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RESEARCH ARTICLE

Dynamics of population growth in secondary cities across southern Africa

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Abstract

Context Two-fifths of Africans reside in urban areas with populations of less than 250,000. Projections estimate that by 2050 an additional one billion people will live in urban areas, causing an acceleration of growth for these smaller urban areas. While research and development have focused on primary cities with large populations, less is known about the dynamics of urban growth in smaller, "secondary" urban areas (SUA's).

Objectives We document the spatial distribution and temporal patterns of SUA's in eight countries across Southern Africa between 1975 and 2015. We further explore the relationships between SUA's growth rates and climate, land use and geographic proximity to other urban areas.

Methods Our analysis integrates spatially explicit gridded population, land use, infrastructure and climate datasets. We use descriptive statistics and spatial lag and ordinary least squares regression models to quantify SUA growth rates across three periods and explore factors that are associated with the SUA growth patterns.

Results Average SUA growth rates are 2.44% between 1975 and 1990. We show that the climate, distance and land use significantly relate to urbanization trajectories. In addition, we find that the proximity of SUA to the largest cities also significantly relates to urban growth.

Conclusions Our results highlight the importance of SUA's within broader African urbanization trends. SUA are undergoing rapid population changes and are important components of economic development processes and livelihoods. Quantifying patterns of SUA urbanization is important for elevating these small but critically important urban areas into the broader context of sustainable urbanization in Africa.

Keywords Secondary cities · Urbanization · Africa · Climate migration · Population growth

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Introduction

In the last century urban populations have nearly doubled. Urban residents now account for more than half of the 7.7 billion global population, with 3.23 billion people living in urban areas in less developed countries alone (UN 2018). Population growth in many urban areas in the Global South has been rapid with growth rates in many cities exceeding the ability of municipal governments to provide basic services. Consequently, tens of millions of people live in poor housing, have inadequate access to water and electricity, and experience food and livelihood insecurity (UN 2018). As cities have grown, so too has their unsustainability, vulnerability and insecurity (Parnell et al. 2013). This current situation, coupled with large projected increases in future urban residents, makes developing healthy, safe and prosperous urban environments a pressing global challenge and an important component of meeting the United Nations' sustainable development goals (Wu 2014; Seto and Ramankutty 2016; Giles-Corti et al. 2016).

The spatial patterns of urban growth have long been a focus of research (Christaller 1933; Lösch 1940), and much is known about the factors that contribute to changing populations. They have been primarily driven by fertility and mortality rates, but rural to urban migration also plays an important role. This is particularly salient in regions like southern Africa where fertility rates are declining and as the age of the population becomes concentrated on working-ages, where mobility is highest (Lerch 2017). At the same time, land-use and land cover are important underlying dimensions of urbanization given the historical development of cities in areas with fertile soils and relatively abundant water resources (Forman and Wu 2016), and the expansion of urban growth into areas formerly used for agricultural production (Satterthwaite et al. 2010). It is important to consider future trajectories of urban growth in the context of resource sustainability given the interplay between urban expansion, food demand and resource limitations (Huang et al. 2015).

Urban planning that meets sustainability goals must therefore understand the sources and determinants of urban growth. There are numerous factors that act as "urban pulls" and rural "pushes." These include a concentration of financial investments in urban areas that create employment and education opportunities not available in rural areas (Bloom et al. 2008; Buhaug and Urdal 2013; UN 2018). In this respect, the proximity of urban areas has been identified as influencing urban growth rates (e.g. Braimoh and Onishi 2007; Christensen and McCord 2016). Additionally, climate has been suggested as a push factor. Droughts and drying trends, in particular, have been shown to cause displacement in Sub-Saharan Africa (Barrios et al. 2006; Henderson et al. 2017). Burke et al. (2015) further argued that climate shocks can generate conflict that then drives migrations. Other studies have shown both increasing and decreasing rates of migration following climate shocks, underscoring the complex interplay of social and environmental processes (Gray and Mueller 2012; Marchiori et al. 2012).

The complexity of urbanization and the need for urban sustainability plans (Forman and Wu 2016) requires an understanding of how urban places are shaped by their ecological, economic and social contexts (Wu 2010; Zhou et al 2017). Most of what is known about urbanization in the Global South, comes from research focused on the large, populous cities (McCall 1955; Fox 2012; Wolff et al. 2019; Mahtta et al. 2019). However, a substantial fraction of the urban population live in smaller urban areas. Cities with populations less than 500,000, for example, comprise about 26.5% of the world's population (Chai and Seto 2019) and more than half of the world's urban population (Buettner 2015). As of 2015, about 117 million lived in urban areas in Africa with fewer than 100,000 people, while an additional 97 million people lived in population centers between 100 and 300 thousand people (Tuholske et al. 2019). In fact, these small urban areas have experienced some of the fastest rates of urban growth (UN 2018). Smaller urban areas thus represent an important, and underemphasized, dimension of urbanization. Where studies have focused on smaller urban areas, they have done so for small spatial extents and short time spans (e.g. Rondinelli 1983; Todes et al. 2010), with the notable exception of Chai and Seto (2019) who characterized small urban areas in two African countries over a 26 year period. In a similar study, Xu et al. (2019) analyzed spatial patterns around 25 African cities from 1990 to 2014 finding that small cities have lower density and are more spatially distant from other urban areas. However, more than 140 million individuals live in urban places with less than 250,000 suggesting the importance of these towns and cities to overall patterns of urbanization in Africa (Satterwhite 2017).

A main constraint on understanding regional patterns of small urban area population growth in Africa has been access to demographic data. In this research we refer to these urban places as Secondary Urban Areas (SUA's). The commonly-used United Nations population database does not provide population estimates for urban areas with populations less than 300,000 people. Moreover, and relevant to city classifications, compiling cross-national data requires a considerable data harmonization due to inconsistent national census processes and periodicity (Cohen 2004; Potts 2018). The diversity in census methods and differing definitions of what constitutes populations across countries further result in variable data quality (Buettner 2015; Borel-Saladin and Parnell 2017; Wardrop et al. 2018). Consequently, only recently has it become possible to estimate growth patterns for smaller urban areas.

Recent advances in remote sensing-based approaches for urban area detection provides an alternative approach to analyzing smaller urban area growth patterns. Remote sensing methods have now produced global products of population density, human settlements and urban agglomerations (Leyk et al. 2019). Gridded population products overcome some of the limitations of decennial census-only approaches (Leyk et al. 2019). The PopGrid Data Collaborative has produced tools to compare different products (POPGRID 2020a), and Leyk et al. (2019) presented a comprehensive review of the multiple data products available.

Remote sensing-based population datasets, when coupled with other high spatial and temporal resolution gridded products for land cover and climate, have created new opportunities to characterize distributions of cities, the expansion of urban areas over time, and the factors that relate to dynamics of growth. Furthermore, Chai and Seto (2019) developed a novel remote sensing approach to identify the process of "micro-urbanization" or the development of smaller urban areas in remote locations. Along with these types of advances, leveraging remote sensing-based data for urban place detection present exciting opportunities for new work in understanding the distribution of smaller urban areas that have previously been difficult to study with census-based data.

The objectives of this research are to quantify the spatial distribution and temporal patterns of secondary urban areas in eight countries across southern Africa between 1975 and 2015. This analysis includes 629 SUA's and identifies climate, land use and geographic proximity relationships to differential trajectories of urban growth. This type of urban growth analysis is newly possible given the availability of multi-temporal gridded population data products that identify individual urban places and their population densities in what have been considered data-poor regions of the world.

Data and methods

We analyze population growth for SUA's in eight countries in southern Africa: Botswana, Lesotho, Malawi, Mozambique, Namibia, South Africa, Zambia and Zimbabwe (Fig. 1). We omit eSwatini (formerly Swaziland) from the analysis because it contains no SUA's that met our criteria (described below). We selected southern African countries because they have strong urbanization trends (UN 2018) and constitute a spatially contiguous area. Our analysis draws on spatially explicit datasets for population, land-use, road networks, and climate. We describe these in the next section.

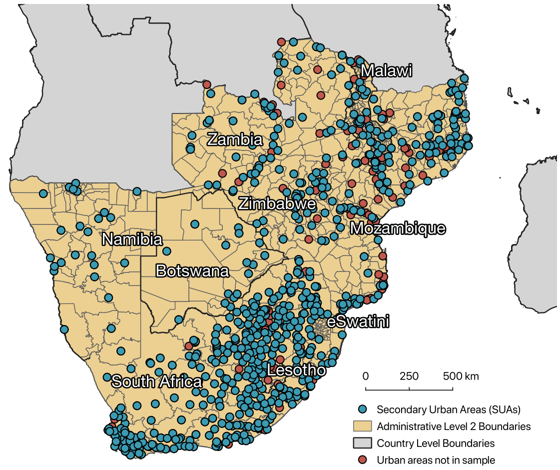

Fig. 1 Study location and SUA included in sample. Sample size for the group of SUA's is colored blue, and those areas not included in the sample are colored red

Data sources and derived variables

Table 1 presents the variables we use in our analysis. In the following section, we describe these variables and data sources.

Urban area population estimates are derived from the Global Human Settlements Population layer (GHS-POP). GHS-POP provides estimates of population for grids with a scale of 250 m resolution by integrating the Gridded Population of the World version 4 (GPWv4) with the Global Human Settlement Layer Built-Up Grid (GHS-Built). Essentially, GHS-POP represents the proportional allocation of GPWv4 to GHS-Built cells based on the built-up area density (GHS 2015). The methods for GHS-POP have been described elsewhere (POPGRID 2020b). GHS-POP estimates are available for 1975, 1990, 2000 and 2015.

We derive two different geographic proximity measures of distances between urban areas, both using the open-source gROADS database that was last updated in 2019 (CIESIN 2013). For each country, gROADS provides the network for all primary, secondary, and tertiary roads as vector data. The two distance variables, measured in kilometers, are: distance to the closest urban place, and distance to the largest city in each country. They are calculated as the distance between the centroids of each urban area and follow the most direct route by road. The distance measures are calculated using the full dataset of 748 urban areas (see Sect. 2.2), which includes the subset of SUA's as well as larger cities. When calculating the distance to the largest city in South Africa, we used the shorter of the distances between the SUA and Johannesburg or Cape Town. We derive measures of precipitation and land use at the ADM-2 level, which is the second level of sub-national administrative boundaries based on the Global Administration Areas database (GADM 2019). In our analysis, we associate each SUA with its corresponding ADM-2 climate and land-use variable.

For the precipitation measures, we use the Climate Hazards InfraRed Precipitation with Station (CHIRPS) data. CHIRPS incorporates satellite imagery with in-situ station data to produce a quasi-global rainfall dataset at 0.05° ($\sim$ 5 km) spatial resolution and covers the period 1981 to present (Funk et al. 2014). We aggregate this data to the ADM-2 level by averaging the values of all grid cells whose center falls within the ADM-2 boundaries. We calculate spatially averaged precipitation variables for three time periods between the four population estimates. Therefore, the averages are for: 1981–1990 (corresponding to what we label as time period 1, or TP1), 1990–2000 (corresponding to TP2) and 2000–2015 (corresponding to TP3). For each of these periods, we create the following variables: (1) average annual precipitation anomaly (or the deviation of the period's annual average precipitation compared to the full-record annual average, represented as a percentage), (2) maximum consecutive years with below-average precipitation and (3) percent of years that experienced less than 75% of the full-record average precipitation. These three variables represent different aspects of rainfall that in theory could each influence rural-to-urban migration, principally through their impact on agriculture (they are at most only moderately correlated with each other; the highest correlation is 0.55). The percent of average rainfall is a general indicator of the climate. A value greater than 100% would suggest a period that was more favorable for agriculture than if the value was less than 100%. However, this indicator obscures annual patterns that could be more

Table 1 Summary statistics of variables included in regression analysis

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Growth rate	− 13.03	0.99	2.23	2.44	3.51	29.44
Distance to closest urban area (km)	4.4	22.3	37.3	49.9	59.1	532.5
Distance to largest city (km)	25.2	618.2	1120.4	1067.0	1452.4	2425.4
Percent of average precipitation	82.2	97.5	100.6	100.5	103.1	115.5
Maximum number of consecutive dry years	1	2	3	2.8	4	8
Percentage of years with below 75% average rainfall	0	0	0	7.2	11.1	55.5
Percentage of ADM-2 in agriculture	0	8.9	16.4	23.5	34.4	95.7

instrumental in driving rural to urban transitions. We therefore include the maximum number of consecutive years with below average rain as a measure of drought duration as well as the percentage of years with less than 75% rain which captures both the frequency and severity of drought.

For land use, we use the global land cover data from the European Space Agency (ESA) Climate Change Initiative (ESA 2017) and calculate the percent of the land identified as an agricultural land in each ADM-2. The ESA data is generated using a Land Cover Classification System developed by the United Nations Food and Agriculture Organization at a 300 m spatial resolution and has a classification accuracy of 75.4% (ESA 2017). We extract the land use data for the years 1992, 2000 and 2015 to correspond with the time points of the population estimates. We use 1992 as a proxy for land use in 1990 because it was the 1st year available.

Identifying secondary urban areas and measuring their growth

We identify SUA's following the two-step approach described in Tuholske et al. (2019). We first identify urban area point locations from OpenStreetMap (OSM). Then, using the 2015 GHS-POP, we identify all grid cells with a population density of 1500 people per km^2 or greater in 2015 that intersect with the OSM point data. This creates an urban polygon. We then augment that polygon by adding adjacent grids that had a population density value of 300 people per km^2 or more to account for adjoining suburban and peri-urban pixels. This process generates 748 total urban areas.

Next, we sum all the gridded population values within the urban area to derive a total urban area population estimate. We perform this for each of the four years: 1975, 1990, 2000 and 2015. We then impose a selection criterion on the 1975 population to include only those urban areas with populations between 500 and 100,000. This threshold retains 629 of the 748 urban areas (85%) and constitutes our SUA sample (see blue circles in Fig. 2). This criteria produces a sample of 629 SUA's that each were larger than 500 in 1975 and smaller than 375,000 in 2015 (Fig. 2). The methodology we use allows us to identify urban areas independent of changing administrative units and allows us to track their population growth through time.

Our definition of SUA is similar to those used in other studies (Rondinelli 1983; Tuholske et al. 2019). Tuholske et al. (2019) used 5000 as a minimum population for an urban area. We chose a minimum threshold of 500 so that we would include urban areas that by 2015 have populations larger than 5000 (Fig. 2). Our maximum value of 100,000 also allowed us to exclude the large, primary cities.

For each SUA, we calculate the rates of change in population for the periods of 1975–1990, 1990–2000, and 2000–2015 by applying a natural log equation:

$$g = (\ln(p1/p0))/t,$$

where p0 is the population estimate at an earlier year, p1 is the population estimate at a later year, and t is the number of years between p0 and p1.

Modeling the factors affecting population growth

The 629 SUA's vary in population and growth rate for each time period. We therefore analyze three times periods using both spatial autoregressive (SAR) and, for one of the time periods, an Ordinary Least Squares (OLS) model as suggested by our model diagnostics (described below). The results are presented in Table 2. We use SAR models to account for spatial autocorrelation between SUA's.

We use the SAR model because the growth of an SUA may not be independent from nearby SUA's. The advantage of SARs is that they can account for spatial autocorrelation (Anselin 2001), which was significantly present in three models according to the Moran I test (Anselin and Rey 1991). We then applied the Largrange multiplier (LM) test which provided the spatial lag and error statistics that determined the appropriate modelling approach (Anselin 2003). In TP1 and TP3, spatial lag and error values were both significant, but only the robust spatial lag statistic remained significant, suggesting a SAR model is a more appropriate model than an OLS. For TP2, there was evidence of spatial autocorrelation, but neither the spatial lag nor error values were significant, suggesting the OLS is the more appropriate model for this time period. We present both the SAR and OLS models for each TP for consistency.

The SAR model requires setting a distance threshold in order to generate spatial weights between

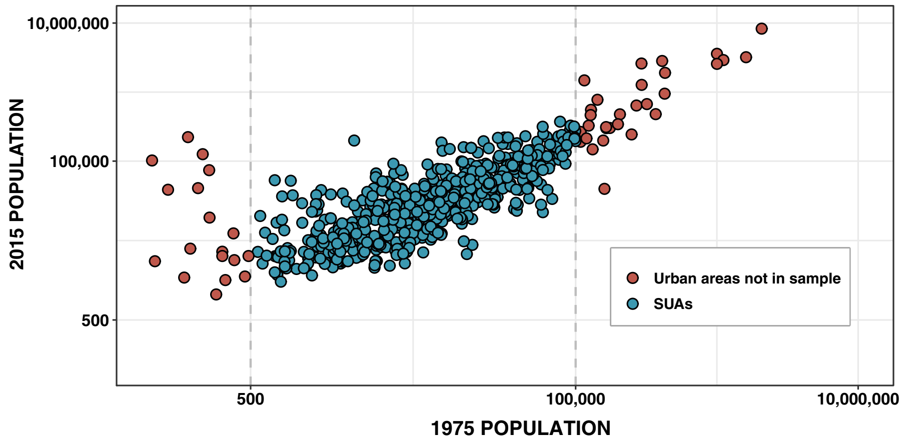

Fig. 2 Population for urban areas in 1975 and 2015. Sample size for the group of SUA's is colored blue, and those urban areas outside of the sample are colored red

SUA's within that distance. We present the results from the SAR models using 100 km as the threshold. We conducted a sensitivity analysis using four thresholds of 50 km, 100 km, 150 km and 200 km, and there was no significant difference between the models. Additionally, we present SAR model coefficients and the decomposed estimates of the direct, indirect and total impact of each independent variable, with significance tests based on 1000 Markov Chain Monte Carlo simulations. This provides a richer set of results and enables us to assess both the direct effects of independent variables (e.g. the effect of an SUA's 1975 population on its growth rates) and indirect effects (e.g. the effect of neighboring SUA's 1975 population on the SUA's growth rates). To evaluate model performance, we provide both R^2 and Akaike information criterion (AIC) for each model. AIC values of SAR models for TP1 and TP3 are lower than the OLS, indicating the SAR is a better model fit. In Sect. 2.1, we described all independent variables used in the regression with the exception of two control variables, one for country and the other for agro-ecological zones. Agro-ecological zones come from HarvestChoice's (2011) map for Sub-Saharan Africa. These two variables are used as fixed effects to account for time-invariant variability at the country and agro-ecological zone levels. We tested all independent variables for multicollinearity and correlation; all correlations were less than 0.55. In Table 1, we provide summary statistics for all non-control variables in the regressions.

We make several simplifying assumptions in our models. First, we assume the ADM-2 boundaries used to characterize the climate and land use are at a spatial scale important for the SUA. For large ADM-2 regions, it is possible that their scale extends beyond the meaningful sphere of influence of the corresponding SUA, and vice versa. Second, we calculate distance metrics using a present-day roads database. Although the transport network may have been different in 1975, both the quality and extent of the road network is likely to have improved over time. This assumption likely causes the distance estimates for some SUA to be underestimated in earlier periods. We used this dataset since it represents the best available information for the countries of analysis. Third, many social and economic factors influence population growth, some of which are idiosyncratic to the SUA. Due to the broad scale of our analysis, we focus on measures that we can obtain consistently across all SUA's. Finally, we note that our procedure of identifying SUA's with Open Street Map and the GHS-POP dataset may have caused us to omit some urban areas, while some areas that had populations less than 500 in 1975 may also have grown to be urban by 2015. Any omitted urban areas would cause an underestimate of distance metrics for some SUA's. Nonetheless, we believe the number of omitted SUA is small.

Results

Growth rates of secondary urban areas

Between 1975 and 2015, the total urban population in southern Africa increased from 22.8 million to 67.3 million people, and close to 50% of this growth

Table 2 Regression results from analysis of annual percentage growth rate for SUA

Dependent variable: population growth rate

	TP1 (1975–1990)					TP2 (1990–2000)				
Variable	OLS	Spatial lag	Direct	Indirect	Total	OLS	Spatial lag	Direct	Indirect	Total
Constant	9.466**	8.164*				− 6.198*	− 6.176*			
	(4.371)	(4.216)				(3.428)	(3.336)			
Spatial spillover—Rho		0.18628***					0.074101			
1975 Population	− 0.00004***	− 0.00003***	− 0.00003***	− 0.000007***	− 0.00004***	− 0.0001***	− 0.0001***	− 0.00005***	− 0.000004	− 0.00006***
	(0.00001)	(0.00001)				(0.00002)	(0.00002)			
Population at the start of time-period						0.00003***	0.00003***	0.00003***	0.000002	0.00003***
						(0.00001)	(0.00001)			
Previous time-period growth rate						0.066*	0.060*	0.06*	0.004	0.06*
						(0.036)	(0.035)			
Distance to closest urban area (km)	− 0.004	− 0.003	− 0.003	− 0.0006	− 0.003	− 0.002	− 0.001	− 0.001	− 0.00008	− 0.001
	(0.003)	(0.003)				(0.002)	(0.002)			
Distance to largest city (km)	− 0.001**	− 0.001*	− 0.0007*	− 0.0001	− 0.0008*	0.001***	0.001***	0.0007***	0.00005	0.0008***
	(0.0004)	(0.0004)				(0.0003)	(0.0003)			
Percent of average precipitation	− 0.059*	− 0.052*	− 0.05*	− 0.01	− 0.06*	0.044*	0.042	0.04	0.003	0.04
	(0.031)	(0.030)				(0.027)	(0.026)			
Maximum number of consecutive dry years	− 0.225*	− 0.207*	− 0.2*	− 0.04	− 0.2*	− 0.078	− 0.070	− 0.07	− 0.005	− 0.07
	(0.120)	(0.116)				(0.077)	(0.075)			
Percentage of years with below 75% rainfall	0.013	0.010	0.01	0.002	− 0.01	0.039***	0.039***	0.03***	0.002	0.04***
	(0.015)	(0.015)				(0.011)	(0.011)			
Percentage of ADM-2 in agriculture	0.015*	0.013*	0.01*	0.002	0.01*	0.00001	0.001	0.0005	0.00003	0.0005
	(0.008)	(0.008)				(0.005)	(0.005)			
Observations	629	629				629	629			
R^2	0.3878					0.2071				
Log likelihood	− 1501.145	− 1493.482				− 1260.13	− 1259.192			
Akaike information criteria (AIC)	3062.29	3049.0				2584.26	2584.4			

Dependent variable: population growth rate

	TP3 (2000–2015)				
Variable	OLS	Spatial lag	Direct	Indirect	Total
Constant	5.396**	4.334*			
	(2.624)	(2.508)			
Spatial spillover—Rho		0.21034***			

Table 2 continued

Dependent variable: population growth rate					
	TP3 (2000–2015)				
Variable	OLS	Spatial lag	Direct	Indirect	Total
1975 Population	− 0.00005***	− 0.00005***	− 0.00004***	− 0.00001***	− 0.00006***
	(0.00001)	(0.00001)			
Population at the start of time-period	0.00002***	0.00002***	0.00002***	0.000005***	0.00002***
	(0.00000)	(0.00000)			
Previous time-period growth rate	0.472***	0.452***	0.4***	0.1***	0.5***
	(0.028)	(0.026)			
Distance to closest urban area (km)	0.004	0.001	0.001	0.0003	0.001
	(0.001)	(0.001)			
Distance to largest city (km)	0.001***	0.0004***	0.0004***	0.00009*	0.0005***
	(0.0002)	(0.0001)			
Percent of average precipitation	− 0.024	− 0.018	− 0.01	− 0.004	− 0.02
	(0.021)	(0.020)			
Maximum number of consecutive dry years	− 0.074	− 0.071	− 0.07	− 0.01	− 0.08
	(0.049)	(0.047)			
Percentage of years with below 75% rainfall	− 0.012	− 0.009	− 0.009	− 0.002	− 0.01
	(0.009)	(0.009)			
Percentage of ADM-2 in agriculture	− 0.007***	− 0.004	− 0.004	− 0.001	− 0.005
	(0.003)	(0.003)			
Observations	629	629			
R^2	0.6014				
Log likelihood	− 969.9077	− 957.938			
Akaike information criteria (AIC)	2003.815	1981.9			

Population, growth rate, precipitation and agricultural variables all vary through time, and represent the relevant values at the time periods studied. Coefficients are presented along with their standard errors in parenthesis

Statistical significance is denoted with an asterix: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Reports regression coefficients and standard errors

Spatial impact analysis where 1000 Markov Chain Monte Carlo (MCMC) simulations are used to calculate p values for direct, indirect and total impacts of unit changes in covariates occurred in SUA's. By 2015, about 41% of the total urban population lived in SUA's (Fig. 3). The 629 SUA's we identified accounts for 85% of all urban areas in southern Africa.

Between 1975 and 2015, the SUA population of our sample increased by 260%, growing from about 10.6 million to 27.6 million. The average growth rate of all SUA's for all time periods is 2.44% (Table 1). However, the average growth rates generally declined across the three time periods and varied by country (Fig. 4). The average annual growth rates range between − 13.0 and 29.4%, but the majority fall within 2.0–4.0%. At the country scale, SUA's in Namibia have the highest average growth rate at 3.7%, while the average growth rate in Lesotho was the lowest at 1.6%. In the most recent time period (2000–2015), 126 of the SUA's had growth rates higher than 2.8%, the average urban area growth rate estimated by the UN for urban populations in less developed regions over a similar time period, and 440 of the SUA's had growth rates higher than 0.64%, the growth rates estimated for developed regions (UN 2018). In addition to comparison with estimates from the United Nations, Turok and Borel-Saladin (2014) found growth rates of large metro areas in South Africa to be 2.29% between 2001 and 2011.We find 83 SUA's in South Africa that higher growth rates over a similar time period (TP3, 2000–2015).

Our sample includes cities with high variance among the three geographic proximity measures (Fig. 5). Across all countries, the average distance to the closest urban area is 50 km and the average distance to the largest city in each country is 1067 km but there is considerable spatial variability within and between countries. The values of each of the two measures are influenced by the combined effects of the number of SUA's and the country's size and shape. The distance to the closest urban area for the majority of countries is less than 50 km although some countries (e.g. Namibia, Botswana and Zimbabwe) have a lower density of SUA's and thus larger distances between urban places.

Relationships between rates of growth and climate, land-use and distance measures

There are several noteworthy associations between growth rates and population and distance measures. First, in relation to population measures, smaller SUA's in 1975 grew at a faster rate in all three time periods than larger SUA's. This is unsurprising because larger populations require higher absolute population increases to grow at the same rate as smaller populations. Furthermore, the 1975 population of the SUA has both direct and indirect effects in all three time periods. The direct effects indicate that the SUA growth rates are affected by their own 1975 population while the indirect effects suggest the SUA growth rates are affected by the 1975 population of all the SUA's within 100 km. These relationships become more robust in TP2 and TP3. In both these time periods, there are also significant positive associations between SUA growth rates and the population at the start of TP2 and TP3 as well as the previous time-period growth rates. These associations between previous growth rates suggest that urban growth decelerates through time. Eventually, the demographic potential for rural-to-urban migration will

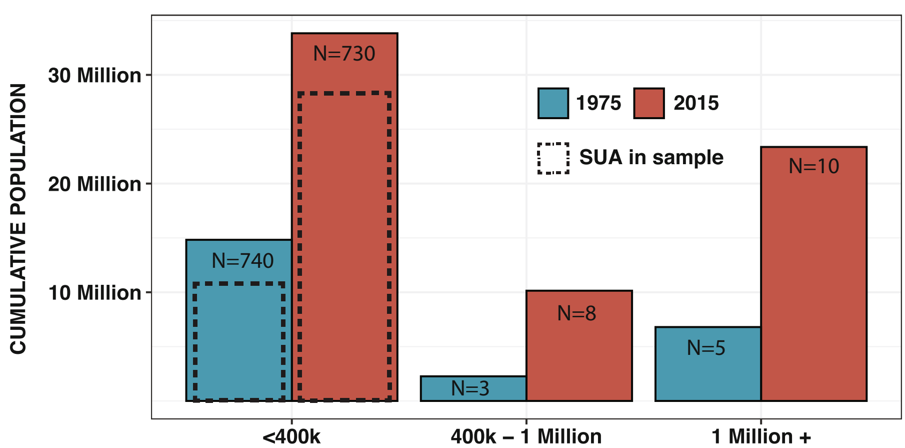

Fig. 3 Total population for urban areas of different size categories. Sample size for each group for population estates in 1975 and 2015. The dashed outline represents the sample of SUA that we draw from for this analysis (n = 629)

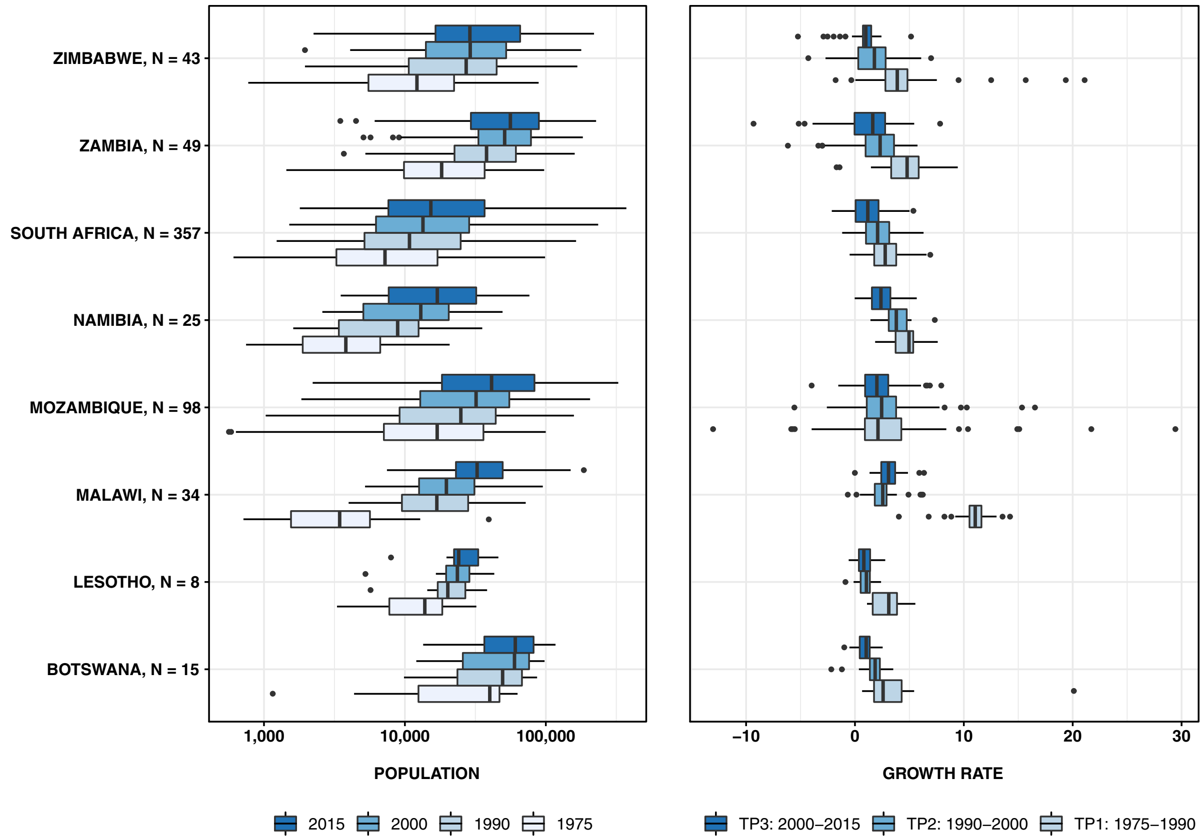

Fig. 4 Left: SUA total population for each of the 4 years by country (and for all data). Right: SUA annual percentage growth rate for each time-period by country. The center line in the box-plots represents the median value. The number of data points for each country is labeled on the y-axis

shrink, as the majority of populations are living in urban areas. Here too are significant direct and indirect effects, suggesting an influence of surrounding SUA's populations on growth rates.

Second, in relation to distance measures, there are no significant associations between SUA growth rates and the distance to the nearest urban area, regardless of the time-period. One explanation for this finding is that the closest urban area is likely a SUA, given the overwhelmingly greater number of SUA's in comparison to urban areas with populations more than 400 thousand (Fig. 3). Given this, moving between SUA's offers perhaps less economic and livelihood benefit than moving between SUA's and larger cities (Rondinelli 1983) and so it is unlikely that being close or far to one of these neighbors has a significant impact on growth rates. Moreover, as distance to the largest city increases, SUA growth rates also significantly increase in TP2 and TP3. This result suggests that SUA's more isolated from the largest city grow at faster rates. This result, however, was not observed in TP1. Rather, there was a significant negative relationship that indicates SUA's in closer proximity to their countries largest city grew faster between 1975 and 1990 Taken together, these results suggest that the draw of the country's largest city was greater initially and diminished as populations grew.

Third, with respect to precipitation, all three precipitation measures display significant relationships with SUA growth rates depending on the time-period. The percent of average precipitation has a negative relationship with growth rate in TP1, indicating that growth was higher with reduced precipitation. During this time-period, as average rainfall decreased by 1%, SUA growth rates increased by 0.050%. In TP2, this variable displays a positive relationship. These are patterns we explore in more detail in Sect. 4.1.

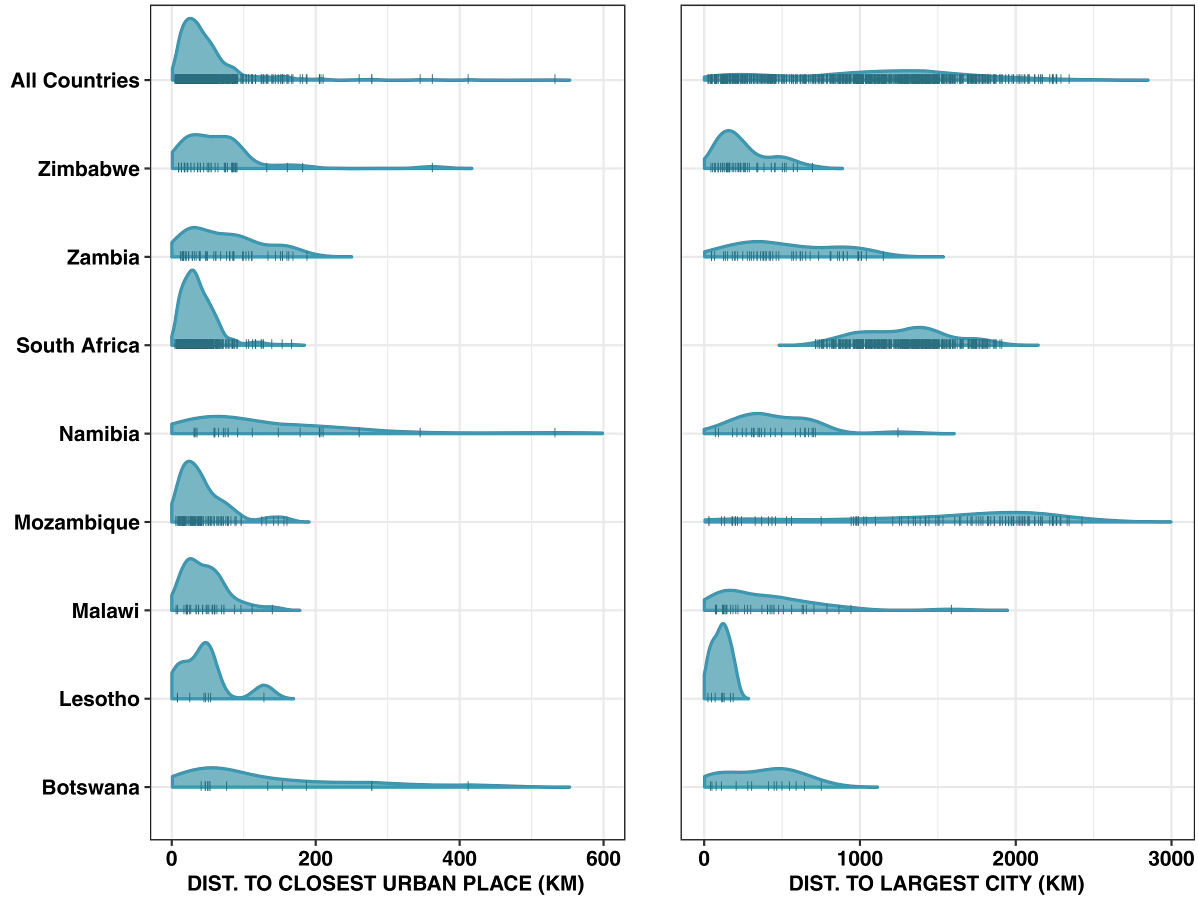

Fig. 5 Distributions of the geographic proximity measures for each and all countries. Small vertical lines on x-axes denote data points. Left: Distance to the closest urban place for each country. Right: Distance to the largest city by country. Curve displays density distribution of observations and strokes display individual observations

We find significant associations between consecutive dry years and SUA growth rates, only in TP1. These suggest that as the number of dry years decrease, urban growth rates increase, perhaps as a function of increased agricultural productivity allowing people to become more mobile and migrate to an urban area.

That the climate metrics show variable relationships across the time periods with growth rates warrants a closer look. The box plots in Fig. 6 show the distribution of each of the climate metrics for the three time-periods. The distribution of the percent of average precipitation displays a shift towards wetter conditions for TP2 relative to the others, whereas TP2 also has a higher percentage of years with below 75% precipitation. Although the precipitation anomaly appears to show only modest average deviations, some SUA's experienced $\pm$ 10% deviations over the 10- or 15-year periods, and consequently experienced years with even greater deviations. The character of more extreme conditions is partially captured in the measure of percent of years below 75% precipitation. Here too we can see that TP2 had the highest central tendencies and variability.

Finally, the area dedicated to agriculture, as expressed as a percentage of the district's total area, displays significant direct relationships with SUA growth rates in TP1. This result suggests that as the percentage of ADM-2 land classified as agriculture increased, SUA growth rates also increased. Additionally, the sign of this relationship flips to negative in TP3.

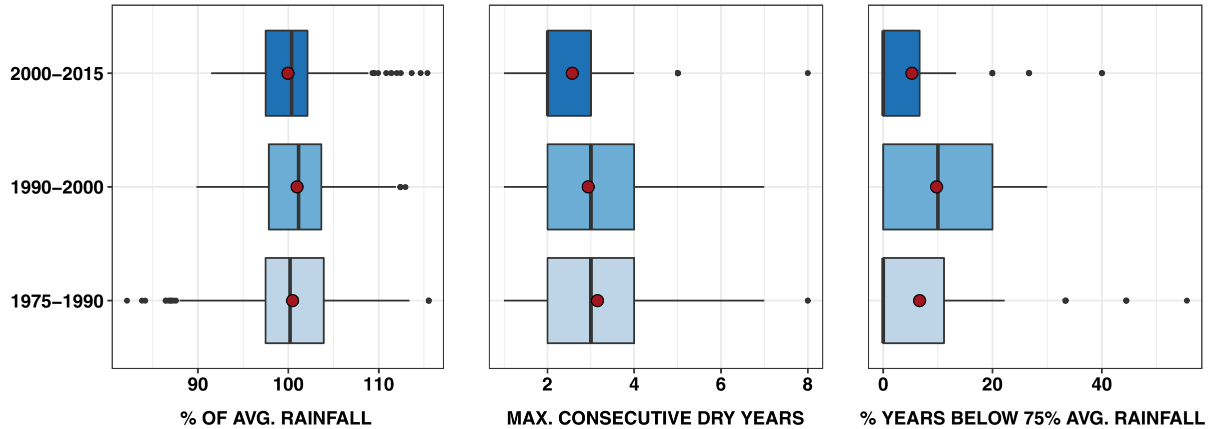

Fig. 6 Box and whisker plots of the climate metrics used for each time period. Red dot denotes mean values for each time period. The lines within the boxes represent the median value while the box outline denotes the interquartile range. The whiskers extend outwards 1.5 times the interquartile range, and the black dots represent outliers

Discussion

Climate and urban growth

In our analysis, we have considered the effect of precipitation on growth rates, hypothesizing that precipitation would impact agricultural yields and rural livelihoods in ways that would contribute to a rural to urban movement of people (e.g. Zhao et al 2018). However, it is doubtless complicated; migration is highly contextualized (Sen 1982). The decision-making processes are complex (Foresight 2011), and social, economic, demographic and political factors can be important in dictating the migratory patterns of rural people (Hunter et al. 2015; Cattaneo et al. 2019). Climate is therefore only one of the many factors that potentially influence it. It is difficult to explain such a complex decision with any one factor (Foresight 2011) without detailed qualitative work.

Climate has been cited as both a push and pull factor on migration (McLeman and Hunter 2010). The precipitation metrics we analyze support this as important associations with rates of SUA growth are found to be more influential between 1975–1990 and 1990–2000 but the signs of the associations differed. We thus observe some evidence that both wetter and drier precipitation conditions relate to increased urban growth rates. On one hand, periods of above-average precipitation may lead to increased urban growth through voluntary migrations. In this case, favorable rainfall leads to increased agricultural productivity (e.g. Black et al. 2011) that in turn increases rural household income. Rural families are thus able to leverage their better financial states and move to urban areas so they can capitalize on the social and economic advantages that cities offer (Parnell and Walawege 2011). On the other hand, climate may force people to move out of necessity. Extreme events like drought are often a focus of climate migration studies (Parnell and Walawege 2011), and in our data we attempted to capture this type of condition with the variable quantifying the number of years with below 75% of average precipitation. We observed that during the 1990–2000 period, the SUA growth rates were indeed positively associated with this variable. One plausible explanation for this relationship is that numerous years of relatively drier conditions may lower agricultural yields that ultimately compel rural residents to seek alternative livelihoods in urban areas (Barrios et al. 2006; Brückner 2012). Taken together, we cautiously interpret rainfall as both a pull and push factor, recognizing intra-annual rainfall patterns are important and small but frequent deviations in rainfall, or slow rainfall onset, may be as important as larger, more acute changes (Cattaneo et al. 2019). Furthermore, this metric our use of annual averages obscures the intra-annual rainfall patterns, agriculture is influenced by-other climate measures like temperature and combined effects of temperature and moisture (Henderson et al. 2017; Zhao et al. 2018).

Geographic proximity of secondary urban areas

We find that SUA's growth rates are significantly associated with their distance to the primary city (i.e. the largest city in the country) in all three time periods central place theory offers an explanation for these patterns. It suggests that urban growth occurs in areas where there is room for growth (Christaller 1933; Lösch 1940). When urban areas are clustered, growth rates tend to vary across them. Primary cities often have the highest levels of infrastructure and economic development and are often located in areas with abundant resources and on optimal trade routes (Rondinelli 1983; Fox 2012). They thus exert a primary influence on the surrounding urban landscape and the landscape of connectivity is incredibly important in dictating sustainable urban development (Ahern 2013). SUA's in close proximity to these primary cities are less likely to experience high rates of growth, potentially because people who move opt for the greater opportunities and services in the primary city. This process reinforces primary city status and limits urbanization in the regions surrounding large cities.

In addition, to the relationships between distance variables and SUA growth rates, we find significant direct and indirect relationships between population and future growth rates. In TP2 and TP3, the population at the start of the time period influences future growth. The significance of these variables increases from TP2 to TP3, suggesting that as SUA's continue to grow and mature, their relationship with the surrounding urban landscape also becomes more important. For example, in TP3, a significant indirect impact from the previous time periods population and growth rate suggests that SUA's are not only affected by their own development, but also by SUA's within 100 km. If this continues in the future, it is likely to shape the spatial distribution of urban areas and the location of rapidly urbanizing populations. In this case, SUA's will grow rapidly if neighboring other rapidly growing urban areas. One explanation for clustered growth patterns is that important services become available within close proximity, whereas if an SUA is isolated, it must be self-contained. There is doubtless a complicated pattern of urban growth as proximity to one urban area does not display a statistically significant result but has both positive and negative coefficients depending on the time period. Nonetheless, there is a clear relationship between the previous SUA population and its growth rate.

Relationships between agricultural land use and secondary urbanization

In assessing the relationship between agricultural land use surrounding SUA's and the corresponding population growth, we provide an initial analysis of whether SUA's operate within a local food system. In local food production systems, agricultural lands nearby to an urban area produce most of the food consumed in that urban area. Although African countries produce the majority of the food they consume (Reardon and Timmer 2007), it is often unclear how much the surrounding rural areas contribute to individual cities. As a step towards answering this question, our results showed that during TP1, higher rates of urban growth were associated with higher percentages of land employed in agriculture. This suggests that as SUA's grow faster, more of the surrounding land is engaged in agriculture.

One local food system hypothesis is that as urban populations grow, agricultural land in the surrounding areas also grows to meet increased demand. We observe this in TP1, but the pattern does not hold in other time periods. For example, in response to past food insecurity, parts of southern Africa have developed complex food transport systems to sustain urban livelihoods in times of food strain (Frayne et al. 2010; Crush 2013; Crush and Battersby 2016). In cases where the SUA's do operate in local food systems, the declining agricultural land could have implications for food security in the absence of yield increases. The reduction in agricultural land use may also be driven by urban area expansion (d'Amour et al. 2017). To move beyond this speculation requires closer examination. As urban food systems in Africa generally need to be better understood (Smit 2016), we submit that food systems for SUA's are even less understood.

Conclusion

Urban areas account for more than 55% of the global population fraction that is expected to increase in the future (UN 2018). Urban growth thus has an increasingly important role in the spatial distribution of global population. In places of high growth rates like in Southern Africa (UN 2018), economic, social and infrastructure development will be tested. While the focus of urbanization has primarily been on large primary cities, smaller secondary urban areas account for large fractions of the total urban population.

This analysis describes different urban growth patterns of secondary urban areas in eight countries in southern Africa and how growth rates changed in time between 1975 and 2015. We show that SUA's accounts for about 85% of urban population centers and nearly half the total urban population. This underscores their importance as units of analysis when considering, for example, achieving sustainable development goals. We further analyzed the influence of land use, climate, and geographic proximity on growth rates in both space and time. We find secondary urban areas experienced higher growth rates when distant from primary cities, had variable rainfall patterns and a greater amount of surrounding agricultural land to provide resources for a growing population. Alongside this, we present a discussion of the importance of secondary urban areas to sustainable landscape development in Africa. These results are important for understanding intra-city dynamics and the contribution of local food systems to urban populations in southern Africa. While urbanization processes are complex, knowledge about urban growth patterns are critical for effective management, resource allocation and urban region planning (Cohen 2004; Wu 2010; Forman and Wu 2016), and serve as a tool to integrate secondary urban areas into academic study and development work on African urbanization and urban sustainability.

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