

Research Paper

Imposing consistent global definitions of urban populations with gridded population density models: Irreconcilable differences at the national scale

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HIGHLIGHTS

- No common global definition exists of urban populations.
- I calibrated three global population models to generate urban and rural classes.
- The models indicated a different urban or rural status than reported for 32 countries.
- Reconsideration of the urban status may change the narrative of urban trajectories.

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ABSTRACT

No common global definition exists of urban populations, resulting in a lack of shared standards across countries for equivalent comparisons. Therefore, I used global population models of Landsat, Worldpop, and Gridded Population of the World to generate a provisional classification of population density classes to define urban and rural by human population densities, which is an enduring attribute to differentiate urban lands from rural lands. I calibrated 2015 population density models to the United Nations 2015 global urban population estimate of 53.9% and then balanced among the population models to reach approximately the same population percentages for rural, exurban, suburban, and urban thresholds. Because the three population models varied in population distribution, with the greatest concentration of population densities in the Landsat model and the greatest dispersion in the Gridded Population of the World, different urban density thresholds were necessary for each population model. After calibration, Worldpop, which is available from years 2000 to 2020, closely matched global urban population estimates during those years. However, without an inconstant definition, for example across populous countries, low urban percentages were not plausible in India simultaneously with moderate urban percentages in China and high urban percentages in the United States. All three population models with adjusted thresholds agreed on a divergent reported urbanized or rural status for 32 countries, representing about 30% of the global population, and greatly reduced urban percentages for another 13 countries. Reconsideration of the urban status of these countries, and the surrounding regions, may change the narrative of urban condition trajectories, prospects, and related applications for research, planning, and management. While population models and adjustments to population density thresholds are not perfect, omitting multifaceted social, economic, political, and demographic histories, they do create a pathway for comparison of urban status across countries on an equal basis, unlike urban definitions that vary by country.

1. Introduction

According to the [United Nations \(2019\)](#), 54% of the world's 7.4 billion population lived in urban areas during 2015. The landmark of global population transition to an urban majority occurred during 2007. Nevertheless, urban definitions vary across countries because no common global definition exists of urban populations ([United Nations,](#)

[2019](#)). Criteria may be based on administrative boundaries, minimum population agglomerations, population density, and economics, infrastructure and services, including paved roads, electricity, piped water, sewers, schools, and health services ([Potts 2017; United Nations, 2019; Wineman et al. 2020](#)). Specifically, 59 out of 233 countries use administrative designations as the sole criterion to distinguish between urban and rural areas ([United Nations, 2019](#)). For 37 countries, population size

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or population density are the criteria, but the urban threshold ranges between 200 and 50,000 inhabitants (United Nations, 2019).

Attempting to incorporate complex social, economic, political, and demographic histories and transformations that are multidimensional into measurement of urban populations compromises a shared definition of urban populations and successful cross-country comparisons. High human population densities and built environments are permanent urban characteristics that differentiate rural and wildlands characteristics of low human densities and associated buildings. Economics and employment are distinct from the permanent characteristics of population and housing densities that differentiate rural lands from built lands even though economic factors, particularly employment, may be included in a definition of urban (Potts 2017; United Nations, 2019; Wineman et al. 2020). Employment in the agricultural sector is a dynamic component of employment specialization and industrialization trajectories to post-agrarian societies. This process is related to urban growth, because specialization in employment that is disconnected from natural resources permits urban concentration where non-agricultural economic activities occur (Satterthwaite 2007; Potts 2017; Wineman et al. 2020). However, many countries are on unique developmental trajectories and cycles that defy common urban definitions and comparisons.

Furthermore, population densities can be detached from economic growth. The percentage of urban dwellers is not a consistent indicator of economic development or income status, as evidenced by informal settlements (United Nations 2015). For another example, Monrovia, Liberia with 800,000 inhabitants during 2006 produced the equivalent gross domestic product, or standard measure of the value added created through the production of goods and services, as a French town of 6,500 inhabitants (Moriconi-Ebrard et al. 2008). Vibrant economies can occur in rural areas, without requiring urban population increases, particularly as working from home increasingly becomes an alternative to urban offices (Satterthwaite 2007; Bosworth and Bat Finke 2020). It would not be logical to identify rural lands where wildlands and housing intermix as urban lands simply because the inhabitants are not primarily farmers. That is, few people work in the agricultural industry in post-agrarian societies, yet many people may live dispersed in great extents of low population densities and housing densities due to advanced transport and communications (Satterthwaite 2007). Remote opportunities have allowed counterurbanization to rural locations for natural amenities (Halfacree 2008; Rees et al. 2017).

Enumeration of human populations delivers critical basic information, which can be applied across many fields, but population estimation is challenging and contains measurement error (Moriconi-Ebrard et al. 2008). A census records individuals only at one point in time and then may be rarely updated (Satterthwaite 2007; Heinrigs 2020). Comprehensive census updates may occur every decade in countries that are able to prioritize census efforts, although smaller samples occur more frequently. Yearly estimates require modeling of projections. Accuracy of census information starts to degrade immediately after collection because human populations are dynamic due to births, deaths, and migration. Issues include accounting for institutionalized populations, military members, and transient students, seasonal workers and residents, nomads, and refugees. Spatial dynamics occur through unplanned agglomerations and informal settlements (Moriconi-Ebrard et al. 2008; Heinrigs 2020).

The United Nations does not correct definitions of urban across countries unless definitions by a given country have inconsistencies due to change over time. This has resulted in divergence in how urban areas are defined from other sources, specifically the Africapolis database (e-geopolis 2022), which applies remote sensing to identify built agglomerations and cross-references to demographic data to assign a population count to each agglomeration (Heinrigs 2020). According to the United Nations, West Africa was 49% urban during 2006 compared to an estimate of 30% urban from Africapolis (Moriconi-Ebrard et al. 2008). Conversely, Africa is more urban, based on agglomerations, than

reported by the United Nations (Heinrigs 2020). Measurement of minimum population thresholds for settlements generates disagreement due to representation of only large agglomerations by the United Nations (Angel et al. 2018; Heinrigs 2020).

However, global gridded models of continuous population counts per 30 arc-seconds (i.e., less than 1 km²) offer consistent population estimates that are not attached to administrative boundaries or agglomerations. Landscan (e.g., Cheriyyadat et al. 2007; Bright et al. 2016) and Worldpop (Lloyd et al. 2017; WorldPop, 2018) distribute populations through disaggregation of census blocks using models that incorporate ancillary variables such as land cover, urban land use, distance to roads, slope, and nighttime lights (i.e., dasymetric interpolation). The Gridded Population of the World (GPW) results from areal-weighting across the land surface, which distributes populations uniformly across the census blocks but may maintain closer fidelity to input data (Doxsey-Whitfield et al. 2015; CIESIN, 2016). The Gridded Population of the World also adjusts counts to match the 2015 revision of United Nations country totals, which likely increases conformity to international reference standards. Other options are available, such as the Global Human Settlement Layer, but this layer has extremely concentrated human populations (Freire et al. 2016; Schiavina et al. 2019).

The population density models distribute populations differentially, requiring custom adjustment. To illustrate the problem, the U.S. Census Bureau (2013) has a density requirement of at least 386 inhabitants per square kilometer, along with minimum population counts and contiguity. Following a simplified urban threshold of 386 humans per km², the global urban population would be 61.75%, 68.89%, 79.42%, and 89.69% according to respectively, Gridded Population of the World, Worldpop, Landscan, and Global Human Settlement Layer during 2015, all of which exceed the United Nations 2015 global urban population estimate.

One solution to the lack of a standardized definition for urban populations is to classify continuous population density models into urban and rural density classes, so that gridded population data can represent urban populations. My objective was to impose consistency in measuring urban populations across countries by applying rural and urban class thresholds to population densities based on gridded population models calibrated to the United Nations 2015 global urban population estimate of 53.93%. To be clear, this urban definition is simply tied to identifiable urban land characteristics of high population densities and built land cover, which are associated by population models. By limiting the definition only to constant urban attributes, the definition avoids inconsistencies that arise from dynamic processes, such as economic transformation, which may be unrelated to urban measurements or else not relevant to predominantly service economies that can occur throughout a range of population densities due to remote and telework options. Definitions have faltered due to conflating measurement of urban populations with spatiotemporally dynamic socioeconomic issues. Population density thresholds permit standardized calculation of urban proportions across countries, rather than relying on national reporting based on inconstant standards that are fluid, changing with population patterns. Although assigned thresholds are subject to revision, adjusting to equilibrate urban classification across countries offers an altered understanding of relative urban patterns. Specifically, after equalizing models to define urban and rural by population densities based on the United Nations global urban population during 2015, questions included how do the population models diverge by country from reported census data by the United Nations and how similar are the population models, given that this is the first comparison of the population models at a global scale, to my knowledge.

Methods.

Population models.

For global population densities, I used population counts from LandScan (Antarctica removed), Worldpop, and Gridded Population of the World, with the latter layer adjusted to the United Nations country totals (CIESIN, 2016; Bright et al. 2016; WorldPop, 2018; cell size of

Table 1For thresholds of counts per km², population density classes, percentage of the population, and percentage of area during 2015 for three different population models.

2015 Landscan				2015 Worldpop				2015 GPW				
Threshold	Class	Pop %	Class	Pop %	Class	Pop %	Class	Pop %	Class	Pop %	Class	Pop %
0 to 1	Wildland	0.00	Rural	2.09	Wildland	0.15	Rural	2.64	Wildland	0.15	Rural	3.02
1 to 15	Inhabited	2.09			Inhabited	2.49			Inhabited	2.88		
15 to 100	Exurban low	6.70	Exurban	22.48	Exurban low	10.11	Exurban	21.26	Exurban low	13.25	Exurban	26.78
100 to 250	Exurban mid	7.41			Exurban high	11.15			Exurban high	13.53		
250 to 550	Exurban high	8.38			Suburban low	13.86	Suburban	21.57	Suburban	16.17	Suburban	16.17
550 to 800	Suburban low	5.68	Suburban	21.25	Suburban high	7.71			Urban low	8.41	Urban	54.03
800 to 1000	Suburban mid	3.92			Urban low	4.81	Urban	54.53	Urban low	5.07		
1000 to 1900	Suburban high	11.65			Urban low	12.63			Urban high	12.61		
1900 to 4500	Urban low	16.57	Urban	54.18	Urban high	14.20			Urban high	11.31		
>4500	Urban high	37.60			Urban high	22.89			Urban high	16.63		
2015 Landscan				2015 Worldpop				2015 GPW				
Threshold	Class	Area %	Class	Area %	Class	Area %	Class	Area %	Class	Area %	Class	Area %
0 to 1	Wildland	61.05	Rural	85.48	Wildland	51.79	Rural	78.57	Wildland	44.37	Rural	73.34
1 to 15	Inhabited	24.43			Inhabited	26.78			Inhabited	28.97		
15 to 100	Exurban low	9.08	Exurban	12.84	Exurban low	13.64	Exurban	17.50	Exurban low	17.76	Exurban	22.41
100 to 250	Exurban mid	2.52			Exurban high	3.85			Exurban high	4.65		
250 to 550	Exurban high	1.24			Suburban low	2.07	Suburban	2.71	Suburban	2.41	Suburban	2.41
550 to 800	Suburban low	0.46	Suburban	1.17	Suburban high	0.64			Urban low	0.70	Urban	1.84
800 to 1000	Suburban mid	0.24			Urban low	0.30	Urban	1.22	Urban low	0.31		
1000 to 1900	Suburban high	0.47			Urban low	0.52			Urban high	0.52		
1900 to 4500	Urban low	0.32	Urban	0.51	Urban high	0.28			Urban high	0.22		
>4500	Urban high	0.19			Urban high	0.13			Urban high	0.09		

0.0083 degrees, 30 arc-seconds). I also generated a mean model of LandScan and Worldpop combined. To ensure consistency in calculation of approximate surface area of cells in the World Geodetic System 1984 geographic (longitude/latitude) coordinate system, I quantified cell area for each layer (Hijmans and van Etten 2012). Area was approximately 0.85 square km at the equator. For population density, I simply divided each cell population count by cell area in square km.

Preliminary thresholds for population density classes from exurban low to urban high density.

As a starting point for approximating thresholds between population density classes, I applied EPA's 2010 Integrated Climate and Land Use Scenarios (United States EPA, 2017) for the United States as a guide. The five residential density classes were exurban low (6% of the contiguous United States), exurban high (3% of the contiguous United States), suburban (1% of the contiguous United States), urban low (0.85% of the contiguous United States), and urban high (0.06% of the contiguous United States), which were based on number of residential units per ha. For 80,000 random samples of the residential density classes, I extracted population densities from 2010 Landscan (Bright et al. 2011). To determine the relationship between population densities and residential density classes, I partitioned the datasets into training (75%) and testing sets, trained the model with 10-fold cross-validation and the C5.0 classifier, and then predicted for the testing sets (Kuhn 2008; R Core Team 2021). I then iteratively changed the population density ruleset until the percentage area of each class matched with the percentage area of the Integrated Climate and Land Use Scenarios residential density classes.

Calibration to 53.9% global urban population during 2015.

I generated a provisional classification of population density classes by calibrating to the United Nations - global urban population estimate of 53.9% during 2015 derived from census data (United Nations, 2021) and then balancing among the 2015 population density models to reach approximately the same population percentages for rural, exurban, suburban, and urban thresholds, after summing population counts by different density classes. I also calculated country-wise mean absolute error by comparing the difference between percentage urban population between the four datasets and census data for 88 countries with populations ≥ 10 million. These countries accounted for 95% of the global population.

Thresholds based on comparison of urban percentages.

With the information from comparisons, I revised the provisional classification thresholds of population densities. I compared urban

percentages among the models and the U.N. census estimates globally and across countries. For Worldpop, which is available annually starting in 2000, with no apparent disclaimers about comparisons by year, I examined the percentage urban globally during years 2000, 2005, 2010, and 2018, the latest U.N. revision, along with 2006 and 2007, when the U.N. calculated the changeover from a predominantly rural population to an urban population.

2. Results

Preliminary thresholds for population density classes from exurban low to urban high density.

For preliminary thresholds based on five U.S. residential classes, I adjusted values determined by the classifier to match approximate areas of each residential class. Accuracy of the relationship between population densities and residential density classes for the United States was 0.68, but accuracy varied widely by class. I classed the following (2010 Landscan) population densities per square km: 0–1 as wildlands and 1–20 as inhabited (combined 89.5% of the contiguous United States), 20–100 as exurban low density (6.2% of the contiguous United States), 100–500 as exurban high density (2.4% of the contiguous United States), 500–1500 as suburban (1.3% of the contiguous United States), 1500–4500 as urban low density (0.6% of the contiguous United States), and > 4500 as urban high density (0.6% of the contiguous United States).

Comparison of global and national urban percentages.

Compared to the United Nations global urban estimate of 53.93%, in interval classes of 100, Landscan had the least difference at 1900 humans per km² (urban percentage of 54.18%), Worldpop had the least difference at 800 humans per km² (urban percentage of 54.53%), GPW had the least difference between 600 (52.04%) and 500 humans per km² (56.20%), and the ensemble Landscan and Worldpop model had the least difference between 1100 (52.98%) and 1000 humans per km² (54.83%). However, when not globally-weighted, compared to the United Nations census estimates for 88 countries with populations ≥ 10 million, for Landscan, deviation by country was least (mean absolute error = 13.33) at 1400 humans per km² and error increased (mean absolute error = 13.80) at the global threshold of 1900 humans per km². For Worldpop, deviation by country was least (mean absolute error = 14.66) at 500 individuals per km²; error increased (mean absolute error = 15.29) at the global threshold of 800 humans per km². For GPW,

Table 2 (continued)

Country	U.N. Count	U.N.	Landscan	Worldpop	GPW
Togo	7,416,802	40.10	50.63	36.50	28.99
Trinidad and Tobago	1,360,092	53.30	57.88	50.26	35.48
Tunisia	11,273,661	68.10	53.89	50.89	37.59
Turkey	78,271,472	73.60	55.83	65.06	43.55
Turkmenistan	5,565,284	50.30	37.62	19.00	14.42
Uganda	40,144,870	22.10	28.89	22.92	25.32
Ukraine	44,657,704	69.10	46.74	49.15	49.92
United Arab Emirates	9,154,302	85.70	74.56	48.94	63.83
United Kingdom	65,397,080	82.60	66.69	84.80	84.98
United States	319,929,162	81.70	36.80	62.44	68.56
Uruguay	3,431,552	95.00	68.70	84.59	86.84
Uzbekistan	30,976,021	50.80	49.14	28.81	16.72
Venezuela	31,155,134	88.20	75.06	53.17	36.43
Vietnam	93,571,567	33.80	64.99	55.00	56.59
Yemen	26,916,207	34.80	41.03	35.03	32.90
Zambia	16,100,587	41.90	32.99	27.39	19.04
Zimbabwe	15,777,451	32.40	28.54	28.76	29.57
Mean		58.76	49.31	46.66	42.59

minimum error (mean absolute error = 19.99) occurred at 200 individuals per km² and error increased (mean absolute error = 21.51) at the (near) global threshold of 500 humans per km². For the ensemble Landscan and Worldpop, deviation was least (mean absolute error = 12.84) at 700 individuals per km², but the ensemble Landscan and Worldpop model had the least error, resulting in relatively low error (mean absolute error = 13.64) at the global threshold of 1000 humans per km².

Thresholds based on comparison of urban percentages.

I finalized the generalized classes of population density with modifications of class groupings depending on the population model (Table 1). To match the global urban estimates for each model, which did increase country-wise error rates, I subdivided the initial suburban class into 550 to 800 humans per km², 800 to 1000 humans per km², and 1000 to 1900 humans per km², which aligned with thresholds for three population models and the combined Landscan and Worldpop model. To create a suburban class for GPW, I added another threshold at 250 humans per km², resulting in a total of 10 population density classes. For each of the four population models, including the combination of two models, I assigned a density class for thresholds to produce approximately equal rural (wildlands and inhabited), exurban, suburban, and urban percentages.

Comparisons based on provisional thresholds.

The model estimates of urban percentage by country, for 157 countries ≥ 1 million, at the fitted thresholds overall were more similar to each other than to census-derived estimates (Table 2). For model comparisons of urban percentages by country, Landscan and GPW were

most divergent (mean absolute error = 14.48 and $r = 0.68$) and Worldpop and GPW were most similar (mean absolute error = 6.71 and $r = 0.93$), with Landscan and Worldpop relatively similar (mean absolute error = 10.74 and $r = 0.77$). These correlations endured spatially for all cells classed into rural, exurban, suburban, and urban, but the suburban classes had the poorest fit. The U.N. estimates had correlations ranging from $r = 0.54$ with GPW, $r = 0.64$ with Landscan, $r = 0.69$ with Worldpop, and $r = 0.71$ with the ensemble Landscan and Worldpop. Mean absolute error at these fitted thresholds for this expanded set of countries increased from the ensemble Landscan and Worldpop (mean absolute error = 14.98), Landscan (mean absolute error = 15.41), Worldpop (mean absolute error = 16.77), to GPW (mean absolute error = 22.15).

Irreconcilable differences at the national scale: rural and urban designations.

Agreement occurred among all of the models, regardless of the threshold of urban percentages, that models could not reconcile the U.N. reported national urban percentages. For example, the 12 most populous countries, with populations ≥ 100 million, ranged from the reported highly urbanized (91%) Japan and (82%) United States, and North and South America in general, with the reported less urban nature (56%) of China and rural (33%) India (Tables 2 and 3; Fig. 1). The population models typically had more moderate values than the U.N. reported national urban percentages. As for the population models, Landscan had lesser urban population values whereas GPW had greater urban population values.

The three population models with adjusted thresholds diverged from U.N. reported predominantly urban or rural populations, with agreement for 32 countries out of 157 countries (Table 2; Fig. 2). The following 24 countries, representing 306 million humans, were rural according to all three models compared to the U.N. urban designation: Angola, Austria, Azerbaijan, Botswana, Cameroon, Croatia, Czech Republic, Finland, Georgia, Ghana, Hungary, Latvia, Libya, Lithuania, Mauritania, Nicaragua, Norway, Poland, Romania, Slovakia, Slovenia, Turkmenistan, Ukraine, and Uzbekistan. The following eight countries, representing 1.97 billion humans, were urban according to all three models compared to the U.N. rural designation: Bangladesh, Egypt, India, Mauritius, Pakistan, Philippines, Sri Lanka, and Vietnam.

Irreconcilable differences within classes.

Similarly, the three population models with adjusted thresholds diverged by 20 or more percentage points from reported urban percentages for 27 countries in common. The following 20 countries, representing 271 million humans, were 20 or more percentage points less than U.N. reported urban percentages according to all three models: Argentina, Belarus, Belgium, Botswana, Bulgaria, Cuba, Czech Republic, Denmark, Finland, France, Gabon, Germany, Hungary, Libya, Lithuania, Netherlands, Norway, Oman, Puerto Rico, and Sweden. Specifically, 13 countries, of Argentina, Belarus, Belgium, Bulgaria, Cuba, Denmark,

Table 3

Urban percentage for 12 countries with populations ≥ 100 million at different urban thresholds of count per km² for three models compared to U.N. census estimates during 2015.

Threshold	U.N.	Landscan				Worldpop				GPW			
	N/A	1900	1800	1700	1600	1100	1000	900	800	800	700	600	500
Bangladesh	34.3	56.0	57.8	59.8	62.1	62.5	68.3	74.6	80.9	87.5	93.1	95.8	97.3
Brazil	85.8	72.7	73.6	74.4	75.2	75.9	76.9	77.9	79.0	76.3	77.5	78.8	80.2
China	55.5	55.7	56.5	57.5	58.4	50.0	51.8	54.0	56.6	46.6	50.2	54.7	60.2
India	32.8	56.8	57.6	58.6	59.6	42.1	45.4	49.1	53.1	45.9	50.5	55.6	61.7
Indonesia	53.3	58.3	59.4	60.5	61.7	50.1	52.6	55.3	58.1	47.9	54.1	58.5	63.9
Japan	91.4	71.6	72.6	73.6	74.6	71.0	72.6	74.2	76.0	63.9	66.1	68.0	71.1
Mexico	79.3	66.2	66.8	67.4	68.0	74.2	75.1	76.1	77.2	73.9	74.7	75.4	76.2
Nigeria	47.8	61.3	62.4	63.3	64.4	37.3	39.1	41.1	43.4	28.9	32.1	36.1	41.0
Pakistan	36.0	54.9	56.2	57.5	59.1	45.6	47.8	50.4	53.5	36.3	43.8	53.1	63.5
Philippines	46.3	63.2	64.0	64.9	65.8	55.7	57.4	59.5	61.7	58.5	61.2	64.5	68.4
Russia	74.1	55.5	56.0	56.5	56.9	48.8	50.2	51.7	53.3	44.5	45.5	47.8	48.8
United States	81.7	36.8	39.0	41.3	43.7	53.8	56.6	59.5	62.4	60.9	63.9	67.0	70.1
Mean	59.9	59.1	60.2	61.3	62.5	55.6	57.8	60.3	62.9	55.9	59.4	63.0	66.9

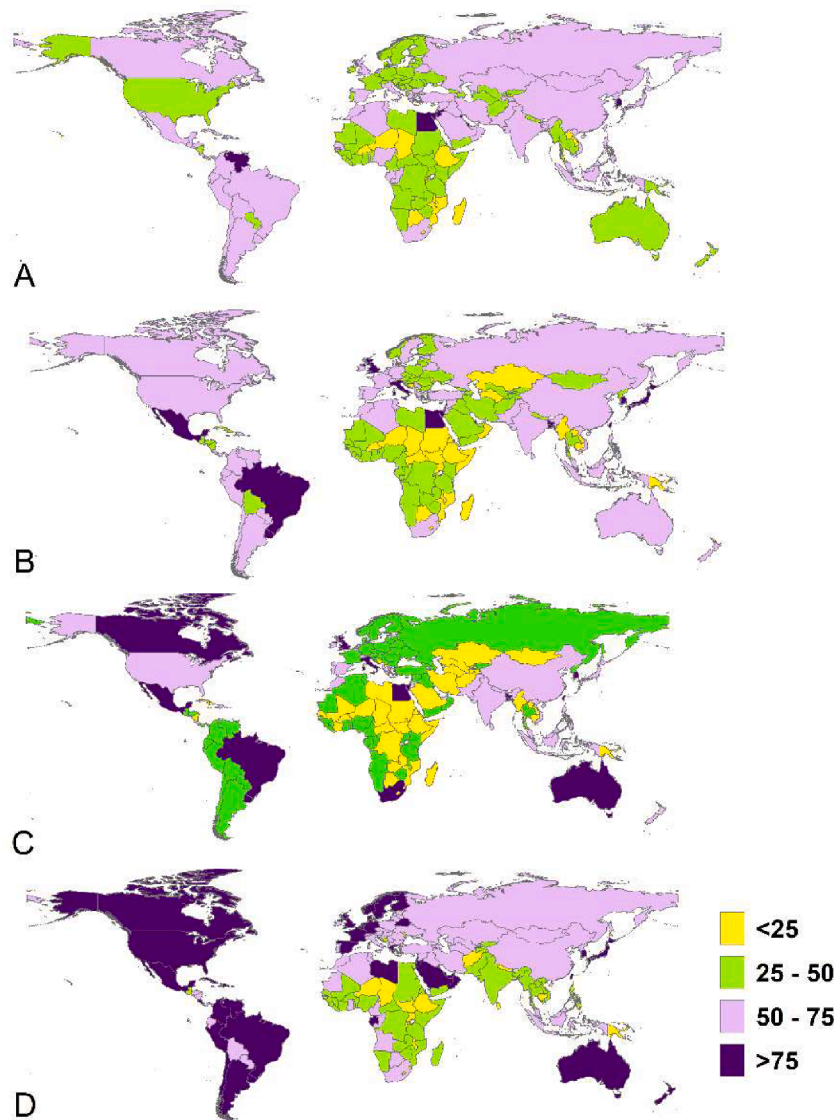


Fig. 1. National urban percentages during 2015 for (A) Landsan, (B) Worldpop, (C) Gridded Population of the World, and (D) United Nations.

France, Gabon, Germany, Netherlands, Oman, Puerto Rico, and Sweden, were not already distinguished in the 24 countries that differed from U.N. urban designations. The following seven countries were 20 or more percentage points greater than U.N. reported urban percentages according to all three models: Bangladesh, Egypt, India, Mauritius, Nepal, Sri Lanka, and Vietnam. However, all but Nepal was contained within the group of eight countries that were urban compared to the U.N. rural designation.

Constancy over time.

Over time, Worldpop remained coordinated with the U.N. urban percentage estimates (Table 4). Mean absolute error for years 2000, 2005, 2010, 2015, and 2018 was 0.49. The 2000 modeled estimate of 47.98% had greater departure than other years from the U.N. estimate of 46.68%. The turnover from a global rural to a global urban percentage occurred during 2007, increasing from 49.95% during 2006 to 50.31% during 2007, which paralleled the U.N. timing of transition.

3. Discussion

Irreconcilable differences at the national scale.

Here, I developed a provisional classification system for application of modeled population densities to determine urban populations,

creating shared meaning of urban populations across countries. The United Nations relies on disparate national definitions of urban populations. However, after imposing consistent global definitions of urban populations with thresholds for gridded population densities, the population models diverged by country from reported census data by the United Nations, as detected previously with the Africapolis settlement database (Moriconi-Ebrard et al. 2008; Heinriks 2020). In combination, all three population models shared a changed status for 32 countries representing 30% of the global population and an additional 13 countries comprising 270 million people were >20 percentage points less urban than the U.N. report (Fig. 2). According to the three population models, more populous countries, such as India, Bangladesh, Pakistan, the Philippines, and Vietnam, were urban rather than rural, whereas most European countries either were less urban than reported or rural rather than urban.

The population models produced consistent agreement that particularly the most populous countries could not have simultaneously low urban population values, for example in India and Pakistan, moderate urban population values in China and Indonesia, and high urban population values for the United States and Brazil. Instead of the U.N. reported census estimates of 82% urban for the United States, 56% urban for China, and 33% urban for India, urban percentages ranged from 53%

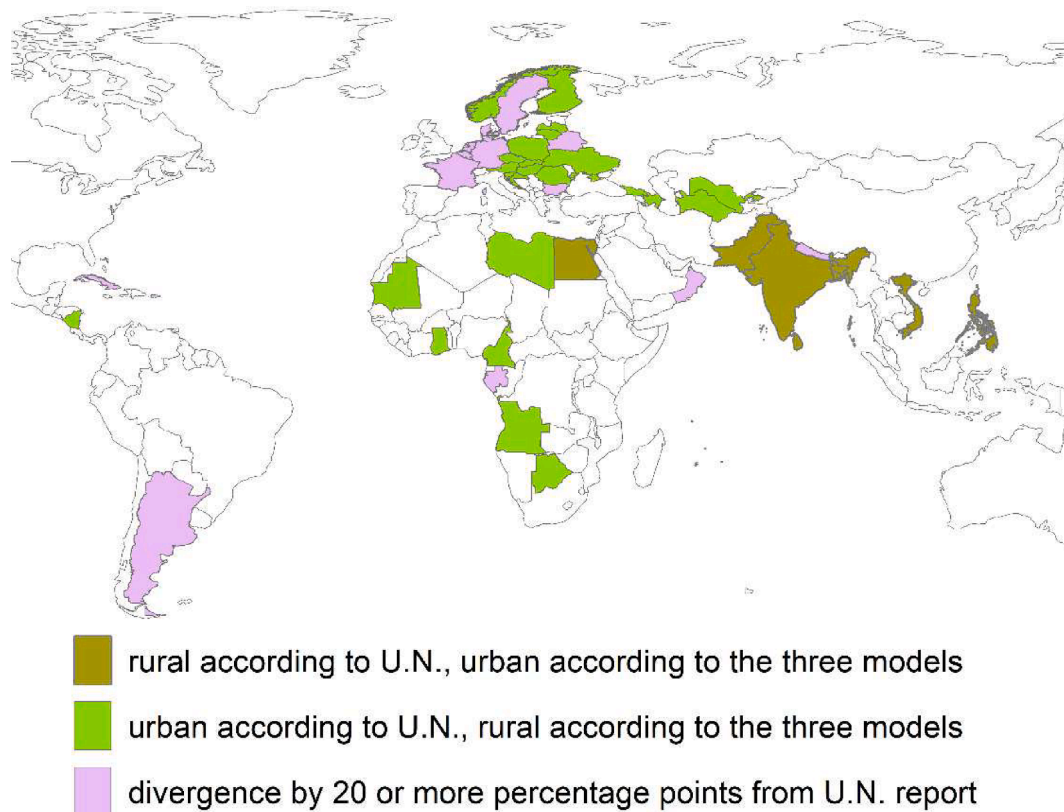


Fig. 2. Countries that departed by urban or rural class from United Nations according to the three population models or divergence by ≥ 20 percentage points based on the population models compared to urban percentages reported by the United Nations.

to 69%, with the exception of 37% urban for the U.S. in the Landscan model (Table 2). Definitions may cause areas at urban population densities to be reported as rural rather than urban; countries likely understate their urban populations, such as India that requires in the urban definition at least 75% of the male working population to be engaged in non-agricultural pursuits (Satterthwaite 2010; United Nations, 2019).

A change in the urban–rural threshold value cannot correct the wide range of distributions of the reported urban estimates. Additional modification can create overall improvement in fit; however, each model produced unique country values that would not be possible to resolve. For instance, even for the 12 most populous countries, each population model generated national urban percentages both less than and greater than values of the other population models.

How similar were the population models?

Another outcome of this research was evaluation of the population models. All of the population models distribute census population data within census units. The GPW model applies a simple areal-weighting method to disaggregate the census population spatially; uniform distribution or proportional allocation with relative coarseness should remain faithful to the input data (Doxsey-Whitfield et al., 2015). Although GPW was intended to produce greater fidelity with U.N. national estimates, the GPW model was less similar to U.N. national estimates than the other models according to mean absolute error and correlation. Both Landscan and Worldpop rely on urban indicators, including land cover, urban land use, roads, and nighttime lights, to better populate urban and rural land (Cheriyadat et al. 2007; Lloyd et al. 2017). Error will occur due to factors such as misidentification in the extent and intensity of urban land and mismatches between infrastructure and populations, such as industrialized areas and vacant buildings. Despite differences among models, these three models were in accord that, compared to urban percentage from standardized application of population densities, relying on disparate country definitions of urban populations produced

irreconcilable differences from reported national urban percentages. Two or more population models, or an ensemble, may be necessary to help establish the range of uncertainty.

The population models vary in population distribution, with the greatest concentration of population densities produced by the Landscan model and the greatest dispersion generated by GPW. Worldpop had intermediate dispersion, although closer in dispersion to GPW than Landscan. Discrepancies in the urban–rural threshold arose specifically in the range of 500 to 1900 individuals per km^2 , resulting in widely different percentages of urban populations; consequently, assigned density thresholds necessarily varied by model. Compared to the United Nations global urban estimate of 53.93%, and without identifying extremely specific values, Landscan had the least difference at 1900 humans per km^2 (urban percentage of 54.18%), Worldpop had the least difference at 800 humans per km^2 (urban percentage of 54.53%), GPW had the least difference at 550 humans per km^2 (54.03%), and the ensemble Landscan and Worldpop model had the least difference at 1000 humans per km^2 (54.83%). Fitting population models to the global urban estimate, which is area-weighted, did increase country-wise error rates.

Furthermore, I did not present formal results from the Global Human Settlement Layer because this model had an extreme departure from the U.N. reported values (Angel et al. 2018). Mean absolute error for country urban percentages was 26.7 compared to the U.N. reported urban percentages, with severe reversal in urban percentages of the United States, China, and India from U.N. urban percentages. Due to this deviation, the Global Human Settlement Layer should be used with caution as the basis for analysis of populations.

Although the varying thresholds adjusted for different spatial patterns, it is not clear if the more concentrated Landscan model or the moderate dispersion of the Worldpop model is a more accurate picture of population density. Worldpop produced values intermediate between

Table 4
Population densities during years 2000 to 2020 based on Worldpop.

Class	Threshold	Pop %	Class	Pop %
2000 Worldpop				
Wildlands	0 to 1	0.18	Rural	3.10
Inhabited	1 to 15	2.92		
Exurban low	15 to 100	11.65	Exurban	24.65
Exurban high	100 to 250	13.00		
Suburban low	250 to 550	15.52	Suburban	24.27
Suburban high	550 to 800	8.74		
Urban low	800 to 1900	16.45	Urban	47.98
Urban high	>1900	31.53		
2005 Worldpop				
Wildlands	0 to 1	0.18	Rural	2.94
Inhabited	1 to 15	2.76		
Exurban low	15 to 100	11.03	Exurban	23.58
Exurban high	100 to 250	12.55		
Suburban low	250 to 550	15.28	Suburban	23.80
Suburban high	550 to 800	8.53		
Urban low	800 to 1900	16.83	Urban	49.68
Urban high	>1900	32.85		
2006 Worldpop				
Wildlands	0 to 1	0.17	Rural	2.89
Inhabited	1 to 15	2.72		
Exurban low	15 to 100	10.88	Exurban	23.26
Exurban high	100 to 250	12.38		
Suburban low	250 to 550	15.31	Suburban	23.89
Suburban high	550 to 800	8.58		
Urban low	800 to 1900	16.98	Urban	49.95
Urban high	>1900	32.98		
2007 Worldpop				
Wildlands	0 to 1	0.17	Rural	2.85
Inhabited	1 to 15	2.68		
Exurban low	15 to 100	10.77	Exurban	23.20
Exurban high	100 to 250	12.42		
Suburban low	250 to 550	15.22	Suburban	23.65
Suburban high	550 to 800	8.43		
Urban low	800 to 1900	16.94	Urban	50.31
Urban high	>1900	33.38		
2010 Worldpop				
Wildlands	0 to 1	0.16	Rural	2.74
Inhabited	1 to 15	2.58		
Exurban low	15 to 100	10.59	Exurban	22.32
Exurban high	100 to 250	11.73		
Suburban low	250 to 550	14.89	Suburban	23.14
Suburban high	550 to 800	8.25		
Urban low	800 to 1900	17.45	Urban	51.80
Urban high	>1900	34.35		
2018 Worldpop				
Wildlands	0 to 1	0.14	Rural	2.49
Inhabited	1 to 15	2.35		
Exurban low	15 to 100	9.85	Exurban	20.81
Exurban high	100 to 250	10.96		
Suburban low	250 to 550	13.45	Suburban	20.91
Suburban high	550 to 800	7.46		
Urban low	800 to 1900	17.53	Urban	55.79
Urban high	>1900	38.26		

Landsat and GPW, although country-wise error was less for Landsat than Worldpop. Values in the middle may be the most accurate representation, and indeed, some research has applied around 1200 to 1300 humans per km² as the cutoff between suburban and urban densities; these densities support mass transit and reduced per capita vehicle miles traveled (Lopez and Hynes 2003). The ensemble Landsat and Worldpop model minimized differences and reduced error, but model averaging may produce a model that is not representative of any particular set of conditions and also has no oversight from a modeling group.

Worldpop has several advantages over Landsat. Access is unrestricted at 100 m and 1 km during the years 2000 to 2020. The other apparent benefit of Worldpop is models of populations during 2000 to 2020 are compatible with each other. Conversely, Landsat models are updated with improvements that have not been incorporated into older versions; development supplants comparison.

Constancy of thresholds.

Similarly to the lack of clarity in how concentrated or dispersed populations are, the global urban percentage is not known, but urban definitions and classifications are useful constructs. The United Nations is the authority for urban statistics, with general consensus that the global urban report is a reasonable representation of the urban situation, with some fluctuation depending on changing criteria used to define urban areas (Satterthwaite 2010; Angel et al. 2018). Calibration of population density thresholds to the U.N. reported 2015 global urban population then maintains agreement with the global urban population.

A consideration is that thresholds for urban density may be on a sliding scale depending on reference conditions. That is, the thresholds were calibrated to the 2015 global urban population, but separation over time may occur due to factors such as changing total population or differential census information. After adjusting the models to an equal basis of the 2015 U.N. global urban population estimate of 53.93%, Worldpop paralleled the global urban population estimates between 2000 and 2018. Nonetheless, the Worldpop estimate for global population at year 2000 was 1.3 percentage points greater than the U.N. estimate, indicating a potential difference over time. However, the global human population may not double again (United Nations 2019), resulting in 2015 thresholds that may remain relatively stable and set an anchor to provide a common frame of reference. Thresholds are flexible and can be adjusted by fine-tuning with additional sources of data.

To date, these models do not have an historical time series of urban population estimates back to 1950, which is the start year for the U.N. urbanization prospects reports. Comprehensive global satellite imagery dates back to the early 1980s (Goward et al. 2021). The Global Human Settlement Layer (Freire et al. 2016; Schiavina et al. 2019) has a population model during 1975, albeit the urban density threshold would need to be adjusted to 3200 inhabitants per km² to have a global urban population near 53.93% during 2015. It is possible to hindcast back to 1950, similarly to the United Nations forecasts to 2050. Indeed, projects such as the History Database of the Global Environment (Klein Goldewijk et al., 2010) model hundreds to thousands of years to the past, albeit based on different model variables.

Revisiting urban definitions and potential applications.

To determine urban populations for planning and management applications, population density is the most constant metric over time. The percentage of urban land cover also is a characteristic of urban lands, but is less direct for measuring populations, particularly as human populations are dynamic while concrete is enduring (Moriconi-Ebrard et al. 2008; Heinrigs 2020). Depopulations occur, resulting in abandoned lots (i.e., greyfields) and uninhabited ghost cities are built. Additionally, human infrastructure, such as roads and energy extraction, can be prevalent in rural lands.

The criteria used by countries to decide whether to define a place as urban include population density, minimum population size of settlements or agglomerations, administrative boundaries, level of infrastructure, or a combination of these and other criteria, specifically economic information (Potts 2017; United Nations, 2019; Wineman et al. 2020). Due to changing spatial patterns over time as, for example, population growth creates new urban mergers, inconsistent population measurement occurs based on administrative boundaries and minimum population size in urban agglomerations (Satterthwaite 2007). Regarding infrastructure, cities existed before services such as piped water and sewer, education, and health care were available, and did not change in time or space based on national standards, resources for development, and technological advances. Three million people lived in London during 1860, when sewers were constructed, which did not change the status of London from rural to urban. More than a century later, hundreds of millions of city dwellers in Asia and Africa have little or no access to basic services, such as water taps (Satterthwaite 2007). An estimated 863 million people during 2012 were counted as urban residents in developing regions, but reside in informal settlements, which lack access to improved water, sanitation, and other infrastructure and services (United Nations 2015).

To reiterate, attempting to compress complex socioeconomic histories into a single metric of percentage urban population is not beneficial either for understanding the histories or enabling a standard urban definition (Potts 2018). Measuring urban percentage of population densities is different than measuring employment percentage in the agricultural, industrial, and service sectors. If the objective is a combination of both, then this would be a population density-employment index, and socioeconomic indices can become increasingly multifaceted requiring examination, for example, by various component analyses.

For research applications, gridded population data can now represent urban populations, extending the usefulness of the gridded population data and opening new research avenues. In addition to being able to compare countries on an equal basis, calibrated population density classes are applicable to other issues. For example, interactions between population density classes and different components of climate change can be measured (Hanberry 2022).

4. Conclusions

To impose a consistent global definition of urban populations based on population densities, I relied on population densities by equilibrating population density models with the United Nations global urban population during 2015 to assign urban and rural density classes. It was possible to reconcile the distribution differences in population density models by adjusting the urban density threshold, but shared, credible divergence from United Nations urban population estimates occurred for 32 countries out of 157 countries compared to the reported census data by the United Nations. For these countries, encompassing about 30% of the global population, the urban trajectory may need to be reassessed. The thresholds activate the gridded population data to represent urban populations, which is a progressive step in standardized comparisons of rural and urban population densities across countries for planning and management, offering new perspectives and potential applications that may open new areas of investigation. Nevertheless, one critical caveat is that urban is defined in many ways, such as through employment or other economic data, and population density on its own does not encompass complex social, economic, political, and demographic histories and transformations into measurement of urban populations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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