]. Total urban population grouped by settlement size varies considerably by gridded population data sets (Fig. 2a), though across all data sets urban settlements with 1 to 5 million people encompass the greatest share of urban population by settlement size category (Fig. 2a) While UN data shows that 65% of urban Africans lived in urban areas with fewer than 1 million people in 2015 [1], our estimates range from 42% for LandScan 2015 to 50% for GHS-Pop 2015. However, unlike UN data, we provide population estimates for urban settlements with fewer than 300,000 inhabitants. For example, our results indicate that according to GHS-Pop 2015, 97 million people live in urban settlements with 100-300 thousand people and 117 million people live in settlements with fewer than 100 thousand people.

We estimate populations for between 2,536 individual labeled urban settlements with WorldPop 2015 and 4,784 with GHS-Pop 2015 (Fig. 3b). Our results show that 78% (WorldPop 2015) to 85% (LandScan 2015) of urban settlements contain fewer than 100,000 people (Fig. 3b). For example, among the 4,045 individual urban settlements identified in LandScan 2015, only 604 have greater than 100,000 people. Accordingly, the median population of urban settlement ranges from 20,245 for LandScan 2015 to 32,184 for WPE 2016.

Urban settlements with greater than 1 million people skew the distribution, with the WorldPop 2015 having the highest mean settlement population of nearly 190,000 people.

Intersecting OSM urban settlement location data with gridded population data sets to identify urban settlement populations significantly reduces noise produced by density thresholds alone and provides independent validation that an urban settlement exists at a given location within a gridded population data set (Table 1). But the density thresholds we employ results in substantially divergent urban settlement boundaries across datasets, as well as differences in agglomeration connectivity. This is especially evident for heavily urban regions, such as the Nile River Basin. With WorldPop 2015, we identify over 50 disparate urban settlements in the Nile River Basin, still with one housing over 40 million people living in the Cairo agglomeration. But with GHS-Pop 2015, only 15 individual settlements are mapped and the largest contains over 80 million people. The divergences among the gridded population are also evident from the difference in the of distribution of urban settlement population (Fig. 3b), with LandScan 2015 capturing substantially more small urban settlements compared to the other datasets.

4.2 Change in Urban Population Distribution 2000 - 2015 by Country

Including agglomerations with greater than 5 million people, our analysis of GHS-Pop shows that Africa's urban population expanded from 382.68 million to 607.92 million from 2000 to 2015, a 59% increase. This exceeds UN estimates

Figure 3 Urban population group by

stating that the continent had 286 million urban residents in 2000 and 491 million in 2015 [1]. Across the continent, the largest urban settlements absorbed the

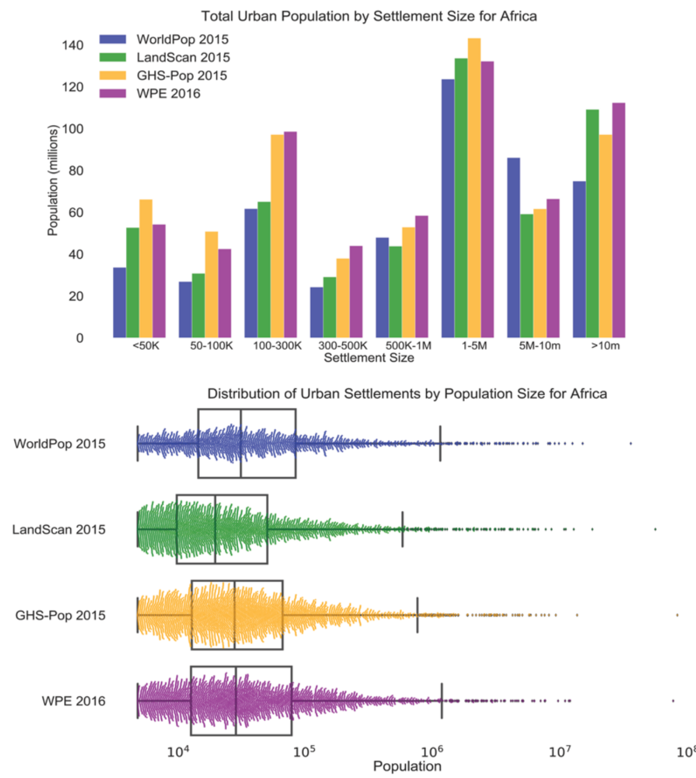

Figure 2 (a) Total urban population by settlement size and (b) distribution of individual urban settlement populations for WorldPop 2015, LandScan 2016, GHS-Pop 2015 and WPE 2016.

greatest share of urban population growth (Fig. 3). Urban areas with 5 - 10 million people expanded by 225%. However, as noted above with the example of the Nile River Basin, there is evidence that much of this growth among large settlements is a result of urban agglomerations growing together. For small- and medium- sized urban settlements, those with 100 - 300 thousand people, 300 - 500 thousand, and 500 - 1 million inhabitants expanded 40%, 44%, and 61% respectively.

Even with urban settlements with greater than five million people removed, the Lorenz curves and Gini coefficients indicate that the distribution of urban settlements in Africa is becoming more unequal, with larger cities absorbing a greater proportion of urban population

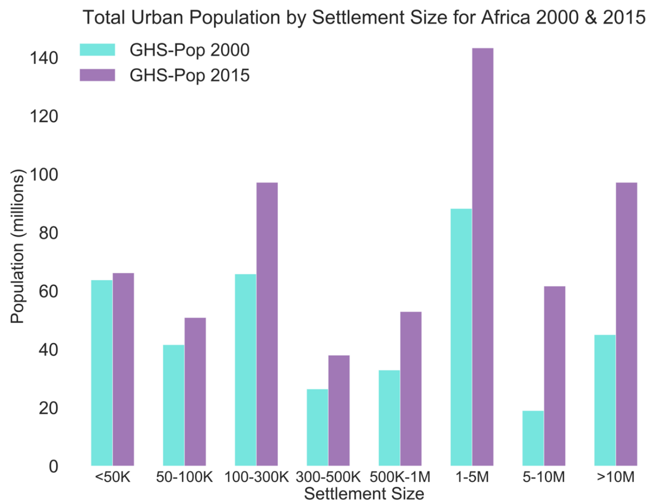

Figure 3 Urban population group by settlement size for GHS-Pop

growth. For most African countries, urban settlement Gini coefficients increased, signaling that the share of total urban population living in the largest urban settlement increased between 2000 and 2015 (Table 3). Countries with larger changes in Gini coefficients tended to have relatively larger increase in median population. Nonetheless, substantial variation exists across countries (Table 3). Decreasing Gini coefficients for countries like Botswana indicate that smaller urban settlements may be growing faster than larger urban settlements. For countries like Ghana, a decrease in the number of urban settlements between 2000 and 2015 suggest that settlements grew together (Table 3). Additionally, the noticeable deviations in rank-size α values from 1 suggest that the rank-size distribution of African urban settlements does not follow Zipf's law (Table 3), though this is not unexpected [108,112,113]. Visually this is quite apparent for countries like Nigeria and Ethiopia, where the log ranked size plotted against the log population is nonlinear (see supplement).

The Lorenz curves can be employed to examine differences in urban settlement distributions that are not apparent from the Gini coefficients alone. We see that both the shape and changes in Lorenz curves vary widely across African countries (Fig. 4 - see supplement for all countries). We can quantify these differences in the Lorenz curves with ranked settlements size quantile thresholds. For example, in Kenya in 2015, the bottom 90% of urban settlements had fewer than ~272,000 people and housed about 28.6% of Kenya's urban population in 2015. In contrast, about 54% of Ethiopia's urban population in 2015 lived in the bottom 90% of urban settlements, those with ~150,000 people or fewer, showing that urban Ethiopians tend to live in smaller urban settlements compared to urban Kenyans.

We can also assess how distributions are changing overtime. For instance, Ghana exhibited a large shift between 2000 and 2015, decreasing from 39% to 30% of its urban population living in the bottom 90% of urban settlements ranked by size. The 90% threshold increased in Ghana to about 100,000 in 2015 from about 80,000 in 2000. Africa-wide, excluding agglomerations with greater than five million people, about 36% of the total urban population lived in the bottom 90% of urban settlements in both 2015, down from 37% in 2000. The 90th percentile threshold, however, increased from 124,000 to 173,000 residents from 2000 to 2015. Because United Nations population data is not provided for all individual urban settlements this type of analysis is not possible.

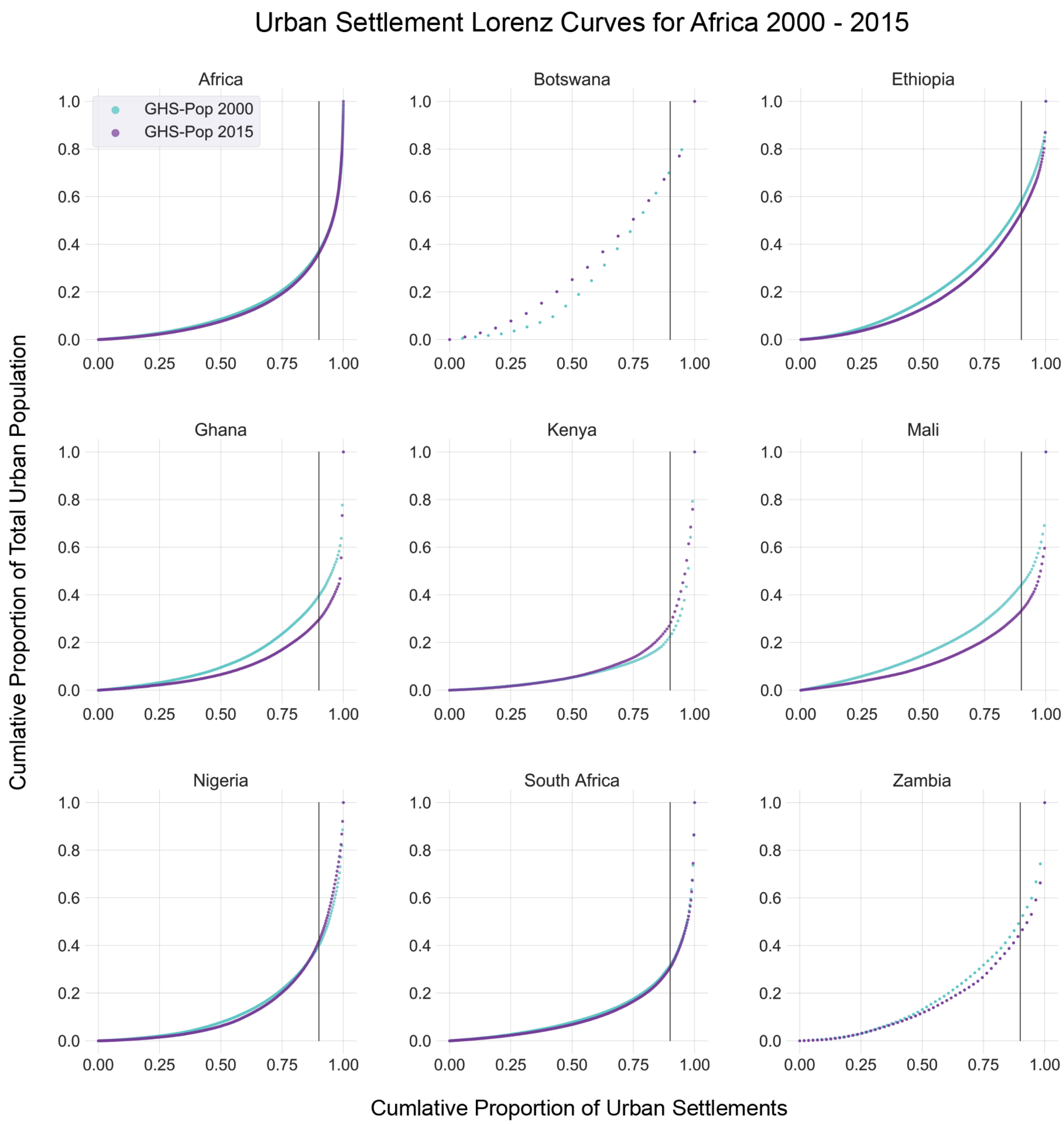

Figure 4 Urban settlement Lorenz curves using GHS-Pop 2000 and GHS-Pop 2015 data for Africa and select countries (see supplement for all countries). The vertical line delineates the 90th percentile of settlements ranked by size. Plots are arranged alphabetically. Botswana's Lorenz curve shifted to the left, signifying that smaller urban settlements absorbed a greater share of urban population growth between 2000 and 2015. Note that agglomerations with greater than 5 million people have been removed.

Table 3 Changes in urban population distribution in Africa measured by GHS-Pop 2000 and GHS-Pop 2015 Countries where settlements with greater than five million people removed have been removed demarcated with (num.) (see Table 1).

Country	Count 2000	Count 2015	Median 2000	Median 2015	Gini 2000	Gini 2015	α 2000	α 2015
Algeria	426	400(1)	19,881	26,643	0.65	0.59	-1.01**	-0.94*
Angola	71	80(1)	40,950	44,901	0.64	0.64	-0.65*	-0.69*
Benin	75	81	20,390	24,659	0.67	0.77	-0.84*	-0.73*
Botswana	19	16	48,728	61,392	0.45	0.37	-0.62	-0.97
Burkina Faso	73	82	26,733	30,689	0.62	0.71	-0.83*	-0.82*
Burundi	92	94	21,663	28,130	0.48	0.61	-1.09*	-0.91*
Cameroon	120	125	29,262	32,755	0.70	0.76	-0.77*	-0.7*
Cape Verde	8	10	16,800	17,383	0.32	0.37	-1.14	-1.05
Central African Republic	63	74	14,224	14,654	0.61	0.63	-1.03*	-1.01*
Chad	38	45	68,704	88,544	0.55	0.59	-0.65	-0.55*
Comoros	7	10	8,918	12,276	0.62	0.66	-0.44	-0.53
Congo	17	32	16,825	14,572	0.82	0.81	-0.49*	-0.6*
Côte d'Ivoire	103	107	23,139	27,446	0.73	0.75	-0.88*	-0.85*
DRC	260	292(1)	22,471	30,868	0.68	0.72	-0.8*	-0.72*
Djibouti	1	2	431,331	261,159	0.00	0.48	0***	-0.18***
Egypt	34(2)	21(2)	130,921	84,871	0.72	0.55	-0.49*	-0.56
Equatorial Guinea	7	7	13,952	20,062	0.55	0.60	-0.53	-0.44
Eritrea	4	5	78,033	58,831	0.58	0.67	-0.44	-0.35*
Ethiopia	338	394	34,785	43,123	0.53	0.59	-0.96*	-0.87*
Gabon	14	14	19,455	20,018	0.66	0.68	-0.68	-0.62*
Gambia	13	14	18,233	24,277	0.67	0.76	-0.67*	-0.61
Ghana	228	220	19,853	21,813	0.69	0.77	-0.89*	-0.81*
Guinea	92	96	16,859	20,073	0.67	0.72	-0.92*	-0.84*
Guinea-Bissau	19	20	19,313	25,216	0.58	0.66	-0.79*	-0.68*
Kenya	118	124	20,743	27,902	0.80	0.78	-0.72**	-0.68*
Lesotho	12	11	19,948	23,262	0.58	0.60	-0.73	-0.68
Liberia	20	26	17,415	22,135	0.71	0.75	-0.74	-0.74
Libya	52	58	15,736	16,102	0.76	0.79	-0.69*	-0.67**
Madagascar	57	68	14,951	22,193	0.70	0.75	-0.96*	-0.91*
Malawi	38	43	16,778	31,871	0.67	0.79	-0.86*	-0.7*
Mali	157	185	11,894	13,981	0.61	0.72	-1.16*	-0.99*
Mauritania	17	19	12,288	18,343	0.75	0.78	-0.67*	-0.65*
Mauritius	7	4	26,062	68,326	0.71	0.56	-0.47	-0.43
Morocco	200	204	23,212	26,240	0.74	0.77	-0.79**	-0.75**

Mozambique	131	140	31,225	38,357	0.62	0.65	-0.86*	-0.79*
Namibia	19	23	16,158	21,779	0.54	0.60	-0.89	-0.78*
Niger	49	71	26,958	24,747	0.66	0.71	-0.7*	-0.67*
Nigeria	315(1)	312(3)	47,794	61,423	0.70	0.71	-0.72*	-0.63*
Rwanda	48	42	21,999	32,626	0.58	0.72	-0.97*	-0.73*
Reunion	10	6	47,740	144,870	0.43	0.30	-0.68	-0.73
Senegal	78	86	22,702	30,342	0.72	0.75	-0.67*	-0.66*
Sierra Leone	35	39	13,246	15,998	0.69	0.76	-0.76*	-0.71*
Somalia	48	53	18,727	31,353	0.72	0.69	-0.76*	-0.72*
South Africa	303	329(1)	17,931	20,331	0.74	0.76	-0.84**	-0.8**
South Sudan	52	73	30,769	38,124	0.52	0.56	-0.79*	-0.77*
Sudan	88	98(1)	47,260	54,186	0.71	0.61	-0.62*	-0.62*
Tanzania	156	163(1)	16,574	27,088	0.70	0.65	-0.93**	-0.9*
Togo	33	37	38,722	42,500	0.67	0.72	-0.68*	-0.63*
Tunisia	82	81	32,559	32,828	0.67	0.71	-0.84*	-0.81*
Uganda	134	139	21,075	31,447	0.64	0.67	-1*	-0.91*
Zambia	56	55	52,955	65,434	0.60	0.64	-0.73*	-0.7*
Zimbabwe	44	43	29,509	33,291	0.73	0.76	-0.77*	-0.7*
Africa	4481(3)	4773(11)	22,871	28,482	0.71	0.72	-0.85**	-0.79**

** $p < 0.01$, * $p < 0.05$

4.2 Change in Urban Population Distribution 2000 - 2015 by Moisture Zone

The change between 2000 and 2015 in the share of urban Africans living in the largest urban settlements by size substantially varies across moisture zones. In arid regions, the share of total urban population living in larger urban areas, excluding settlements with greater than 5 million people, decreased substantially between 2000 and 2015. This is evident from the Lorenz curve clear leftward shift (Fig. 5). The bottom 90% of urban settlements in arid regions increased from 30% of the total urban population in 2000 to 40% in 2015. The 90th percentile threshold increased from 64,000 in 2000 to 86,000 in 2015. This indicates that small and medium sized urban settlements are growing faster compared to larger urban settlements across Africa's arid regions. We observe a similar, but considerably less pronounced, shift toward smaller and medium-sized urban settlements in sub-humid regions. About 35% of the total urban population in sub-humid regions lived in the bottom 90% of cities in 2000 increasing to

37% in 2015, with the threshold increasing to 145,000 from 115,000 people.

By comparison, in semi-arid and humid regions of Africa, larger cities are absorbing a

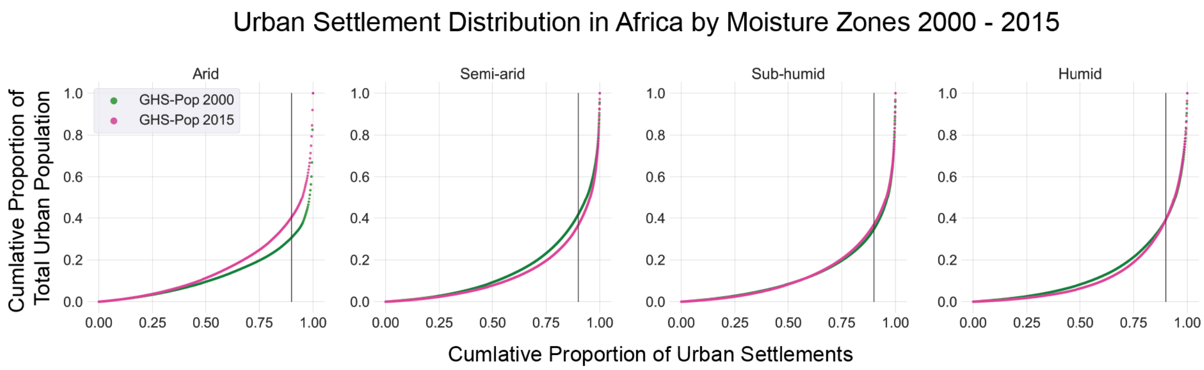

Figure 5 Urban settlement Lorenz curves using GHS-Pop 2000 and GHS-Pop 2015 for moisture zones in Africa. The vertical line delineates the 90th percentile of settlements ranked by size. The noticeable left-shift of the arid curve between 2000 and 2015 indicates that smaller urban settlements are absorbing more urban population growth than larger urban settlements. Note that agglomerations with greater than 5 million people have been removed.

greater share of urban population growth. In 2000, the bottom 90% of urban settlements—132,000 people or less—encompassed 42% of total urban population in semi-arid regions, dropping to 37% in 2015. Urban population distribution remained more stable in humid regions from 2000 - 2015. About 40% of urban dwellers resided in the bottom 90% in both 2000 and 2015, though the 90th percentile threshold increased from 137,000 to 254,000 people.

5. Discussion and Conclusions

The conventional narrative on urban population growth in Africa centers on primary and capitals cities. Yet UN estimates state that 65% of urban Africans lived in cities containing 1 million or fewer people in 2015 [1]. While our estimations are lower than UN numbers, showing that 50% of urban Africans live in urban settlements with 1 million or fewer in 2015, we confirm that small- and medium-sized urban areas contain a considerable portion of Africa's urban population. This may not be unique to Africa. UN data states that 54% of urban South Americans live in urban areas with fewer than 1 million people, though South America is 85% urban and Africa is only 41% [1]. But unlike UN data, our methodology provides an avenue to estimate the population of and the geographic distribution of these smaller urban settlements. We are able to detail how urban populations are distributed within and between countries, and across non-political geographies such as moisture zone. Indeed, this study offers the first assessment of urban population distribution in Africa using a consistent definition of urban settlement across countries.

Our results highlight that small- and medium-sized urban settlements in arid regions in Africa may be growing substantially faster than larger urban settlements. This finding complements recent research that shows climate change may be amplifying urban growth in drying regions of Africa [10]. Studies have shown that pastoralist and dryland farmers are facing heightened challenges in light of climate change [86,87]. We reason that, although decisions driving rural-to-urban migration are complex [89], these arid urban settlements may be growing in part because of ease of migration from rural communities to proximate market towns and regional hubs. These smaller towns may offer a greater chance at poverty alleviation compared to large urban centers as rural populations move to cities [114]. However, in the coming decades, an increasing number Africans will live in arid regions arid due to climate change [115] and, as these regions become hotter and drier, questions about the stability of these urban systems abound [10]. Unlike other urban population data sets for Africa, our results can readily be incorporated with raster datasets with continuous environmental variables, like precipitation and temperature, to gauge how pressure from climate change and climate shock may affect urban settlement populations at fine spatial scales and across non-political boundaries.

Pinpoint population measurement for among small and medium-sized urban settlements is key to accurately measuring SDG targets and indicators for sustainable urban development, poverty reduction and food security [76,116]. As noted, market towns and regional hubs may provide the best avenues of poverty alleviation [114]. We can hypothesize that smaller urban settlements have stronger economic connectivity within local economics, with food systems that rely on agriculture sourced from proximate areas, and stronger labour ties between with rural areas [40]. The economies in large African cities, in contrast, have greater connectivity into trans-African and global economy and thus greater exposure to external market forces [34,117]. Additionally, urban-rural land use teleconnections and food system linkages may vary by urban settlement size across agro-ecological zones [25,103]. The disparate connectivity surely presents unique food security and economic challenges that cascade across the urban hierarchy.

Last, we show that the distribution of African urban settlements does not follow Zipf's Law. This is not unexpected. Numerous studies have shown divergences from Zipf's Law for city rank size distributions [108,113,118]. While other rank size power law estimators have been proposed, the use of Lorenz Curves and urban settlement Gini coefficients provides a clear method to compare inequality within and between urban hierarchies.

Our results reveal divergences between gridded population data sets in measuring urban populations with a consistent methodology and also provide a contrast to United Nations urban population estimates. Differences between our results with UN urban population data may be a result of the UN relying on individual countries' definitions of urban areas, which can vary greatly [1]. We find variation among gridded population datasets, both in the number of settlements identified, the boundaries and populations of individual settlements defined by population density, and the aggregated number of urban Africans. But combining OSM urban settlement location data with gridded population data significantly reduces noise produced by density thresholds alone and provides independent validation that an urban settlement exists at a given location within a gridded population data set (Table 1). This is a key finding in particular for GHS-Pop where 46,100 unique urban settlements are identified in 2015 without the OSM integration. As such, the producers of GHS-Pop offer a GHS Settlement Grid product based on the GHS-Pop that may over-estimate the number of urban settlements in Africa.

But our results are not without limitations. First, the gridded population datasets that we employed all use census data from some countries, like Nigeria, that have been shown to be unreliable [119] and from several countries that have not conducted a census in over a decade [24]. Second, there is variation between datasets, both in the number of settlements identified, the boundaries and populations for individual settlements, and the aggregated total number of urban Africans. Variation may be due to divergences between spatial-covariates derived from remote sensing imagery and auxiliary GIS datasets. (For example, WorldPop uses Nighttime Lights satellite imagery, while WPE 2016 and GHS-Pop 2015 do not). Additionally, because of the fluctuations in spatial boundaries for individual urban settlements, pairwise comparison of populations is not currently possible. As discussed with the case of Egypt, applying density thresholds in heavily urbanized regions can be problematic. Future research should address the discrepancies between datasets and develop best-estimates across gridded population datasets or pixel-level confidence intervals for individual data products.

Africa's urban population is expanding rapidly. This paper offers insights into not only how to pinpoint urban population pressures, but also presents a methodology to evaluate how these pressures may be changing. Growth of small and medium-sized urban settlements has implications for how rural-to-urban migration may unfold in the coming decades and what structures of urban governance can enhance the potential for desirable pathways of urban development. Our estimates indicate that small- and medium-sized urban settlements house the majority of urban Africans today and that these types of settlements may be growing fastest in arid regions—areas that are most vulnerable to climate change.

CHAPTER III – GLOBAL URBAN POPULUATION EXPOSURE TO EXTREME HEAT

1. Main Text

More than half of humans live in urban settlements [1] that are increasingly exposed to extreme heat due to climate change [16–20]. As temperatures rise, these urban populations face serious threats to human health [14]; labor productivity, economic output, and poverty reduction [120–124]; and increases in mortality [17,18], violence, and political instability [125,126]. Despite the urgent implications, there has been no globally extensive, fine-scale synthesis of urban population exposure to extreme heat. As such, we have limited ability to implement targeted strategies to temper the harmful and inequitable impacts extreme heat places on urban populations [127–129].

Recent coarse-grained (1.5° resolution) analysis showed that 31% of the world's population is exposed to extreme heat conditions for at least 20 days each year [17]. But developing a longitudinal, fine-resolution global analysis of urban population exposure to extreme heat has been stymied by a lack of observational data. In-situ temperature reporting has declined over the past three decades [130], especially in rapidly urbanizing, low-latitude countries most susceptible to extreme heat [17]. From 1983 to 2016, station-based daily observations of temperature maxima declined globally from 5,900 to 1,000 [130]. Additionally, multi-temporal, fine-scale urban population estimates have also not existed [76,131]. Like temperature data, this data limitation is especially acute in Africa [131], which is expected to host nearly half of the planet's 2.3 billion new urban residents by 2050 [1].

Here we estimate daily urban population exposure to extreme heat for 13,115 cities from 1983 to 2016. We define urban population exposure to extreme heat—referred to henceforth as exposure—in person-days, the number of days per year where the heat index exceeds 40.6 °C (≥ 105 °F) multiplied by the total urban population exposed [16]. To accomplish this, we harmonize a new quasi-global, fine-resolution (0.05° spatial resolution) daily temperature maxim estimates with the first globally uniform, geo-located urban population and spatial extent dataset. For each urban area, we calculated area-averaged daily heat index maximums (HI_{max}) following the US National Oceanic Atmospheric and Administration's procedure [132]. HI_{max} is derived from the Climate Hazards center InfraRed Temperature with Stations daily temperature maximum ($CHIRTS_{daily}$) and down-scaled daily humidity estimates from ERA5 climate reanalysis [133]. $CHIRTS_{daily}$ has been shown to be the most accurate fine-resolution, global daily temperature maximum product in crucial data-sparse regions such as Sub-Saharan Africa, the Middle East, and Southern Asia [134].

We calculate the average annual rate of increase in exposure (person-days yr^{-1}) at the global, regional, national, and municipality-level from 1983 - 2016. At each spatial-scale, we measure and map the relative contribution to the increase in exposure from population growth versus urban warming. This analysis does not decouple urban warming due to the urban heat island (UHI) effect——an amplification of temperatures in urban areas relative to proximate rural areas due to the features of the urban environment [135]—from urban warming due to climate change. We do identify which urban areas have warmed the fastest by measuring the increase in the number of days per year where HI_{max} > 40.6 °C. Finally, we examine anomalously warm years for select regions to showcase our data's ability to identify previously un-documented heat waves in data-sparse regions.

Globally, exposure increased almost 150%, from 118 billion total person-days in 1983 to 291 billion person-days in 2016 (Fig. 1a). Exposure grew by 5.2 billion person-days yr^{-1}, of which population growth contributed 3.9 billion person-days yr^{-1} (Fig. 1b). Urban warming represented the remaining 26% of the annual rate of increase in exposure, contributing 1.4 billion person-days yr^{-1} (Fig. 1c).

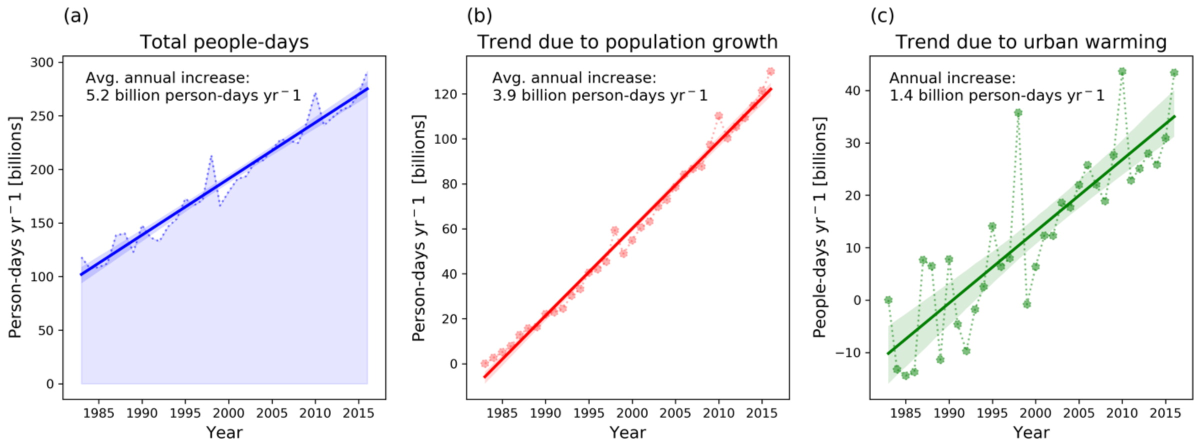

Figure 1 **(**A) Total urban population exposure to extreme heat from 1993 - 2016, with the contribution from population growth (B) and urban warming (C) decoupled.

Southern Asia experienced the greatest change in the amount of exposure, which increased by 1.9 billion person-days from 1983 to 2016, 36% of the global total. Southeastern Asia followed, increasing by 994 person-days yr^{-1}. Urban warming contributed 28% of the annual rate of increase in exposure in Southern Asia and 26% in Southeastern Asia. In contrast, throughout Europe the annual rate of increase in exposure was substantially lower, but urban warming contributed a greater share of the trend. For example, urban warming contributed nearly 97% of the 8 million person-days yr^{-1} increase of the rate of exposure in Eastern Europe.

For Africa, exposure increased from 15 billion people-days in 1983 to 50 billion people-days in 2016. Of this five-fold increase, urban warming contributed 17% of the annual rate of increase in exposure from 1983 – 2016. Sub-Saharan increased by 887 million person-days yr^{-1}, with 16% of the annual rate of increase in exposure from urban warming. Of the 137 million per-days yr^{-1} added rate of exposure in Northern Africa, urban warming contributed 23%.

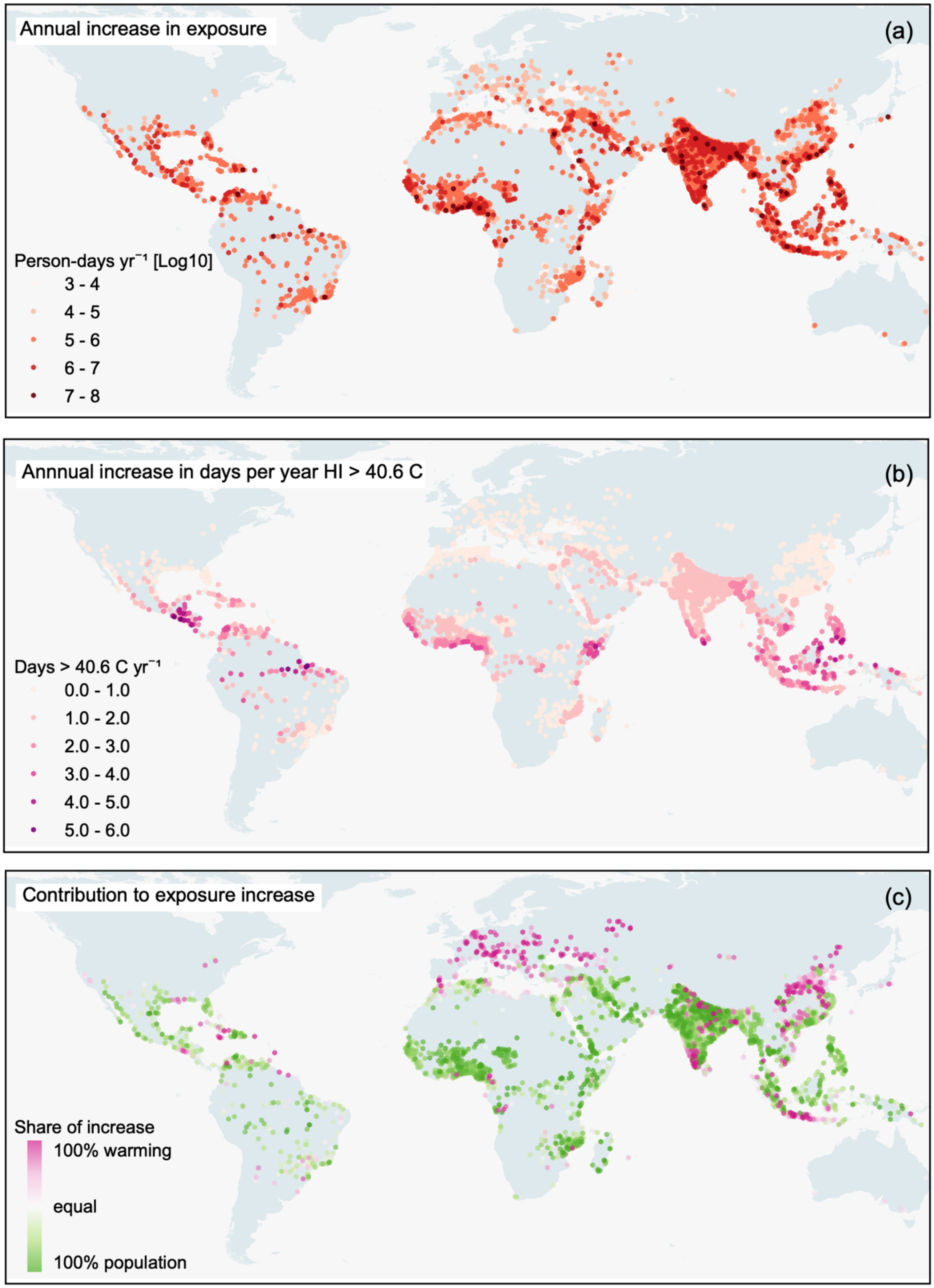

Figure 2 (a) Municipality-level increase in the rate of urban population exposure to extreme heat from 1993 - 2016 and (b) the rate of increase in the total number of days per year where the urban heat index exceeded 40.6 °C. (c) The share of population versus urban warming in the rate of increase of total population exposure.

At the municipality-level, the annual rate of increase in exposure from 1983 - 2016 was statistically significant ($p < 0.05$) for 62.7% of urban areas globally (Fig 2a). The rate of exposure increased in most low-latitude urban areas, across a range of climate zones. For example, the annual rate of increase in exposure was significant for nearly 90% of urban areas in India. In West Africa, person-days yr^{-1} increased in 82% of urban areas in Nigeria and 97% of cities in Senegal. Rapidly growing mega urban agglomerations in the Global South had the largest annual rate of increase in exposure, on the order of 10^7 - 10^8 person-days yr^{-1}. Dhaka (110 million person-days yr^{-1}), Bangkok (94 million person-days yr^{-1}), Jakarta (93 million person-days yr^{-1}), Guangzhou-Hong Kong (89 million person-days yr^{-1}), and Manila (87 million person-days yr^{-1}) were the top five urban agglomerations, respectively. Nonetheless, many large European cities, like Rome and Athens, as well as several cities in the United States' Sunbelt region, exposure increased by 10^6 - 10^7 person-days yr^{-1}.

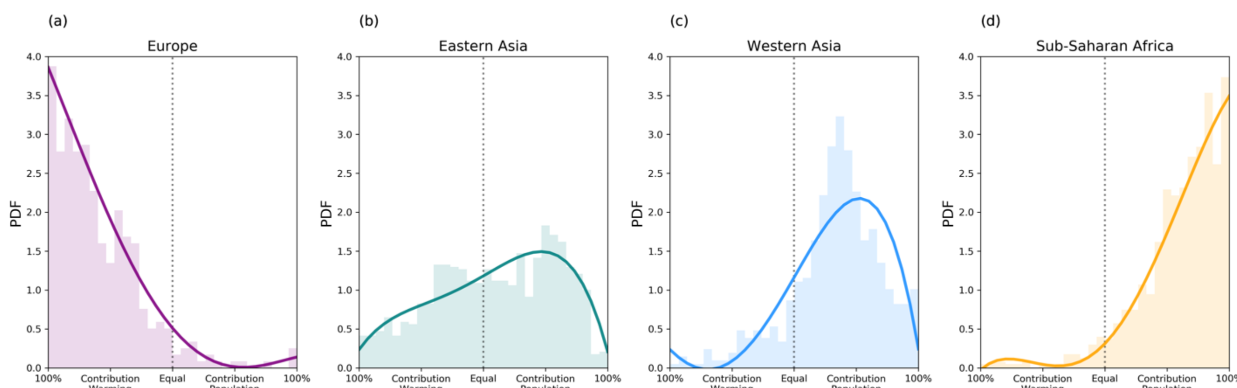

Fig 3 The comparative contribution to the increase in the rate of urban exposure to extreme due to population growth versus urban warming varies considerably across select regions. Fourth degree polynomial OLS linear fits were estimated to visually highlight the differences in distributions.

We estimate the increase in total number of days per year when the HI_{max} exceeded 40.6 °C to identify which urban areas are warming the fastest (Fig 2b). Over 4,100 urban areas, across a range of climatic zones, added at least one day per year where the heat index exceeded 40.6 °C. In other words, these urban areas experienced an additional month of extreme heat by 2016 compared to 1983. Strikingly, 150 urban areas across Central America, the Amazon

Basin, Western and Easter Africa, and Southern Asia added three or more days per year of extreme heat. This includes major cities like San Salvador (3.84 yr^{-1}) and Colombo (3.05 yr^{-1}).

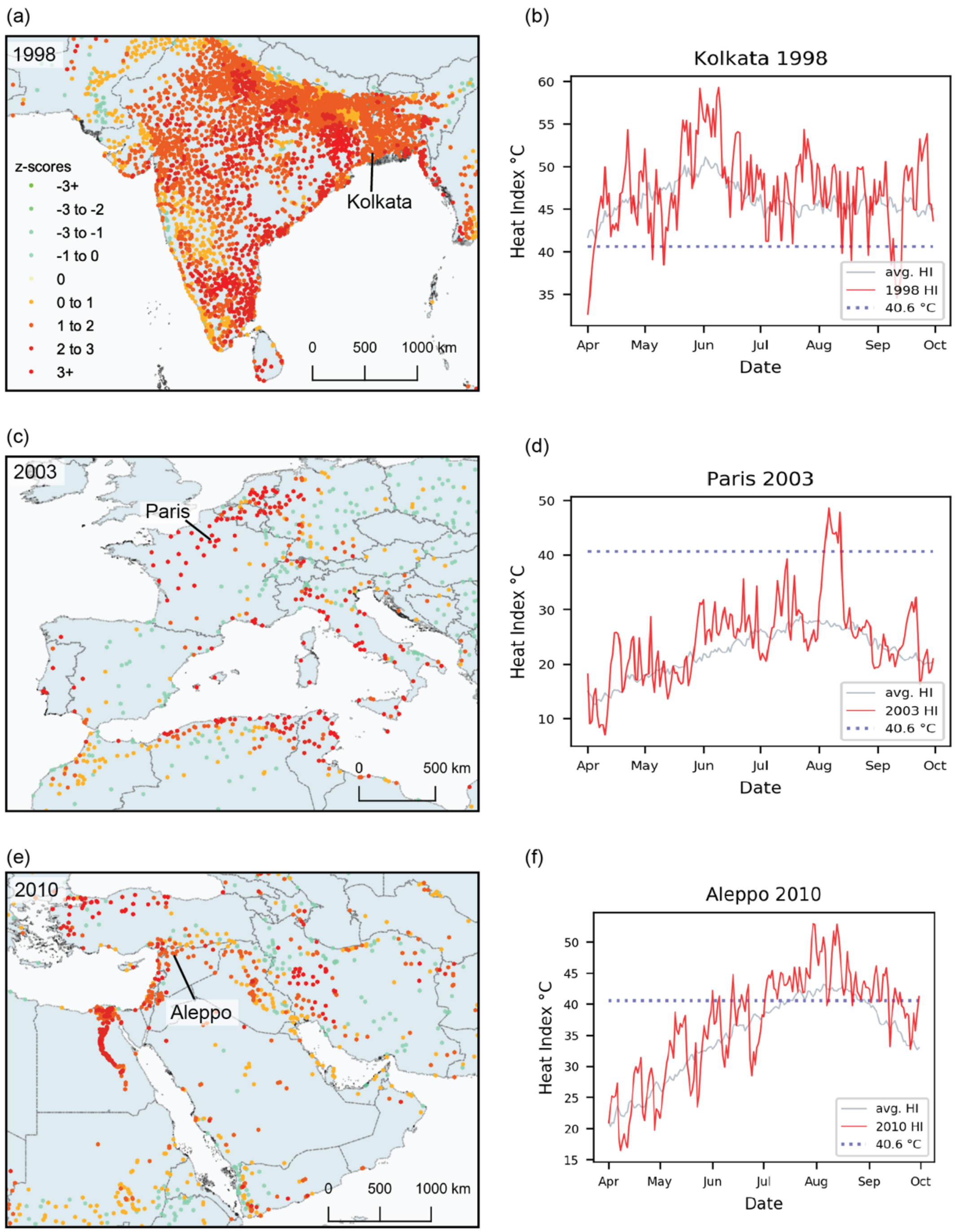

Figure 4 Anomalously warm years can be used to identify heat waves in individual cities.

Population growth was the primary contributing factor to annual rate of increase in exposure for the vast majority of cities across the planet (Fig. 2c). However, across Europe, inland China, coastal South Western India, and Java in Indonesia urban warming drove the increase in exposure. Surmised to the regional-level, the distribution of the contribution from urban warming versus population growth from 1983 - 2016 reinforces the stark geographic contrasts (Fig 3). The left skewed distribution for Europe (Fig. 3a) shows that urban warming drove the upward trajectory of person-days yr^{-1}. In Eastern Asia (Fig. 3b), we find a mix of warming and population growth, trending toward population growth in Western Asia (Fig 3c.), and Sub-Saharan Africa (Fig 3d).

In addition to assessing large-scale patterns and regional trends in annual exposure, we examine the dynamics of localized urban heat waves over the past three decades (Fig 4). For example, in 1998 heat waves in India were purported to kill thousands of people [136]. Accordingly, we find 1998 to be an extreme anomaly in the numbers of days where the heat index exceeded 40.6 °C for urban areas across India (Fig. 4a). We can then identify the duration and magnitude of individual heat waves at the daily scale for individual urban areas. In Kolkata, for fourteen continuous days in May-June 1998 HI_{max} exceeded 50° C (Fig 4b). During this period the average HI_{max} exceeded the 34-year HI_{max} average by 6.2 °C.

Similarly, we find extreme heat anomalies across Western European urban areas in 2003 (Fig. 4c). This well-documented hot summer killed up to 70,000 people in Europe [137]. We pinpoint the peak heatwave during August 2003 in Paris (Fig. 4d), with a 9-day period where HI_{max} was above 40.6 °C and exceeded longer-term daily averages by as much as 21.2 °C.

This approach can be used to pin-point poorly-documented heat waves in data-sparse regions as well. For instance, our dataset reveals that 2010 was anomalously hot across Middle Eastern urban areas (Fig. 4e). In Syria, this coincided with the final year of a 4-year drought. The occurrence of this drought was 2 to 3 times more likely because of climate change [138], which may have increased rural-to-urban migration and contributed to the political strife [138,139].

During the final summer of the drought, in Aleppo, Syria, we document a 36-day period in July and August 2010 with HI_{max} above 40.6 °C (Fig. 4f). Over this time, the average HI_{max} exceeded the 34-year-daily average by 4.2 °C. We find that a peak heat wave rolled through Aleppo from July 29 to August 6, during which HI_{max} exceeded 34-year daily averages by as much as 11.8 °C. This heat wave occurred just six months prior to the beginning of the Syrian uprising. While the likelihood of heat waves has increased for the Eastern Mediterranean since the 1960s [140], to our knowledge, urban heat waves during the summer of 2010 in Syria have not been documented nor quantified until now.

Our results call into question the future sustainability and equitability for many of the planet's ever-expanding urban areas. Across spatial scales, elevated temperatures sharply limits economic output [121–123]. Yet poverty reduction in urban areas ultimately hinges on increasing labor productivity [120]. Accordingly, the increased urban exposure to extreme heat across regions like Sub-Saharan Africa and South Asia, which currently house hundreds of millions of poor urban [141], highlight that extreme heat may crucially limit the urban poor's ability to realize the economic gains associated with urbanization [2,120,122]. Given that climate change is increasing the frequency, duration, and magnitude of extreme heat across the globe [16–20], our results have alarming implications for achieving the United Nations

Sustainable Development Goals 1 and 11—ending poverty and ensuring sustainable and equitable cities.

2. Materials and Methods

All data harmonization and analysis is conducted in Python 3.6.7 and maps are produced using QGIS 3.4.

2.1 Daily Temperature and Humidity Data

The new Climate Hazards center InfraRed Temperature with Stations daily temperature maximum ($CHIRTS_{daily}$) dataset provides a globally extensive, high-resolution (0.05°) daily maximum temperatures estimates from 1983 – 2016 [134]. By combining cloud-free harmonized geostationary satellite thermal infrared (TIR) observations with 15,000 in-situ station observations, the CHIRTS algorithm first estimates maximum temperatures ($CHIRTS_{monthly}$) monthly average estimates that are highly accurate ($R^2 = 0.8 – 0.9$) across the planet [130]. Next, daily temperature maximums values (e.g. $CHIRTS_{daily}$) are calculated by applying the difference between downscaled monthly average temperature maximums from European Centre for Medium-Range Weather Forecasts ERA5 Reanalysis (ERA5) [133] and $CHIRTS_{max}$ to daily ERA5 maximum temperature observations. This is expressed as:

$$CHIRTS_{daily} = ERA5_{daily} + (\overline{CHIRTS_{monthly}} - \overline{ERA5_{monthly}}) \text{ (eq. 1)}$$

Preliminary validation of $CHIRTS_{daily}$ against Global Historical Climatology Network and Global Summary of the Day databases show that $CHIRTS_{daily}$ consistently outperforms the commonly used Princeton University's Global Meteorological Forcing Dataset for land surface modeling [142]. Daily humidity data is produced by down-scaling ERA5 humidity estimates following the same processes to down scale ERA5 temperature data. ERA5 tempature and humidity data is downscaled from 0.67° longitude by 0.50° latitude to 0.05° by 0.05° using a bilinear interpolation.

2.2 Population Data

We use population estimates and spatial boundaries for 13,115 cities from the Global Human Settlement Layer Urban Centers Database (GHS-UCDB) produced by the European Commission Joint Research Council [105]. Released in 2019, GHS-UCDB is the only well-documented global, geo-located urban population and extent dataset. First a symbolic machine learning algorithm is applied to over 33,000 Landsat imagery from 1975 – 2014. The resulting product, GHS-Built, is a 1-km globally extensive raster dataset of total built surfaces across the planet in 1975, 1990, 2000, and 2015. Next, GHS-Built is spatially-intersected with un-modeled, census derived gridded population dataset—the Gridded Population of the World version 4 (GPWv4)—which is constructed by equally apportioning of the finest scale census data available across grid cells within a given census boundary. Population from GPWv4 is reallocated to grid cells based on the percentage of built area from GHS-Built. This resulting gridded population raster is called GHS-Pop.

Finally, a spatial smoothing algorithm is applied to GHS-Pop to find contiguous 1-km grid cells that have >1,500 people in GHS-Pop 2015 or > 50% of the pixel is built environment, which is then used to isolate urban settlement polygons boundaries. These polygons are then overlaid on the GHS-Pop rasters from 1975, 1990, 2000, and 2015 to calculate total population inside each polygon. Those with fewer than 50,000 people are removed. The GHS-UCDB dataset also contains the built area estimates for each urban settlement for all time points using the Landsat-derived estimates in the GHS-Built rasters. To estimate populations for each GHS-

UCDB polygon for each year from 1983 - 2016, we apply a stepwise linear interpolation to the 1975, 1990, 2000, and 2015 GHS-UCDB population estimates for each urban-area.

2.3 Data Harmonization

We convert the GHS-UCDB polygons to a raster dataset in the same coordinate reference system and spatial resolution as $CHIRTS_{daily}$ (WGS 84). We then calculate the daily area-averaged $CHIRTS_{daily}$ and ERA5 RH for each urban area from 1983 - 2016. We recognize the limitations of using an area-average to characterize the maximum daily 2-m air temperature and HR of an entire urban area, especially for large agglomerations that span multiple climatic zones [128]. However, widely-cited global and continental-scale urban heat studies report a single temperature for urban areas and it is unclear the spatial extent characterized by the temperatures employed in these studies [17,18,128]. We also note that $CHIRTS_{daily}$ is available at a finer spatial resolution than the temperature datasets used in recent global retrospective and predictive extreme temperature studies [17,18] and urban heat island effect studies [128].

2.4 Daily Urban Heat Index Estimates

We calculate daily maximum heat index values (HI_{max}) for each urban area following the National Ocean and Atmospheric Administration's guidelines (NOAA). The documentation is provided by the US National Weather Service (NWS) here: https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml. The final dataset contains ~150 million area-averaged daily maximum HI_{max} observations for more than 13,115 urban areas from 1983 - 2016.

First, area-averaged $CHIRTS_{daily}$ (referred here to as T_{max} for simplicity) values are transformed from Celsius to Fahrenheit. Next, daily HI_{max} values are calculated using Steadman's equation and averaged (eq. 2):

$$HI_{max} = \frac{(0.5 \times (T_{max} + 61.0 + ((T_{max} - 68.0) \times 1.2) + (0.094RH)) + T_{max}}{2} \quad \text{(eq. 2)}$$

If the resulting value is greater than 80 F, then we calculate HI_{max} for each city following Rothfusz equation (eq. 3):

$$HI_{max} = -42.379 + 2.04901523T_{max} + 10.14333127RH - 0.22475541T_{max}RH - .00683783T_{max}^2 - 0.05481717RH^2 + 0.00122874T_{max}^2RH + 0.00085282T_{max}RH^2 - 0.00000199T_{max}^2RH^2 \quad \text{(eq. 3)}$$

We then adjust the Rothfusz heat index values per NOAA's guidelines. For a given city on a given day, if T is between 80 and 112 degrees F and RH <13%, we subtract adjustment 1 from HI_{max} (eq. 4). If T is between 80 and 87 degrees F and RH > 85%, we add adjustment 2 to HI_{max} (eq. 5). We then convert all resulting maximum daily heat index values back to Celsius.

$$ADJ1 = \frac{0.25 \times (13 - RH) \times \sqrt{(17 - ABS(T_{max} - 95)}}{17} \quad \text{(eq. 4)}$$

$$ADJ2 = \frac{RH - 85}{10} \times \frac{87 - T_{max}}{5} \quad \text{(eq. 5)}$$

2.5 Urban Population Exposure to Extreme Heat

We subset the data to include only daily area-averaged HI_{max} greater than 40.6 °C, a commonly-used threshold to identify dangerous heat events [9,18,143]. By using a heat index (also referred to as apparent temperature), rather than 2m air temperature, we account for the nonlinear biophysical response to the relationship between humidity and air temperature [17]. Core body temperatures are almost universally maintained around 37 °C and skin temperatures around 35 °C [144]. Hyperthermia, elevated core body temperature, occurs when sustained elevated skin temperatures, resulting in death with core body temperatures around 42-43 °C [145]. While acclimatization can reduce the burden of heat [144], acclimatization only improves sweating mechanisms and the cooling effects of acclimated people have limits. As relative humidity increases, the evaporative cooling effects of sweating decreases and once relative humidity reaches 100%, sweating continues but evaporative cooling stops. Even acclimated or healthy humans face mortality with prolonged skin temperatures of 37–38 °C [146,147]. Thus, it is reasonable that sustained periods of time with HI > 35 °C are intolerable [148]. Accordingly, our use of 40.6 °C HI_{max} threshold is a conservative estimator of urban exposure to extreme heat.

We quantify urban exposure to extreme heat in person-days for each GHS-UCDB urban area from 1987 - 2016. Person-days is a widely-used metric to compare and contrast exposure to extreme heat across geographies and time periods [9,18,143]. For a given year (Y_i) and for a given urban area (j), we multiply the urban area's population (N_{ij}) by the number of days for year i where the HI_{max} > 40.6 °C ($Days_{ij}$ - eq. 6).

After summing exposure in person-days for each year at municipality, national, regional, and global scales, we evaluate annual rate of increase in exposure from 1983 – 2016 (person-days yr^{-1}) across spatial scales by fitting simple ordinary least squares linear regression models (OLS). For example, at the municipality-level, we estimate the rate of change (β_{exp}) from 1983 - 2016 in person-days yr^{-1} as exposure (Exp_{ij}) for year i from 1983 - 2016 with equation 7.

$$Exp_{ij} = N_{ij} \times Days_{ij} \text{ (eq. 6)}$$

$$Exp_{ij} = \beta_0 + \beta_{exp} Y_i + \varepsilon \text{ (eq. 7)}$$

Next, we fit simple OLS regression models to estimate the rate of change in the number of days per year where HI_{max} > 40.6 °C for each urban area (eq. 8). For both the rates of increase in exposure and days per year where $HI_{max} > 40.6$ °C, we subset the data to include only urban areas with statistically significant trends ($p < 0.05$).

$$Warming_{ij} = \beta_0 + \beta_{j-days} Y_i + \varepsilon \text{ (eq. 8)}$$

2.6 Contribution to Exposure from Population Growth verses Warming

We quantify the share of exposure from population growth versus urban warming for each urban area. For a given year *i* and urban area *j*, the share of person-days yr^{-1} from urban warming ($Heat_{ij}$) is calculated by multiplying the urban area's population constant at 1983 by the number of days per year $HI_{max} > 40.6$ °C (eq. 9).

$$Heat_{ij} = N_{83j} \times Days_{ij} \text{ (eq. 9)}$$

The share of exposure from population is calculated by multiplying $Days_{ij}$ by the increase in population since 1983 (eq. 10).

$$Pop_{ij} = (N_{ij} - N_{83j}) \times Days_{ij} \text{ (eq. 10)}$$

To measure the rate of change in $Heat_{ij}$and Pop_{ij}, we apply simply OLS regressions to estimate the average rate of increase in person-days yr^{-1}. The resulting coefficients, β_{pop} and β_{heat}, are the average rate of change in person-days yr^{-1} from population growth and heating, respectively. We use these coefficients to generate a bounded index to measure the relative share in the increase of exposure from urban population growth versus urban warming from 1983 - 2016. To this end, for a given urban area *j*, we normalize the annual rate of increase in person by subtracting the rate of person-day increase from population-growth from the rate of person-day increase due to warming divided by the annual increase in total coefficient of total person-day (eq 11). We then plot the distribution of this index for across all regions.

$$Index = (\beta_{pop} - \beta_{heat}) \div \beta_{exp} \text{(eq. 11)}$$

2.7 Extreme Heat Anomalies & Heat Waves

At the municipality-level for each year *i*, we identify the degree to which the number of days where $HI_{max} > 40.6$ °C varied from the average rate of change from 1983 - 2016. First, we use the OLS regression models for the number of days where $HI_{max} > 40.6$ °C (eq. 8) to predict values for 1983 - 2016. For each urban area for each year, we then subtract the observed numbers of days where $HI_{max} > 40.6$ °C from the predicted number of days where $HI_{max} > 40.6$ °C. To identify anomalously warm years at the municipality-level, we calculate the z-score of these residuals and then plot them for a given geography (Fig. 5).

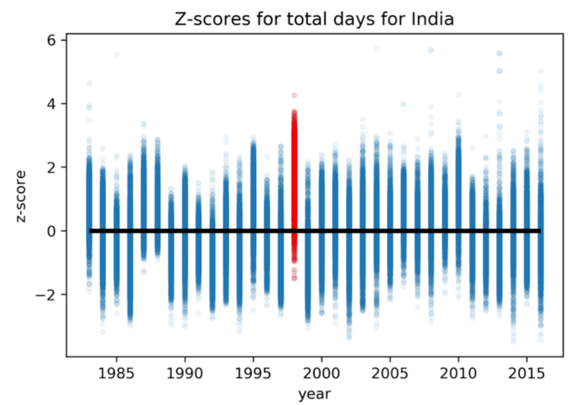

Figure 5 Municipality-level z-scores for the residual differences between the predicted number of days per and the observed number of days year where $HI_{max} > 40.6$ °C

While no universal definition for heat waves exists [20], we can use the z-score maps to identify spatial extreme heat anomalies. For example, [136], Figure X shows that across urban-areas in India, 1998 was an anomalously warm year in terms of the days per year where the number of days where $HI_{max} > 40.6$ °C, especially when the distribution of z-scores is plotted against the 34-year record (Fig. 6). We find a similar observation for France in 2003 and in Syria in 2010.

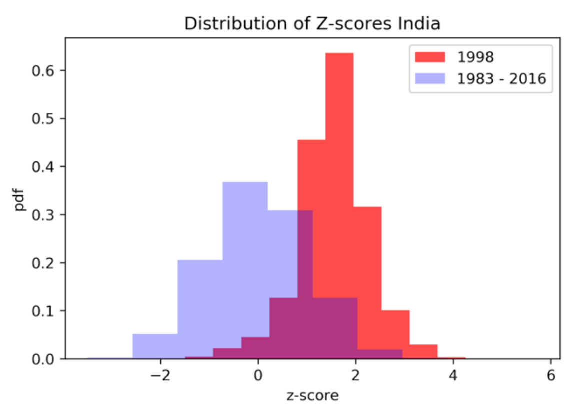

Figure 6 Municipality-level z-scores for the residual differences between the predicted number of days per and the observed number of days year where $HI_{max} > 40.6$ °C in 1998 and the entire 34-year record for India.

We then compare the daily HI_{max} for major cities for the anomalous years—in this case Kolkata, Paris and Aleppo—to the 34-year daily average to identify the duration, intensity and population exposed to anomalous heat waves.

CHAPTER IV – CONCLUSION

Food security, urbanization, and climate change are intractably linked. Yet, the results explored here reveal that these linkages are extremely complex. Detangling these processes to ensure the future equitability and sustainability of Africa requires fine-resolution and accurate data. While poverty may limit a household's ability to secure sufficient food, household-level urban food security is highly spatially heterogeneous. A single metric may not suffice to describe food security in one Africa city, much less an entire continent. Similarly, without fine-scale and reliable open access census data, measuring urban population dynamics will increasingly depend on novel geospatial and remote sensing analysis. These population estimates require analogous fine-scale climate data to understand how urban populations will be directly impacted by climate change. This is exemplified by the heterogeneous results of the global synthesis of urban population exposure to extreme heat explored in this dissertation.

Across all three themes—food security, urbanization, and climate change—ensuring a sustainable and equitable future for Africa's ever-growing urban settlements will require targeted approaches built on accurate fine-resolution data. This body of work takes the first crucial step towards building a foundation for holistic, yet fine-scale, analysis of these complex human-environmental dynamics.

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