

Daily patterns of global urban populations reveal how cities breathe

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Article

Keywords:

Posted Date: October 9th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11053040/v1>

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Daily patterns of global urban populations reveal how cities breathe

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Abstract

Urban populations are dynamic, yet globally consistent data used to understand and plan cities are usually residential, ambient or otherwise temporally static. We combine LandScan Mosaic daytime and nighttime population grids with independently delineated physical boundaries for more than 50,000 urban centers to measure urban population breathing: expansion, contraction and internal redistribution between day and night. Global urban population is 148 million higher by day than at night, but this net increase conceals 731 million in offsetting gains and losses. Small and intermediate centers contribute more redistribution than their population share. Larger centers tend toward aggregate balance: wider footprints contain more fine-scale variation, while coherent redistribution across broad relative zones declines with population. Radial and directional signatures define a continuous global morphology spanning broad stability, outward expansion, inward concentration and directional reorganization. These patterns show where static population denominators may misrepresent infrastructure demand, service needs and exposure.

The size and internal geography of urban populations change through the day, yet the global evidence used to understand and plan cities remains largely static. In 2025, 4.76 billion people—57.8% of the global population under national definitions—lived in urban areas; by 2050, that population is projected to reach 6.50 billion.¹ Within cities, these daily shifts reshape demand for transport, utilities and public services, as well as access to opportunity and exposure to hazards. Infrastructure is fixed and capacity-constrained; the population it serves is not. Understanding this changing population geography is central to Sustainable Development Goal 11 because where people are located shapes health, accessibility and climate resilience.^{2,3} Residential and ambient estimates remain essential for demographic accounting, but no single static population surface can capture the size and spatial distribution of urban populations at different times of day.

A city's population has more than one geography. Usual residence provides a demographic anchor, time-specific presence describes where people are located during a reference period, and mobility connects the places through which daily life unfolds. Activity-pattern and temporary-population research has long distinguished where people live, where they are present and how long they spend there.^{4,5} The appropriate population denominator therefore depends on the question: people exposed to a flood, using transit or relying on emergency services may not be those recorded as residents nearby.

Population models have become increasingly spatially detailed, but not necessarily more time-aware. Gridded population modeling has progressed from simple redistributions of census counts to dasymetric products that use settlement, land-cover and infrastructure information to allocate population within reporting zones.^{6–8} Most global products nevertheless represent usual residence or an ambient 24-hour average. LandScan USA was an early

national-scale exception, releasing daytime and nighttime grids at approximately 90-m resolution.⁹ Applications to transport-corridor exposure, water-network planning and park use show how time-specific populations can change estimates of exposure and service demand.^{10–12}

Time-specific population models generally redistribute residential populations among activity locations using land use, occupancy schedules, spatial microsimulation or data fusion.^{13–17} Other approaches infer population fluctuations from mobile-network data.^{18–20} Together, these studies have revealed daytime contraction and persistent activity centers in particular cities.^{17,19} Time-specific population data can also materially change estimated hazard exposure^{21–23} and show how experienced segregation differs from residential segregation.²⁴ Yet coverage, observation windows and spatial units differ, and proprietary mobility samples can be selective.²⁵ Before LandScan Mosaic, no public gridded product offered globally consistent daytime and nighttime distributions, and no study had compared how population geography changes within urban centers worldwide.

We combine the public LandScan Mosaic 2025 daytime and nighttime grids^{26,27} with more than 50,000 Global Urban Envelopes (GUEs).^{28,29} We use *urban population breathing* to describe the expansion, contraction and internal redistribution that distinguish these modeled states; the term does not imply observed trips, unique movers or a continuous daily cycle. GUEs represent contiguous physical settlements delineated from built form, nighttime lights and place labels—not from gridded population counts. Population therefore remains an analytical outcome rather than an input to the urban boundary, avoiding one source of circularity in population-threshold delineations.³⁰ We hold each 2025 polygon fixed to isolate change inside the same settled footprint. Wider functional regions provide a complementary perspective and are examined in the Supplementary Information.

We examine three dimensions of urban breathing: daytime–nighttime balance, internal redistribution at fine and broad scales, and the directional geography of change. The global net difference is small relative to offsetting center-level gains and losses. Larger centers are closer to total balance; their wider footprints encompass more fine-scale variation, while broad redistribution declines with population. Across regions and size classes, these changes form a continuous morphology organized around stability, outward expansion, inward concentration and directional redistribution. The analysis reveals when similar totals conceal very different internal geographies.

1 Results

1.1 Urban populations balance globally but diverge locally

Across 50,001 fixed urban-center boundaries, modeled population totaled 4.023 billion at night and 4.171 billion by day in 2025 (Fig. 1a). The daytime total was 148 million higher, equivalent to 3.7% of nighttime population, but this net difference concealed substantial regional and center-level variation. The median center was 5.5% smaller by day: 43.1% of centers lost more than 10% of their nighttime population, 29.8% were approximately balanced and 27.2% gained more than 10%. The global surplus therefore arose from a smaller number of large daytime gains rather than from increases across most urban centers.

Every broad world region included centers with both daytime gains and losses (Fig. 1b,c). The spread was widest among smaller centers, while the largest centers clustered more closely around equal daytime and nighttime totals. Within their fixed physical envelopes, Cape Town remained almost unchanged and Dubrovnik was 12.5% larger by day, whereas Aspen and Chongqing were 22.7% and 49.4% smaller. These examples show that gains and losses span both geography and urban scale rather than defining a single regional pattern.

Total population change captures whether a center gains or loses people, but not how population is rearranged within it. We therefore used Jensen–Shannon (JS) divergence to compare the share of each center’s population in every grid cell by day and by night. JS is zero when the two spatial distributions are identical and approaches one as they cease to overlap. Median native-cell JS was 0.130. Even among the 14,898 centers whose totals differed by no more than 10%, 18.4% fell above the global upper quartile of JS. Near-equal totals could therefore mask substantial internal redistribution.

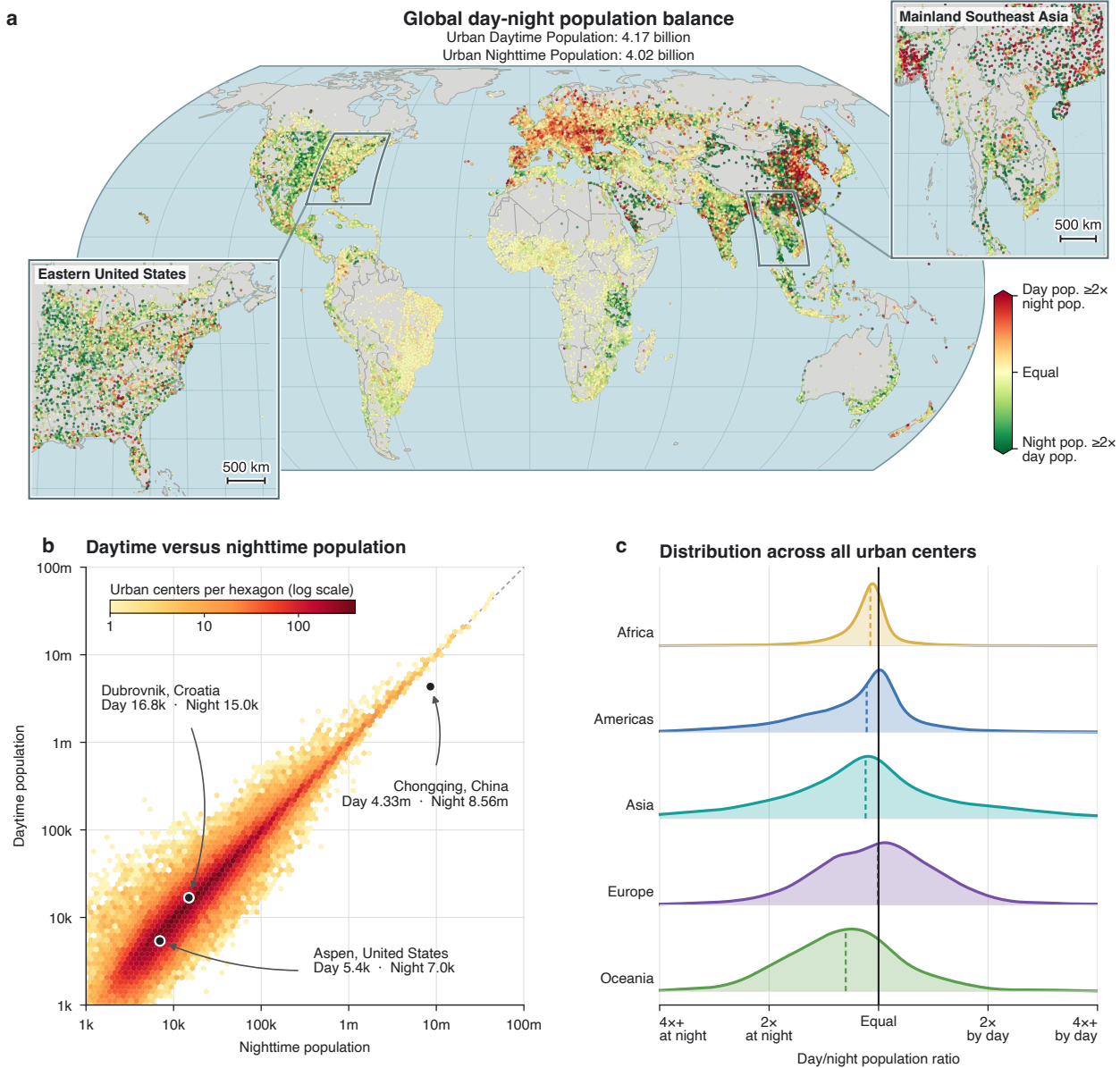


Fig. 1 Global day–night population redistribution. **a**, Population balance across 50,001 GUE urban centers. Green indicates more people at night, yellow equal totals and red more by day. **b**, Daytime and nighttime totals on matched logarithmic axes. Hexagon color represents the number of urban centers on a logarithmic scale. **c**, Distributions of the day-to-night population ratio across five broad world regions; dashed lines mark medians and the solid line marks equality.

1.2 Redistribution changes across urban scales

The net daytime increase of 148 million was the remainder of much larger changes in opposite directions (Fig. 2a). Center-level daytime gains summed to 439.6 million people and nighttime surpluses to 291.8 million, giving 731.4 million in absolute difference, or 18.2% of nighttime population. This quantity compares two modeled states rather than counting movers. Asia and Europe had net daytime gains, while Africa, the Americas and Oceania had net nighttime surpluses.

Small and intermediate centers were numerically dominant and carried a disproportionate share of change (Fig. 2c). Centers below 50,000 nighttime residents made up 79.1% of the sample and 14.5% of nighttime population, but 25.6% of absolute difference. Taken together, centers below 1 million represented 99.0% of the sample and 80.4% of absolute difference. Conversely, centers with 1 million to fewer than 5 million residents produced 38.6% of the net daytime gain despite representing fewer than 1% of centers. Thus, smaller and intermediate centers accounted for most absolute redistribution, while large centers shaped the signed daytime surplus.

Overall balance and internal redistribution scaled differently with urban-center size (Fig. 2b,d). From the smallest to the largest class, median signed change moved toward zero, from -6.8% to -0.04% , and the share whose daytime and nighttime totals differed by no more than 10% rose from 27.0% to 87.7%. Native-cell JS fell from 0.135 to 0.087 between the first two classes, then rose to 0.197 in the largest. After aggregation to the same 32 relative zones, median JS instead declined from 0.048 to 0.008.

These gradients reflect the joint scaling of population and urban extent. Median equivalent radius increased from 1.22 to 20.68 km across the six classes, so the native-cell comparison encompassed progressively more land and cells. Within regions, the positive association between population and native-cell JS became negative when centers of similar area or cell count were compared; the negative association across the common 32 zones persisted (Supplementary Fig. S4). Expanding footprints therefore substantially explain the unadjusted rise in fine differentiation, while broad redistribution becomes less coherent as population increases.

Chicago and Moscow, for example, were close to total balance ($+0.8\%$ and $+1.5\%$) but had native-cell JS values of 0.394 and 0.398. On the 32 broad zones, these values fell to 0.008 and 0.001: fine-scale gains and losses largely canceled within wider parts of each center. In many smaller centers, more of the settled footprint changed coherently.

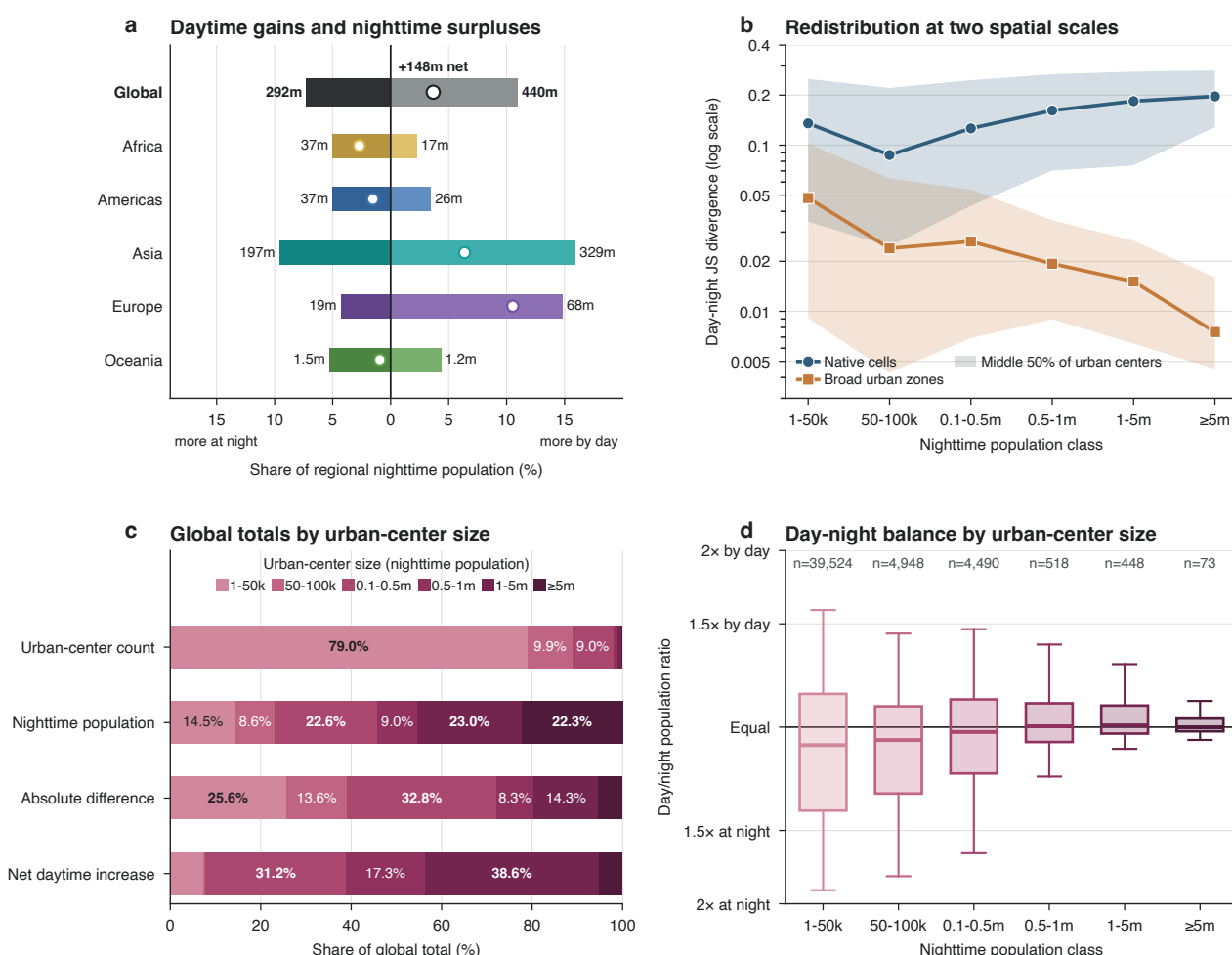


Fig. 2 Global accounting and scale-dependent redistribution. **a**, Offsetting daytime gains and nighttime surpluses globally and across five broad world regions. **b**, Median JS divergence across native cells and the same 32 relative zones in every center. **c**, Composition of urban-center count, nighttime population, absolute difference and net daytime increase across six size classes. **d**, Day-to-night population ratios by class; boxes show interquartile ranges, center lines medians and whiskers the 10th–90th percentiles. Reference lines mark equality and 1.5-fold differences. Larger footprints encompass more local variation, whereas broad relative zones retain less coherent change.

1.3 Balanced centers have contrasting spatial anatomies

Approximately balanced centers differed in whether daytime change followed the center–edge gradient or particular directions (Fig. 3). São Paulo paired a 0.75-km radial shift with a directional fraction of only 17%: population became more central across several directions. Lagos showed the converse pattern. Although 80% of its broad redistribution was directional, radial shift was only 0.16 km because population shares shifted among sectors at similar distances.

Cairo had the largest radial separation among the examples (1.52 km), reflecting outward daytime reweighting. Paris and Dallas also differed in directional organization (68% versus 39%), and their gains and losses occupied different sectors. Dallas shifted inward and had more than twice Paris’s radial separation (1.42 versus 0.63 km), whereas Paris shifted outward. A 25.8-minute mean one-way journey to work in Dallas County provides context for daily mobility within the city,³¹ and such patterns are shown in the relative daytime and nighttime population distributions.

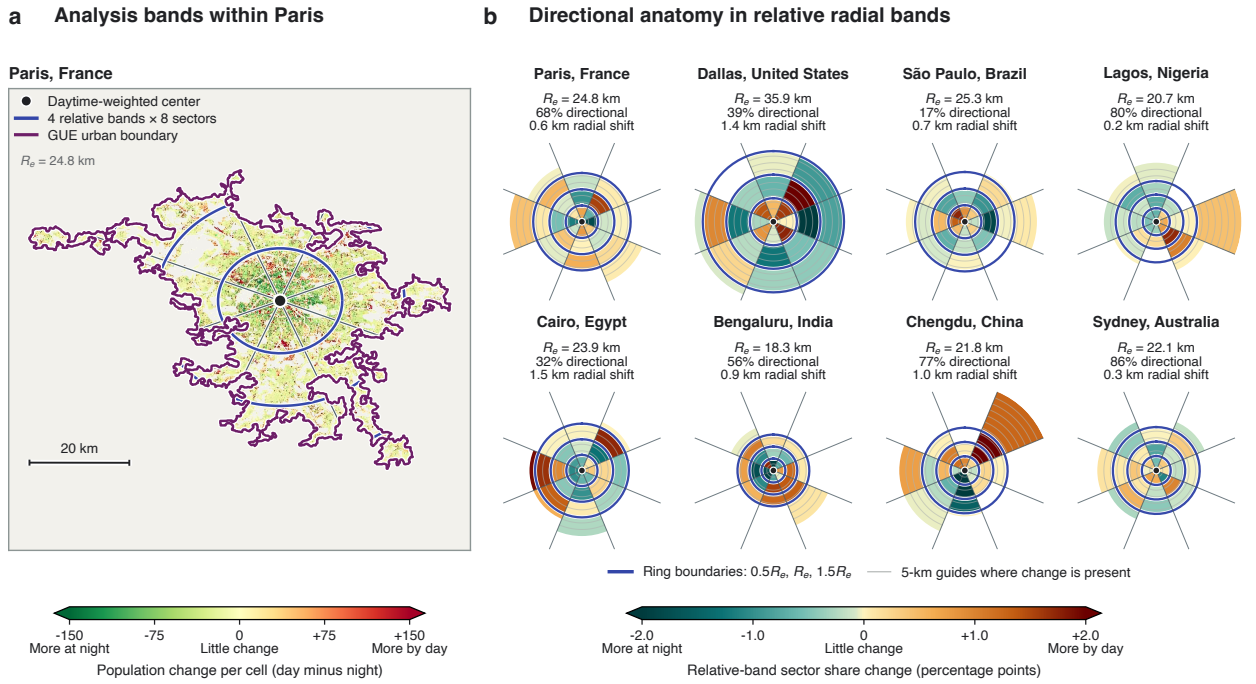


Fig. 3 Directional anatomy across eight urban centers. **a**, Paris illustrates the four relative radial bands and eight sectors used to measure directional redistribution; the raster shows daytime-minus-nighttime population change within the fixed GUE. **b**, Eight approximately balanced centers shown on a common 0–65-km scale. Colored wedges show share change in the four relative bands, blue circles mark their boundaries and faint arcs provide 5-km references where change is present. Directional percentages use the same normalized four-band metric as the global morphology.

1.4 Radial patterns vary across regions and urban scale

Urban populations followed no universal radial pattern: regional medians differed, but substantial variation remained among centers within every region (Fig. 4a,b). Within 5–7.5 km of the daytime population-weighted center, the median daytime-to-nighttime share ratio remained close to one in Africa (0.984) and Asia (0.940), but fell to 0.853 in Europe and 0.707 in Oceania. Outer urban areas therefore retained a larger nighttime share in the latter regions. Median radial shift was smallest in Africa (0.017 km) and South America (0.023 km), and largest in North America (0.112 km). Within-region differences often exceeded contrasts between regional medians. Cairo’s 1.52-km shift far exceeded the African median, as did São Paulo’s 0.75-km shift relative to South America. Regional medians therefore describe broad tendencies while masking pronounced variation among cities.

Urban-center size produced a clearer gradient. Median radial shift rose from 0.067 km below 50,000 nighttime residents to 0.675 km above 5 million (Fig. 4c,d), even as daytime and nighttime shares remained similar across more of the relative radial extent in larger classes. This increase partly reflects their greater physical extent and does not imply longer individual travel. Large centers can reorganize across a wider radial extent while remaining close to total balance.

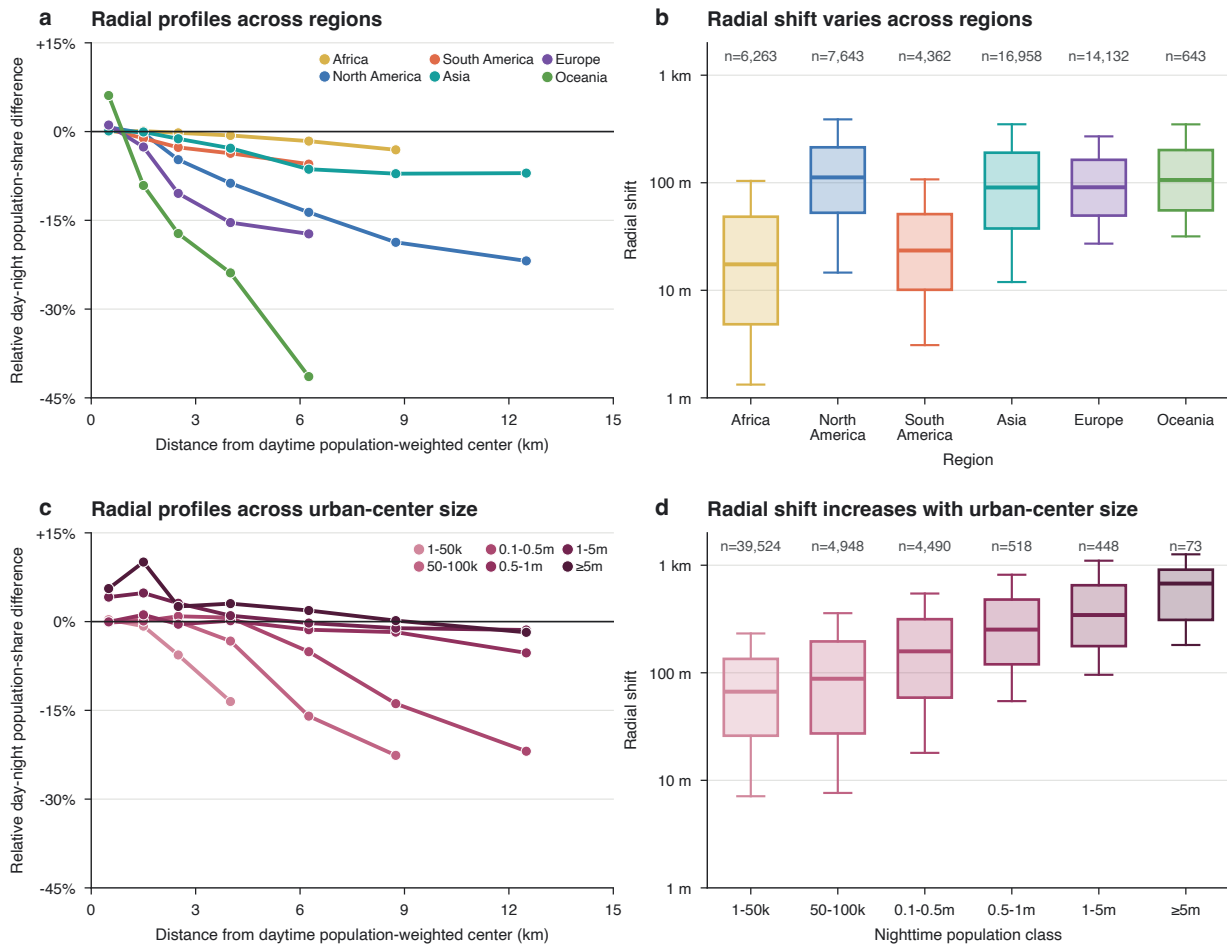


Fig. 4 Global radial redistribution patterns. **a,b**, Median day-to-night population-share profiles and radial-shift distributions across six regions. Profile ratios are expressed as signed relative differences: negative values indicate a larger nighttime share and positive values a larger daytime share, with reciprocal ratios assigned equal magnitude. **c,d**, Corresponding profiles and shifts by nighttime population class. Profiles are shown only where at least 50 centers and 5% of the group contribute; boxes show interquartile ranges and whiskers the 10th–90th percentiles.

1.5 Four recurring regimes organize a continuous morphology

Urban breathing formed a continuous morphology organized around four recurring regimes of broad stability, radial expansion, radial concentration and directional redistribution (Fig. 5). These regimes accounted for 24.4%, 19.2%, 24.5% and 31.9% of centers, respectively. Their median profiles were distinct (Table 1): stable centers redistributed only 2.7% of population share across the 32 broad zones; expansion and concentration centers had median daytime shifts of -9.2% and $+7.6\%$ of equivalent urban radius; and directional centers had a median directional fraction of 73.5%.

Directional fraction describes the organization of redistribution, not its magnitude. The stable regime's median directional fraction of 50.3%, for example, applied to only 2.7% redistribution across the 32 broad zones.

No regime was confined to a region or size class (Fig. 5b–d). The stable regime was most common in Africa and South America, directional redistribution was most common in Europe, and Asia was more evenly divided. Accra and Johannesburg lay near the stable regime, Ahmedabad and Singapore near expansion, Caracas and Beijing near concentration, and London, Seoul and Hyderabad near directional redistribution. Lagos illustrates why magnitude and geometry must be read together: its directional fraction was high, but its redistribution intensity was only 5.2%, underscoring that direction describes organization rather than magnitude.

Table 1 Median morphology of the four descriptive regimes. Values summarize all urban centers assigned to each regime. The four columns correspond to T_{RK} , W_1/R_e , F_{dir} and C in Table 2. Radial reach and daytime shift are expressed relative to equivalent urban radius, R_e ; negative daytime shifts indicate outward redistribution and positive values indicate greater daytime centralization.

Regime	Redistributed share (%)	Radial reach (% R_e)	Directional share (%)	Daytime shift (% R_e)
Stable	2.7	0.8	50.3	0.0
Radial expansion	22.5	8.6	43.8	-9.2
Radial concentration	25.2	11.0	39.5	+7.6
Directional	22.4	4.2	73.5	-0.9

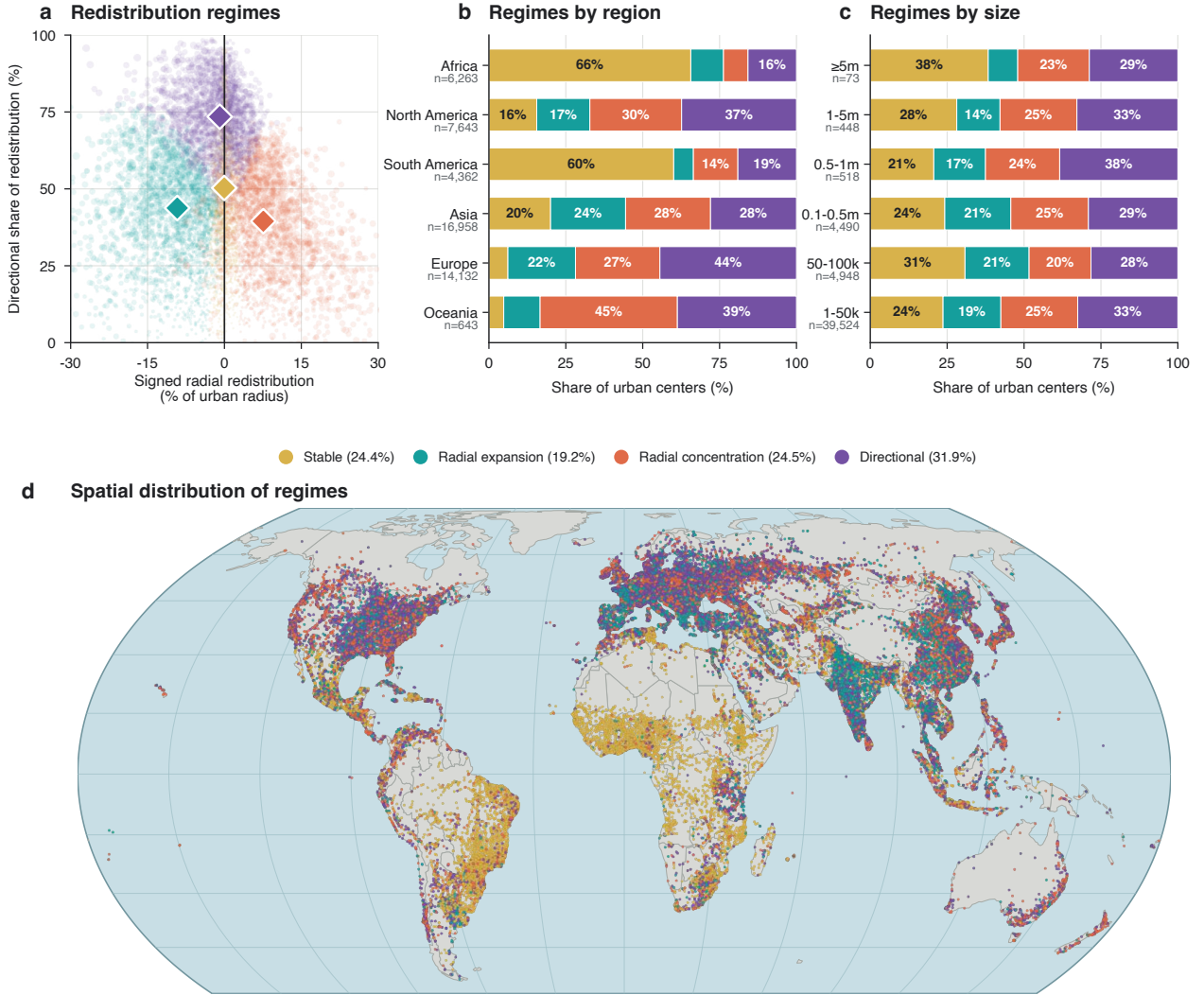


Fig. 5 Four descriptive regimes anchor a continuous global morphology of urban breathing. **a**, Urban centers positioned by signed radial redistribution and directional share; point area scales with redistribution intensity and diamonds mark regime medians. **b,c**, Regime prevalence across regions and nighttime population classes. **d**, Spatial distribution of regimes in an Equal Earth projection. All 50,001 centers enter the analysis; geography and population are not clustering inputs. Median regime profiles are reported in Table 1.

1.6 Contrasting regimes in large urban centers

Four large urban centers translate the global regimes into distinct local geographies (Fig. 6). Accra's cumulative daytime-minus-nighttime share remained close to zero across distance, consistent with its low redistribution intensity of 2.4%. Ahmedabad shifted outward by 9.4% of equivalent urban radius, with daytime share accumulating away from the center, whereas Caracas shifted inward by 7.4%. Hyderabad combined 16.2% redistribution

intensity and a 74% directional fraction with almost no net radial change: gains and losses occurred at similar distances but in different sectors. The same metrics therefore distinguish little broad-scale change, opposing center-edge shifts and strongly directional reorganization.

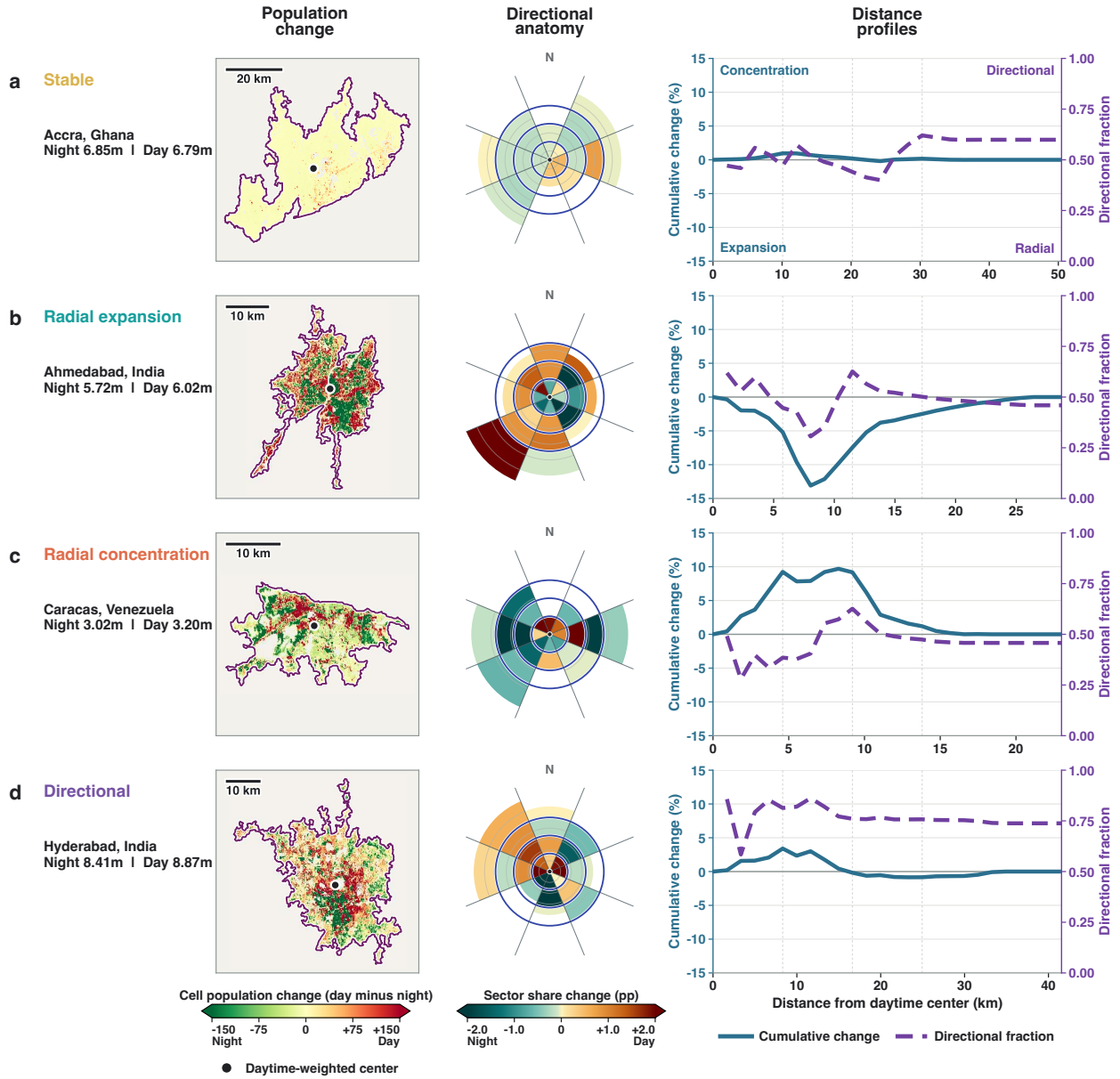


Fig. 6 Large urban-center exemplars of contrasting breathing regimes. a–d, Accra, Ahmedabad, Caracas and Hyderabad illustrate the stable, radial-expansion, radial-concentration and directional regimes. The first column maps daytime-minus-nighttime change per grid cell within each fixed GUE. The second column shows share change across four equivalent-radius bands and eight sectors; blue circles mark the $0.5R_e$, R_e and $1.5R_e$ boundaries, and faint arcs provide 5-km references where change is present. In the final column, the solid blue line shows cumulative day-minus-night share and the dashed purple line shows cumulative directional fraction.

2 Discussion

2.1 Urban breathing is a geography of scale

Day–night population change depends on the scale at which a city is observed. The global daytime surplus of 148 million was the remainder of 731 million in offsetting center-level differences, while proportional differences in total population narrowed with urban-center size. Smaller centers changed more coherently across their settled footprints. Larger centers contained more fine-scale variation, a pattern largely explained by their greater land

area and cell count. Among centers of similar physical extent, greater population was instead associated with less redistribution. Population and physical extent therefore jointly shape the observed morphology.

This finding adds a within-day dimension to a familiar feature of urbanization: population, land and built structure are coupled but do not grow in lockstep.³² A large settled footprint can encompass many local gains and losses, whereas more populous centers of comparable physical extent tend to have more similar day and night distributions. The relationship is therefore not a simple effect of population size. The built form inherited from urbanization helps determine the scale at which daily change becomes visible.

The result is also methodological. Population definition and spatial unit determine what belongs to a city and which interactions are treated as internal, changing observed scaling relationships.^{33–35} Here, the native grid records local variation across the physical envelope, while the same 32 relative zones in every center reveal whether change coherently reweights broad parts of it. Claims about day–night stability or concentration must therefore identify their population data concept, urban boundary and measurement scale.

2.2 The changing morphology of urban populations

No single daily spatial pattern describes all urban populations. Population share concentrated inward in some centers, expanded outward in others, shifted among sectors at similar distances or changed little at broad scales. This range accords with local evidence of midday contraction, persistent activity hotspots, central-city daytime gains and connected activity cores,^{17,19,36} while showing that none is universal. Caracas exemplified concentration, Ahmedabad expansion, Lagos directional reorganization and Accra broad stability. Paris, Dallas and São Paulo reached similar total balance through different internal patterns. Local studies can resolve the schedules, land uses and transport systems behind these configurations; the global atlas establishes their comparative range.

Direction matters because it is not considered by radial average. Coastlines, corridors, topography and mono-centric or polycentric form can organize commuting,³⁷ while mobility networks reveal city-specific links between residential and employment hotspots.³⁸ Our signatures identify where to test such mechanisms, but do not recover the origins, destinations or journeys needed to establish them. The four regimes provide a concise vocabulary for this variation. Their modest separation and occurrence across every region favor a continuous morphology with interpretable anchors, not discrete urban types. Differences in regional prevalence invite further explanation through political economy, infrastructure, land use and urban history.

2.3 Time-specific populations beyond major cities

Time-specific presence changes the population denominator for urban analysis, especially beyond the largest metropolitan areas. Residence identifies where people are socially and administratively anchored; presence indicates where they draw on infrastructure and services at a given time. Exposure, service access and social interaction extend beyond the residential neighborhood.³⁹ Time-specific grids occupy a useful middle ground between censuses and person-level trajectories: complete spatial coverage without claiming to observe individual mobility.

Applied studies illustrate the practical stakes. Commute-adjusted populations increased estimated heat-wave exposure across 16 US metropolitan areas. Daytime mapping also placed more people in seismic-risk areas in Lisbon and in flood- and heat-prone central districts across eight European cities.^{21–23} Day–night estimates have altered exposure counts near highways and affected water-sensor placement.^{10,11} We do not estimate these outcomes, but identify where static denominators are most likely to miss consequential variation.

Small and intermediate centers deserve particular attention. Those below 50,000 nighttime residents made up 79% of the sample and contributed a larger share of absolute difference than of nighttime population. Recent global evidence likewise shows that smaller centers are demographically distinct yet under-examined relative to primary cities.⁴⁰ They are also less likely to be covered by travel surveys or commercial mobility data. Global day–night grids bring them into the same comparative frame as megacities without assuming equivalent urban functions or planning capacity.

Residential indicators remain essential for housing and entitlements, but may poorly represent who uses workplaces, interchanges, schools and public space; experienced segregation can also differ from residential segregation.²⁴ For Sustainable Development Goal 11, time-specific population can improve assessment of access, exposure and service adequacy when combined with local demographic, infrastructure and hazard information.^{2,3}

2.4 Limitations and scope

These results compare two modeled reference states, not a census of commuters. Day and night have no universal clock times, and the grids do not resolve weekday–weekend variation, seasonality, trip chains or trajectories. The 731-million absolute difference is therefore not a count of movers. LandScan Mosaic also inherits uncertainty from population controls, building data, land-use classification and occupancy assumptions; its public release does not include a full uncertainty ensemble.

Results also depend on how an urban area is bounded. GUEs describe physical settlements rather than municipalities or labor markets. Holding them fixed isolates redistribution within one settled footprint, whereas wider functional regions can enclose gains and losses that cross its edge. Direct re-extraction within GHS Urban Centres, GHS Functional Urban Areas and the one-hour Multi-Tier City–Regions (MTCR) product produced smaller total changes within wider boundaries, where opposing changes can cancel, but retained the population gradient and closely matched internal-redistribution profiles (Supplementary Fig. S3). Physical settlements and functional regions are therefore complementary views, not alternative versions of one correct city.

The validation supports comparative pattern analysis but does not establish universal cell-level accuracy. At 1 km, LandScan Mosaic night agreed strongly with official residential grids in Helsinki and selected Brazilian and Japanese centers, while the Helsinki 24-hour model supported the temporal orientation of both states.⁴¹ These comparisons use different reference years, may share census controls and lack a geographically balanced daytime benchmark. Fine-redistribution magnitude also depends on raster resolution and measurement scale (Supplementary Figs. S1–S5 and Tables S1–S2). The regimes should therefore be read as descriptive anchors within a continuum.

2.5 Toward a time-aware urban geography

Urban environmental data increasingly combine high spatial resolution with high temporal frequency; population data usually offer either fine spatial detail across broad extents or temporal detail for selected places and periods. Understanding changing exposure and demand requires bringing these dimensions together. Even a day–night distinction shows that stable totals can contain local gains and losses, population and physical extent alter the observed scale of redistribution, and radial averages conceal directional structure.

Richer local data are the next step. Hourly and seasonal grids, workplace registers, travel surveys and privacy-preserving mobility data could connect these signatures to employment specialization, corridors, topography or mixed land use. Age, income, occupation, disability and transport access also shape mobility and vulnerability, while available data represent these groups unevenly.²⁵ Coupling differentiated populations with hazards and infrastructure would permit direct evaluation of capacity and equity.

Urban breathing connects residential demography, mobility research and comparative urban geography. Stable totals often contain structured redistribution whose magnitude, reach and direction vary across the urban system. Measuring where people are present alongside where they live provides a stronger basis for time-sensitive work on infrastructure, services and exposure, while those applications still require local demographic, institutional and environmental evidence.

3 Data and methods

3.1 Population and urban-boundary data

We analyzed the public daytime and nighttime grids from *LandScan Mosaic 2025: Global Dynamic Population*, version 1.0.²⁷ LandScan Mosaic extends the day–night population framework established by LandScan USA globally.^{9,26} Its aligned 3-arc-second grids, approximately 90 m at the equator, allocate subnational population controls among built locations using building footprints, building-use classifications, floor counts and time-specific occupancy estimates.^{14,15} Residential buildings generally receive greater weight at night, whereas workplaces, schools, retail and other activity locations may receive greater weight during the day. They represent reference states of population presence rather than observations tied to universal clock times. LandScan Mosaic also supplies a single cell-level confidence surface, shared by the day and night grids, that summarizes the spread of simulated population estimates.²⁶

We defined urban areas using the 2025 Global Urban Envelopes (GUEs) in version 4 of Global Urban and Rural Settlements.^{28,29} The public layer contains 50,480 non-overlapping polygons representing contiguous physical settlements identified from built-up intensity, nighttime lights and place labels. We selected GUEs because they cover settlements from small centers to megacities, align temporally with the population grids and, importantly, do not

use gridded population counts in their delineation. Other global products define urban areas from population and built-up thresholds, impervious surfaces, administrative units or commuting and travel-time relationships.^{30,42,43} These boundary concepts answer different questions (Supplementary Table S2). Our primary interest was change inside the same physical settlement, so each center was represented by one fixed 2025 polygon in both population states; wider city-regions are examined in Supplementary Fig. S3.

3.2 Sample and population extraction

We summed daytime and nighttime population over the same valid raster cells within each GUE. Centers with at least 1,000 nighttime residents were retained to limit unstable proportional estimates in very small settlements, yielding 50,001 urban centers across the globe.

We use *region* consistently for geographic summaries. Five-region summaries group Africa, the Americas, Asia, Europe and Oceania; six-region displays separate the Americas into North America (including the United Nations Northern America, Central America and Caribbean subregions) and South America. Geographic fields were missing from the public GUE attributes for 45 retained centers. Their coordinates and place names identify them as Portuguese settlements in mainland Portugal, Madeira or the Azores, so we assigned them to Portugal, Southern Europe and Europe for all regional summaries. Any remaining gaps are assigned from the nearest center with complete geographic attributes using great-circle distance and recorded in an exception ledger; no proximity assignments were required in this sample. This metadata reconciliation changes no boundary, raster cell or population estimate.

Let P_D and P_N denote the daytime and nighttime totals inside a GUE. Nighttime population defined six size classes, from 1,000–<50,000 to at least 5 million residents. For descriptive summaries, centers with $0.9 \leq P_D/P_N \leq 1.1$ were classified as approximately balanced, those above 1.1 as daytime increases and those below 0.9 as daytime decreases; continuous values underlie all other analyses. Polygon area was calculated geodesically, and distances and bearings were measured in a local azimuthal equidistant projection.

3.3 Day–night balance and internal redistribution

All signed differences are daytime minus nighttime. We measured total balance as the difference $P_D - P_N$ and ratio P_D/P_N . For maps and regional distributions, we converted the ratio to the symmetric percentage contrast $100(P_D - P_N)/(P_D + P_N)$. Zero indicates equal totals, the sign identifies whether day or night is larger, and equal proportional differences in either direction have the same magnitude. We also summed positive center-level differences and the absolute values of negative differences separately. Their difference is the net change; their sum is total absolute center-level difference. Because the grids do not identify origins, destinations or individuals, this quantity is not a count of movers.

To isolate internal spatial redistribution from differences in center size or total day–night change, we separately normalized the daytime and nighttime cells inside each GUE to sum to one. Jensen–Shannon (JS) divergence then asks a simple question: do the same cells contain the same shares of the urban population by day and by night? It is symmetric and ranges from zero when the two spatial distributions are identical to one when they do not overlap; base-2 logarithms give this 0–1 scale.⁴⁴ JS measures the overall degree of spatial reordering, but not how far the reallocated shares are from one another.

We calculated JS first on the native raster cells and then after aggregating every center into the same four radial bands and eight compass sectors. Native-cell JS retains fine local differences. The 32-zone comparison asks whether broad parts of the urban center gain or lose population share, using the same relative arrangement for centers with very different areas and cell counts. The zones do not have equal physical areas: the outer band contains every cell beyond $1.5R_e$, where equivalent urban radius $R_e = \sqrt{A/\pi}$ and A is polygon area.

To determine whether the apparent population gradient was instead produced by the larger physical extent of more populous centers, we modeled native-cell and 32-zone JS for all 50,001 centers. We transformed JS as $\log[1 + 100(JS)]$ and population, polygon area and valid-cell count with base-2 logarithms, then standardized every transformed variable. The first model accounted for the five broad world regions; subsequent models also accounted for either polygon area or valid-cell count. Full specifications and results are in Supplementary Fig. S4.

Every calculation was clipped to the focal GUE. Because GUEs do not overlap, cells in neighboring centers were neither borrowed nor counted twice; proximity or commuting relationships among centers were outside the primary analysis.

3.4 Radial and directional morphology

JS measures the overall difference between the daytime and nighttime maps; the remaining metrics describe where that difference occurs. Together they ask four questions: which distances from the center gain or lose population share; how far across the center that difference extends; whether the daytime distribution is more central or more outward; and whether change is organized mainly by distance or by direction. Table 2 walks through each metric calculated. The design builds on comparative radial analyses that rescale distance for differently sized cities,³⁴ mobility studies of activity centers and directional structure,^{19,37,38} and standard distributional distances. The measures are descriptive summaries rather than established indices of urban form.

All metrics compare separately normalized daytime and nighttime shares within the same fixed GUE, so they describe internal morphology independently of total population change. Distances r_i were measured from the daytime population-weighted center. We chose this origin because it is defined consistently from the population distribution and is less sensitive than a polygon centroid to an irregular boundary; it is a reference point, not an inferred central business district. Equivalent urban radius, $R_e = \sqrt{A/\pi}$ for GUE area A , converts absolute distance to a common scale relative to each center's physical extent.

Radial structure. We grouped cells into either fixed-distance rings for geographic interpretation or rings scaled by R_e for comparison across urban centers. Ring ratios show which parts of the center-edge profile contain relatively more population by day or by night, while cumulative curves show how these differences build with distance. Radial shift is the Wasserstein-1 distance (W_1) between the two cumulative profiles: the average radial distance over which population share would need to be reassigned for them to match. This is a distance between distributions, not an observed commute or movement path. Dividing W_1 by R_e gives relative radial reach, which is comparable across differently sized centers. Daytime centralization indicates whether the shift is inward or outward, while fine radial redistribution measures its magnitude without assigning a direction.

Directional structure. We crossed four radial bands ($0-0.5R_e$, $0.5-1R_e$, $1-1.5R_e$ and $> 1.5R_e$) with eight 45° sectors. For each intersecting zone Z_{rk} , $\delta_{rk} = \sum_{i \in Z_{rk}} (p_{D,i} - p_{N,i})$ is the day-minus-night change in population share. Redistribution intensity measures the total share rearranged among these 32 broad zones. We then combined the eight sectors within each radial band, removing compass direction while retaining distance from the center. Directional fraction measures how much of the original redistribution disappears: zero means that change is shared across directions and explained by distance alone, whereas values near one mean that gains and losses occur mainly in different directions at similar distances. The fixed 32-zone arrangement remains comparable from small centers to megacities.

Table 2 Radial and directional metrics used to describe urban population breathing. All calculations compare separately normalized daytime and nighttime population shares. The final column states what each metric reveals and why it is retained. Asterisks identify the four dimensions used in the descriptive clustering. Equations give untransformed metrics; values bounded by 0 and 1 may be reported as percentages.

Metric	Calculation	Meaning and reason for use
<i>Center-edge profile and radial reach</i>		
Ring share ratio, Q_j	$Q_j = \frac{p_{D,j}}{p_{N,j}}, \quad p_{X,j} = \sum_{i \in j} p_{X,i}$	Daytime share divided by nighttime share in ring j : one means equal shares, values above one mean more by day and values below one mean more at night. It shows where along the center-edge profile change occurs. Figure 4 expresses the ratio as a percentage with equal scaling in both directions. ³⁴
Cumulative radial change, $G(s)$	$G(s) = \sum_{i:r_i \leq s} (p_{D,i} - p_{N,i}) = F_D(s) - F_N(s)$	Running day-minus-night share inside distance s . Positive values mean that more daytime share lies within s ; negative values mean that more lies beyond s . The curve shows where differences accumulate or reverse and returns to zero over the complete GUE.
Radial shift, W_1 (Wasserstein-1)	$W_1 = \int_0^\infty F_D(s) - F_N(s) ds$	Average radial distance over which population share would need to be reassigned for the two profiles to match. It distinguishes local reweighting from change spread over longer distances. Units are kilometres, but this is not observed travel.
Relative radial reach*, W_1/R_e	$\frac{W_1}{R_e}$	Radial shift divided by equivalent urban radius, expressing its reach relative to each center's physical extent.
Daytime centralization*, C	$C = \frac{\bar{r}_N - \bar{r}_D}{R_e}, \quad \bar{r}_X = \sum_i r_i p_{X,i}$	Direction of the radial shift: positive means more central by day and negative means more outward by day. It supplies the inward-outward direction that W_1 lacks.
Fine radial redistribution, T_{rad}	$T_{\text{rad}} = \frac{1}{2} \sum_j p_{D,j} - p_{N,j} $	Share that would need to move among fine $0.1R_e$ rings for the radial profiles to match. It measures the amount of radial change without indicating inward or outward direction.
<i>Broad redistribution and directional organization</i>		
Redistribution intensity*, T_{RK}	$T_{RK} = \frac{1}{2} \sum_{r,k} \delta_{rk} $	Share that would need to move among the common four-band by eight-sector zones for day and night to match. It measures the amount of broad redistribution.
Radial component, T_R	$T_R = \frac{1}{2} \sum_r \left \sum_k \delta_{rk} \right $	Redistribution remaining after all compass sectors at the same distance are combined. It isolates center-edge change after opposing directional shifts cancel.
Directional fraction*, F_{dir}	$F_{\text{dir}} = \frac{\max(0, T_{RK} - T_R)}{T_{RK}}$	Fraction of broad redistribution lost when compass direction is ignored. Zero means change is radial; values near one mean gains and losses occur mainly in different directions at similar distances. ^{37,38} Set to zero when $T_{RK} = 0$.

Notation: D and N denote daytime and nighttime; i, j, r and k index cells, fine rings, broad radial bands and compass sectors; $p_{X,i}$ and $p_{X,j}$ are normalized shares; $F_X(s)$ is cumulative share within distance s ; r_i and $\bar{r}_X$ are cell distance and population-weighted mean distance from the daytime center; R_e is equivalent urban radius; and δ_{rk} is day-minus-night share change in zone Z_{rk} . Ring ratios require $p_{N,j} > 0$.

*Included in the descriptive clustering (Section 3.5); centralization entered as C relative to fine radial redistribution.

3.5 Descriptive morphology

We used clustering to summarize recurring combinations within the continuous morphology, not to assign cities to natural or permanent types. Four quantities from Table 2 represented the amount of broad redistribution (T_{RK}), radial reach (W_1/R_e), inward or outward orientation (C), and directional organization (F_{dir}). We log-transformed the two magnitude measures and expressed orientation relative to radial-change magnitude as $C/(T_{rad} + 10^{-6})$, limited to -1 to 1 . Directional fraction was untransformed. Each input was scaled by its median and interquartile range.

We compared k -means solutions for two to eight groups and retained four as the smallest solution separating broad stability, radial expansion, radial concentration and high directionality. The groups overlapped, as expected for a continuum (silhouette score, 0.308), but different starting points produced nearly identical assignments (mean adjusted Rand index, 0.997, where 1 is identical). A fit restricted to approximately balanced centers was moderately consistent with the full-sample result (adjusted Rand index, 0.471). These diagnostics support descriptive anchors rather than natural classes. All 50,001 centers entered the fit. We selected Accra, Ahmedabad, Caracas and Hyderabad after fitting because they are large, geographically varied, recognizable and close to the four anchors.

3.6 Validation and robustness

The LandScan Mosaic data paper evaluates the product’s building, floor-count, and use-class attribution against independent reference data for its demonstration geography in the Philippines,²⁶ while the underlying attribution framework is developed and supported by prior methodological studies.^{45–47} Our purpose was narrower for this analysis: to test whether the released daytime and nighttime outputs were suitable for comparing within-city patterns. We first compared their temporal orientation with Helsinki’s open 24-hour population model.⁴¹ On common 1-km cells, the LandScan Mosaic daytime grid correlated at $r = 0.782$ with the mean Helsinki distribution from 07:00 to 18:59, and the nighttime grid correlated at $r = 0.913$ with the mean from 19:00 to 06:59 (Supplementary Fig. S1). This temporal pattern is consistent with the expected parts of the daily cycle, although the comparator is itself modeled from mobile-phone activity and land use.

We then compared LandScan Mosaic night with official residential grids from Helsinki Region Environmental Services (HSY), the Brazilian Institute of Geography and Statistics (IBGE) and Japan’s Ministry of Land, Infrastructure, Transport and Tourism (MLIT).^{48–50} Across Helsinki and five centers in each of Brazil and Japan, agreement on a common 1-km grid was consistently high: Pearson $r = 0.829$ – 0.945 , Spearman $\rho = 0.828$ – 0.952 and JS divergence = 0.024 – 0.075 (Supplementary Fig. S2 and Supplementary Table S1). These comparisons describe registered residential populations, not complete nighttime occupancy; differences in reference year, census control and the treatment of people away from home prevent them from being interpreted as error estimates. For context, the Helsinki 24-hour model correlated at $r = 0.891$ with the same residential grid during 02:00–04:59, compared with $r = 0.945$ for LandScan Mosaic night. Together, these comparisons support temporal orientation and broad residential geography; they are fitness-for-use checks rather than comprehensive validation.

We also tested whether the results changed with urban-boundary definition, raster resolution, measurement scale or LandScan Mosaic confidence. Direct extraction within GHS Urban Centres, MTCR regions and GHS Functional Urban Areas retained 12,931, 4,207 and 9,027 units, respectively. The population gradient persisted, although wider functional regions produced smaller total changes because they contained more offsetting gains and losses. Among 2,193 matched centers represented in all four products, median native-cell JS differed by at most 0.018 across size classes (Supplementary Fig. S3). In a 60-center panel, moving the urban edge inward or outward by 250 m preserved every balance category and the rankings of total change and JS ($\rho \geq 0.989$ and $\rho \geq 0.995$). Aggregation to approximately 1 km also retained the native-cell JS ordering ($\rho = 0.910$). Models accounting for area or cell count preserved the principal scale relationships (Supplementary Fig. S4), as did progressively restricting the 49,701 covered centers to higher-confidence subsets (Supplementary Fig. S5). These are checks on the comparative analysis, not a second global validation of LandScan Mosaic.

Data availability

LandScan Mosaic 2025: Global Dynamic Population, version 1.0, is publicly available from Oak Ridge National Laboratory at <https://doi.org/10.48690/LSM/1MHC-AQ17>. Global Urban and Rural Settlements version 4, including the Global Urban Envelopes, is publicly available from Zenodo at <https://doi.org/10.5281/zenodo.19630155>. The external comparison datasets are available from their original providers, as described in the Methods and cited references.^{41,48–50} Source data underlying all main and Supplementary figures and tables are supplied with this manuscript.

Code availability

The custom code used for population extraction, analysis and figure generation is available to editors and reviewers from the corresponding author upon request. Public release is subject to Oak Ridge National Laboratory software-release review.

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Acknowledgements

The authors acknowledge the Next Generation STEM Internships Program (NGSI) at Oak Ridge National Laboratory, through which L.P. participated in this research.

Note: This manuscript has been authored by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the U.S. Department of Energy. The U.S. Government retains, and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains, a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for U.S. Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan.

Funding

This research was funded by the United States Department of Defense.

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Competing interests

The authors declare no competing interests.

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