Tachyoneurons - NASA Space Apps 2025

Chosen Challenge: Data Pathways to Healthy Cities and Human Settlements
Description: Climate change brings about new complexities to consider for maintaining the wellbeing of society and the environment in cities. Natural resources, ecosystems, and existing infrastructure all must be monitored to ensure human quality of life remains high. Your challenge is to demonstrate how an urban planner can use NASA Earth observation data to develop smart strategies for city growth that maintain both the wellbeing of people and the environment.

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Project VITAL - A Multi-Dimensional Non-Linear Framework for Urban Resilience

Core Concept:

The goal of this project is to develop a global VITAL score (Vitality, Infrastructure, Temperature, Air, and Livability Score) dashboard that departs from traditional livability metrics in favor of a scientific and rigorous assessment of environmental and population density conditions across cities around the world. The dashboard includes an interactive map where users can click on particular cities to obtain a breakdown of scores across a number of environmental dimensions including chronic exposure to heat, air quality (PM2.5), urban density, water and sanitation readiness, and urban integration (green infrastructure and land-use export compatibility). Scores for each of these environmental dimensions are generated using high-resolution datasets available from a range of validated credible agencies and satellites, including NASA, Copernicus, MODIS and others, using a variety of statistical treatment methods explicitly combining linear scaling (for indicators that increase proportionally with risk), logarithmic scaling (to capture diminishing returns), exponential decay functions (to model rapid reductions in risk), and sigmoid transformations (to represent threshold effects and non-linear escalation of risks).

As a composite score, the VITAL score is synthesizing these sub-metrics into a single score that can capture real-world exposure and vulnerability—recognizing the complex, and non-linear relationships between environmental conditions and human health outcomes. Our methodology is based on previous peer-reviewed research and established environmental indices that attempt to describe relevant exposure and vulnerability patterns for urban populations. Ultimately, the combination of data quality, methodological transparency, and scientific credibility allows our dashboard to be a decision-support tool for urban planners, sustainability researchers and policymakers, generating actionable evidence contextualizing environmental risk and resilience around the world.

Our goal is to generate reliable, evidence-based, metrics, not interactive modelling simulation experiments or percentile-based rankings between cities, rather an objective judgement of city's living conditions purely based on scientific evidence.

Unlike existing metrics like the Environmental Performance Index (Hsu et al., 2016; Yale Center for Environmental Law & Policy, n.d.) and the Environmental Livability Index (Aurassure, 2025), which have provided significant advances in our understanding of vitality and livability conditions, Project VITAL takes that inquiry one step further. The EPI offers a useful perspective about vitality level at the national scale, making comparisons of environmental performance between nations; and the ELI offers insight into overall livability conditions at the regional and larger scale. Far from ELI and EPI which focus on regional and national conditions, the VITAL measure (Vitality, Infrastructure, Temperature, Air, and Livability Score) is designed as a scoring metric at the city-scale where density, infrastructure readiness, and climate exposures are the most apparent. Project VITAL builds upon existing knowledges but offers an even finer layer of analysis around resilience and livability for urban planners, policymakers, and sustainability researchers by providing the ability to analyze very granular data that draws upon high-resolution satellites (NASA, Copernicus, MODIS, from others) and employs statistical scaling techniques to quantify complex non-linear relationships between environmental stressors, urban systems and human health.

Methodology

The VITAL is computed by finding the average among different sub-metrics normalized through non-linear scoring that pertain to how livable a city is. These metrics cover essential aspects of urban life such as heat, urban density, air quality, water and sanitation, and green cover. By combining these factors into a single index, the VITAL provides a clear and measurable way to evaluate and compare the livability of different cities. The resulting score not only reflects current conditions but also serves as a benchmark for identifying areas that require improvement or further development.

To interpret the results, the VITAL score is categorized into five levels:

0-25 = High Health Risk Environment
Description: Scored poorly on most of the VITAL submetrics. Fails Multiple Minimum Standards set by International Organizations and Institutions.

26-50 = Unhealthy
Description: Scored below average in most of VITAL submetrics. Below safe thresholds set by International Organizations and Institutions.

51-75 = Needs Improvement
Description: Decently scored in the VITAL submetrics. Meets some of the standards set by International Organizations and Institutions.

76-99 = Healthy and Sustainable
Description: Scored above average on VITAL submetrics. Close to targets set by International Organizations and Institutions.

100 = Healthy and Fully Sustainable

Description: Full marks on VITAL submetrics. Meets or exceeds standards set by international organizations and institutions.

PM2.5 AIR QUALITY SCORE (PAQS)

PAQS Overview

The PM2.5 Air Quality Score (PAQS) is a composite index that provides a quantitative assessment of long-term urban air pollution risk and related health effects on a 1-100 scale. Particulate Matter (PM) consists of a number of different chemical components, such as organic carbon from vehicle and industrial emissions, sulfates, nitrates, black carbon from diesel engines and biomass burning, ammonium, and Secondary Organic Aerosols (SOA) (California Air Resources Board, n.d.). PM2.5, material that is less than or equal to 2.5 microns in diameter, is especially harmful when we consider it can penetrate deeply into our lungs and into our bloodstream and can contribute to cardiovascular disease, stroke and cancer (Bumrungrad International Hospital, 2025). The PAQS was developed to convert PM2.5 concentrations into an intuitive and standardized score to help urban planners, policymakers and researchers objectively compare air quality in cities and prioritize air quality and related interventions to reduce public health risk.

Data Sources

Annual averages of PM2.5 concentrations were estimated using the Global Annual PM2.5 Grids from MODIS, MISR, SeaWiFS, and VIIRS Aerosol Optical Depth (AOD) data for 1998-2022, V5.GL.04 dataset. The high resolution global grids report city-specific PM2.5 data consistently during decades of handfPDS of years. To prioritize an accurate estimation at the urban scale, city boundaries were obtained from shapefiles sourced from Database of Global Administrative Areas (GADM) managed by University of California, Davis, allowing the PM2.5 grids to be clipped appropriately. This ensures that the PAQS produced represents exposure in populated and high-impact areas rather than surrounding rural areas.

Proposed Methodology

The PM2.5 Air Quality Score (PAQS) is based on a piecewise scoring system that utilizes a combination of linear and non-linear transformations to represent health risks from exposure to fine particulate matter. This approach allows for sufficient sensitivity to the broad range of air pollution concentrations that people can experience in urban settings where both moderate and extreme concentrations of exposure can occur.

The PAQS is defined in the following way: those concentrations that score below or equal to the World Health Organization (WHO) guideline of 5 μg/m³; for example, these concentrations are scored a maximum of 100, indicating a low to non-existent risk to health (World Health Organization, 2021). For concentrations of PM2.5 that range from 5 to 35 μg/m³, scores drop precipitously along a linear axis of exposure, where scores are less sensitive to the health risk of mild to moderate concentration, while still able to be utilized as a comparable outcome across a variety of urban settings. This linear drop in scores accounts for cumulative, but manageable risks to health, as discussed in the epidemiological studies (Pope & Dockery, 2006; Lelieveld et al., 2015).

When PM2.5 concentrations are above 35 μg/m³, the PAQS indicates a non-linear response. A logistic (sigmoid) decay function is utilized and penalizes high PM2.5 concentrations more severely. The non-linear response accounts for the exponential increase in adverse health risk from increased PM2.5 concentration. These augmenting health risks include cardiovascular diseases, respiratory diseases, and premature mortality beyond the safe threshold limits set by previous studies (Burnett et al., 2018; Cohen et al., 2017). The center of the sigmoid curve is 55 µg/m³, which is the midpoint for the exponential increase in hazardous health risk when exposing populations to increased PM2.5 levels, and the slope coefficient (–0.15) gives the decline in hazardous health risk, which is based on dose-response patterns from global burden of disease studies.

At PM2.5 concentrations at or above 75 µg/m³, the PAQS is limited to a minimum score of 1, indicating extreme levels of pollution that are life-threatening and result in acute and chronic health and morbidity risk to exposed populations. By integrating linear scaling and logistic decay, the PAQS achieves a score that balances interpretability and epidemiologic fidelity that represents a sensitive, robust, and policy relevant measure that is comparable across the globe while still sensitive to non-linear health risks from PM2.5.

The formula for PAQS are as follows:

$$PAQS(x) = \begin{cases} 100, & x \leq 5 \\ \mathrm{round}\left(100 - (x-5) \cdot \frac{80}{30}\right), & 5 < x \leq 35 \\ 1, & x \geq 75 \\ \mathrm{round}\left(1 + 19 \cdot \left(1 - \frac{1}{1 + e^{-0.15(x-55)}}\right)\right), & 35 < x < 75 \end{cases}$$

PAQS Formula

Where:

- x (PM2.5 concentration in µg/m³) = The input variable represents particulate matter levels, which determines the air quality score.

- 100 (Perfect Score) = Assigned when x ≤ 5, reflecting compliance with the World Health Organization (WHO) air quality guideline for PM2.5, where health risks are minimal.

- Linear Decline (5 < x ≤ 35) = A decreasing linear function is applied. This reduces the score gradually as pollution increases up to 35 µg/m³, reflecting tolerable but worsening conditions.

- Severe Pollution Penalty (x ≥ 75) = A fixed minimum score of 1 is assigned to represent extremely poor conditions, where public health is severely at risk.

- Sigmoid Transition (35 < x < 75) = A logistic function is applied. This models the nonlinear health risk response, with scores dropping steeply as concentrations move beyond safe levels.

The PAQS is categorized into 5 different levels based on score:

0–25 = Very Poor Air Quality

PAQS denotes extremely contaminated situations with serious health consequences for the population. The duration of exposure is directly correlated with a proliferation of respiratory and cardiovascular issues. Immediate intervention and protective action are critical.

26–50 = Poor Air Quality

PAQS indicates unhealthy information where the level of pollution is known to pose a serious risk to the public. Chronic exposure could inevitably predispose the population towards chronic illness. Strong policy and mitigation action are very much encouraged.

51–75 = Moderate Air Quality

PAQS indicates conditions that could be considered tolerable but still suggests measurable risk, particularly for sensitive groups such as children, the elderly, and others already suffering from health conditions. Cities in this range should track the conditions and initiate incremental improvements.

76–99 = Good Air Quality

PAQS denotes urban air that is relatively clean and healthy, with little risk to the population. Sustainable activities are under way and being applied effectively. Ongoing action will be needed to ensure sustainability.

100 = Excellent Air Quality

PAQS indicates the optimum, where the environment is in the best conditions regarding human health, expectations are met to a high standard, and is indicative of high environmental governance and a model for other cities to reference.

Data was computed in Excel and aggregated on a city scale.

city	mean_pm25	PAQS	PAQS Cateogry
Athens	17.69	66	Moderate Air Quality
Berlin	11.28	83	Good Air Quality
Cairo	45.6	16	Very Poor Air Quality
Delhi	98.22	1	Very Poor Air Quality
Istanbul	22.81	53	Moderate Air Quality
Lagos	39.58	18	Very Poor Air Quality
Manila	32.27	27	Poor Air Quality
New York	7.56	93	Good Air Quality
Paris	13.57	77	Good Air Quality
Sao Paolo	17.48	67	Moderate Air Quality

PAQS Scores

Significance and Limitations

The PM2.5 air quality score (PAQS) provides a scientific-based method for assessing urban air pollution risks, converting detailed population-weighted PM2.5 exposure information into a simple 1-100 score that can be integrated with other sub-metrics in VITAL. The PAQS provides city planners, policymakers, and public health officials with all of the tools to compare air quality differences across cities, flag events at risk, and prioritize interventions aimed at mitigating risks to human health. That said, the PAQS formula is currently designed for practical scoring purposes and lacks any mathematical or statistical development; both the piecewise linear and sigmoid functions were a way of indicating the identifiable trend of a health risk rather than being based on formal dose-response modeling. The score also relies on satellite-derived PM2.5 grids, which while high in resolution, may not identify pollution hot spots or mobility issues of micro-climates within cities. The threshold levels and sigmoid parameters, while grounded in health-related information and epidemiological evidence, are not intended to incorporate the data needed for all population-level vulnerabilities and accumulation of long-term exposures. Future development of the PAQS would incorporate formal calibrations based on a combination of epidemiological modeling doses for formal dose-response relationships, a higher temporal resolution to be able to identify pollution events that last less than 24 hours, and include other pollutants to better assess urban air quality and public health human health.

CHRONIC HEAT SAFETY SCORE (CHSS)

Chronic Heat Safety Score Overview

In urban environments, increase in temperatures as well as heat indices represent primary drivers of human health risks, exacerbating heat-related illnesses, mortality, and socioeconomic vulnerabilities for the populace (Hajat et al.,2014). This section outlines the methodology for developing Chronic Heat Safety Score (CHSS): a composite metric designed to quantitatively assess long-term, year-round chronic heat exposure risks in cities via 1-100 score using meteorological data. The CHSS uses air temperature at 2 meters (T2M), dew-point temperature at 2 meters (D2M), and relative humidity at 2 meters (RH2M) to compute heat indices, followed by a non-linear scoring function that penalizes the CHSS of a city if the values deviate from comfort thresholds. This approach acknowledges non-linear perception of thermal stress, wherein small increments in temperatures above the threshold (e.g, 33C°-35C°) pose greater, significant risks compared to changes in lower ranges (e.g., 20C°-22C°), supported by physiological and epidemiological studies (Parsons, 2014; Gasparrini et al., 2015). The CHSS is tuned using National Weather Service (NWS) heat index categories and benchmarks to ensure practical applicability for urban planning, as well as a global standard for determining implications of heat.

Data Sources

CHSS is constructed using reliable high-resolution gridded meteorological data from the *European Centre for Medium-Range Weather For Medium-Range Weather Forecasts (ECMWF) Reanalysis v5-Land (ERA5-Land)*, which were accessed through the *Copernicus Climate Data Store (CDS),* specifically the *ERA5-Land Post-Processed Daily Statistics from 1950-Present* data set was utilized. (Muñoz Sabater, 2021). Daily average temperatures at 2m (T2m) and Dew-point temperatures at 2m (Dt2m) were extracted from the database to compute for 3 variables: actual vapor pressure (e_a), saturation vapor pressure (e_s), and relative humidity (rh2m). From this, annual averages for each city are aggregated to enable city-scale assessments of heat risk trends, and to compute for the CHSS. Data licensing complies with the *Copernicus Climate Change Service* (C3S) agreement, which permits non-commercial research use under Creative Commons Attribution 4.0 International (CC BY 4.0); in which commercial applications of data sets require explicit permission granted from the European Union (European Comission, 2023).

ERA5-Land offers superior spatial detail over coarser reanalyses, which makes it an ideal candidate for urban heat island studies. Shape files gathered from GEOJSON city boundaries were used to clip the ERA5-Land raster bounding box to study each area, ensuring that all values represent the exact extent of the selected cities. Daily averages were computed over a 6 hour frequency period, which were converted to Celcius, and is then computed as an annual arithmetic mean to represent the CHSS within the entirety of 2024, the most recent year available for data gathering.

Methodology

The Heat Index (HI) is the foundational input for the CHSS, which approximates perceived heat by combining T2M and RH2M, to account for the amplifying effect of humidity on heat stress (Steadman, 1979; Rothfusz, 1990). HI is calculated using Lans P Rothfusz equation derived from multiple regression analyses and is used by the NWS Heat Index Calculator (*Heat Index Equation*, n.d.). Categories to describe the HI are from the NWS guide risk interpretation (NOAA's National Weather Service, n.d.), which also influences the CHSS:

Normal: HI < 27°C (80°F) – Minimal risk.

Caution: 27–32°C (80–90°F) – Fatigue possible with prolonged exposure.

Extreme Caution: 32–41°C (90–103°F) – Heat cramps/stroke risk.

Danger: 41–54°C (103–125°F) – High risk of heat exhaustion.

Extreme Danger: >54°C (125°F) – Severe health threats.

The ERA5-land dataset that was utilized only provided 2m-air temperature (T_{2m}) and 2m-dewpoint temperature (Dt_{2m}), whereas the Heat Index (HI) requires T_{2m} and 2m relative humidity (RH_{2m}). As such, we computed the saturated vapor pressure (e_s) and actual vapor pressure (e_a) from T_{2m} and Dt_{2m} using the Magnus-Tetens approximation (Alduchov & Eskridge, 1996) after converting the values to C°, then derived the formula for RH_{2m} = 100 x (e_a/e_s). The resulting value as well as the equivalent T_{2m} is then plugged into the Heat Index Formula.

Proposed Methodology for CHSS

The CHSS formula follows a piecewise structure based on National Weather Service (NWS) Heat Index thresholds characterizing systematic (1) risk of heat stress categories based on health outcomes. Specifically, the scores are assigned as follows: 100 is assigned for annual means ≤27°C, indicating very low chronic risk (below "Caution" threshold); a 1 point per °C decrease of score is assigned for 27–32°C, as some risk of discomfort and fatigue occurs in mildly sustained warmth; a sigmoid decrease approximately 95 to near 0 for 32–54°C, during "Extreme Caution," "Danger," and "Extreme Danger"; and a maximum of 1 for ≥54°C, which is a life-threatening level of uninhabitability. The sigmoid portion is calculated as:

$$\frac{95}{1 + \exp\left(0.25 \times (T - 40)\right)}$$

Where:

T = annual temperature in C°
40 = inflection point; the midpoint of NWS' "Danger Category", where temperature increases significantly have adverse health effects
95 = represents the highest score possible within the non-linear decay region
1 = logistic shift constant

0.25 = slope coefficient; a larger value 0.25 provides a moderate but rapid decay consistent with the escalating health risks above 40°C. (NOAA's National Weather Service, n.d.)
exp = used to generate the S-shaped (sigmoid) curve common in risk modeling (Brain and Cousens, 1989; Gasparinni et. al, 2015; Science and Decisions 2009)

$$\mathrm{CHSS}(T) = \begin{cases} 100, & T \leq 27 \\ 100 - (T - 27), & 27 < T \leq 32 \\ \dfrac{95}{1 + \exp\left[0.25\,(T - 40)\right]}, & 32 < T < 54] \\ 1, & T \geq 54 \end{cases}$$

CHSS Formula

A sigmoid function is used to simulate the non-linear structure of dose-response relationships identified in heat-health epidemiology, that risks associated with morbidity and mortality disproportionately increase past a physiological tipping point due to physiological responses to extreme heat. Specifically, when we exceed temperatures of 30-35 degrees Celsius, or 86-95 degrees Fahrenheit, a person's ability to thermoregulate begins to break down alongside cascading organ failures and significant morbidity and mortality (Gasparrini et al., 2015). The importance of nonlinear dose-response relationships at extreme temperature thresholds is reflected in established indices of environmental burden, for example with the burden attributable to air pollution (Burnett et al., 2018), and implemented climate change under the IPCC of intensified impacts of urban heat that worsen with climate change (IPCC, 2022). Our selected parameters - that the midpoint is at 40°C (the inflection point of the steepest rate of decline) and that k=0.25 represents the steepness factor - represent a balance in sensitivity for rare high annual means (e.g. arid extremes) while maintaining some temperance for typical climatological subtropical conditions, thereby not over-penalizing tropical cities while allowing for inequities across the globe to be evident.

The CHSS is categorized to 5 different levels:

0–25 = Very High Heat Risk
Description: Indicates a state of extremely dangerous chronic heat exposure. Populations that exist within this metric face extreme, constant health risks, including higher chances of heat illness, mortality, and declining habitability. Immediate adaptation and protective measures are needed.

26–50 = High Heat Risk
Description: Represents unsafe chronic heat exposure. Chronic heat exposure in this category is strongly correlated with heat fatigue, heat stress, and overall increased risks for vulnerable populations. Cities in this metric have considerably high-level climate-warming interventions to lessen the effects of chronic heat.

51–75 = Moderate Heat Risk
Description: Represents exposure to chronic heat risk in which it is manageable but noticeable, particularly for vulnerable populations, including children, elderly populations, and for those who work outdoors. Urban planning initiatives and modifications are needed to curtail further risks.

76–99 = Low Heat Risk

Description: Represents conditions that are generally safe and where populations experience little long-term health risks associated with chronic heat exposure. Cities in this metric demonstrate resilience either through environmental design, heat-mitigation interventions, or naturally favorable climates.

100 = Optimal Heat Safety
Description: Represents the conditions most favorable for human health and comfort. Within this context, heat risks are essentially tailored to controllable levels wherein urban-design characteristics and climate render safety and sustainability opportunities. Cities in this metric offer global examples for chronic heat resiliency.

Limitations
The Chronic Heat Safety Score (CHSS) presents a non-linear, scientific method for the assessment of sustained, long-term exposure to urban heat, with some limitations. It is based on annual mean temperature, and heat indices, which can obscure short-term, extreme events, such as heatwaves (e.g., cities with similar average temperature may be exposed to acute risk differently.). Relative humidity (RH2m) was unavailable from ERA5-Land and was estimated with dew point and air temperature that employed the Magnus-Tetens approximation, which may have led to errors in estimation particularly in more complex microclimate regions. While ERA5-Land provides publicly available gridded data at a high spatial resolution, it may not capture urban microclimate influences from building density and/or green space availability well. The CHSS thresholds are based on NWS, and the sigmoid decay function assumes a midpoint of 40°C, which may not accurately consider all physiological or socio-economical vulnerabilities in the context of climate. Importantly, CHSS can be used as a step toward future metrics, such as an Acute Heat Safety Score (AHSS), that quantify short-term extreme events, to provide additional data and actionable results to inform urban heat risk, while maintaining a framework that can be improved and built on.

POPULATION DENSITY SCORE (PDS)

Population Density Score Overview

The Population Density Score (PDS) is a scientifically derived 0–100 index that evaluates how well a city's population density supports both public health and quality of life. It is built on epidemiological and urban planning evidence showing that very high densities increase risks such as air pollution, overcrowding, and disease spread, while very low densities drive urban sprawl and car dependence. PDS applies a logarithmic scaling of population density to allow fair cross-city comparisons, rewarding densities in the optimal range (~5,000–15,000 people/km²) and penalizing extremes.

To aid interpretation, PDS scores are classified into five livability bands: Unhealthy (1–25), signaling critical overcrowding or sprawl risks; Poor (26–50), reflecting problematic densities that undermine livability; Moderate (51–75), denoting balanced but still improvable conditions; Healthy (76–99), indicating densities that strongly support livability with minimal risks; and Perfect (100), representing the ideal density for sustainable urban health outcomes. This five-tier approach aligns with international practices in urban sustainability metrics, while offering finer differentiation for policy action compared to simpler three-band systems.

The score illustrates key trade-offs across global contexts. European cities such as Berlin and Paris achieve Healthy to Perfect scores by maintaining compact but manageable densities that support walkability and green access without sprawl. North American hubs like New York often fall into the Moderate range, balancing efficiency with health strains from congestion. Rapidly urbanizing megacities in Asia (e.g., Manila, Delhi) and Africa (e.g., Lagos, Cairo) frequently land in Unhealthy or Poor bands due to overcrowding and infrastructure pressures. Meanwhile, Athens represents a healthier density profile in Southern Europe, balancing compact urban form with livability, while Istanbul scores in the Moderate band, reflecting compactness but rising congestion pressures. Latin American cities like São Paulo often achieve Moderate to Healthy scores through managed densification that reduces risks from both extremes.

Data Sources

PDS relies on high-resolution gridded population and land-use data. Population estimates (2023) come from WorldPop's Global High Resolution Population Denominators Project, providing 100m-resolution rasters for accurate urban aggregation (WorldPop, 2023). Urban area (built-up extent in km²) is derived from the Copernicus Global Human Settlement Layer (GHSL), based on Sentinel and Landsat imagery for 2015–2020 epochs, ensuring consistent urban boundary definitions (Copernicus, 2023). City boundaries were clipped using GEOJSON shapefiles to compute density at the metropolitan scale. Data are licensed for non-commercial research under Creative Commons Attribution 4.0 (CC BY 4.0), with annual averages representing 2023 conditions.

- GHSL's multi-temporal layers outperform coarser datasets for density mapping, enabling precise exclusion of non-urban areas like rural sprawl.
- These sources provide reliable inputs for density calculations, normalized against fixed anchors to support consistent PDS scoring and categorization.
- The practical category bands for the PDS (Unhealthy 1–25, Low 26–50, Moderate 51–75, Healthy 76–99, Perfect 100) are based on equal-interval scaling across the 0–100 range. This method, widely used in global assessments such as the UN-Habitat City Prosperity Index (CPI) and WHO Environmental Health Indicators, translates continuous scores into clear policy-relevant tiers (UN-Habitat, 2016; WHO, 2010). The five-band system refines interpretation by distinguishing between critical risk, suboptimal conditions, balanced performance, strong livability, and aspirational benchmarks, offering more nuance than traditional three-tier models while remaining accessible for policymakers.

Methodology

Urban density (D) is the core input, calculated as:

$$D = \frac{\text{Population}}{\text{Urban Area (km}^2)}$$

This yields people per km² in built-up zones. PDS then applies a logarithmic normalization to create a health-oriented score, adapted from urban indices (UN-Habitat, 2020; OECD, 2020). The logarithmic function compresses the wide range of density values (from ~2,000 to over 40,000 people/km²), which is common in environmental metrics to handle skewed distributions and emphasize relative differences rather than absolute ones. This prevents ultra-high densities from disproportionately skewing scores, aligning with how health risks (e.g., disease spread) escalate non-linearly with density. This logarithmic normalization is adapted from methods in the UN-Habitat City Prosperity Index (https://cpi.unhabitat.org/), which uses non-linear scaling for urban indicators to reflect real-world impacts, and OECD's urban density assessments in Cities in the World (https://www.oecd-ilibrary.org/urban-rural-and-regional-development/cities-in-the-world_d0efcbda-en), emphasizing bounded normalization for cross-city comparability.

The formula is:

$$\mathrm{USHS} = 100 \times \frac{\ln(D_{\mathrm{cap}} + 1) - \ln(D + 1)}{\ln(D_{\mathrm{cap}} + 1) - \ln(D_{\mathrm{min}} + 1)}$$

Where:

- ***D*** = City's urban density (people/km²)
- ***Dcap*** = 100,000 people/km², an upper cap to bound extreme outliers (e.g., Manila's 43,530) and simulate a theoretical "unhealthy maximum" without letting real-world maxima dominate.
- ***Dmin*** = Minimum density in the comparison group (~4,230 people/km², Berlin), serving as the reference for optimal compactness to normalize scores relative to peers.

The "+1" addition inside the logarithms avoids issues with ln(0) for very low densities and ensures smooth scaling near zero. The formula inverts the scale for health prioritization: as D increases, ln(D + 1) grows, shrinking the numerator relative to the fixed denominator (the log-range from cap to minimum). This results in higher scores (approaching or at 100) for lower, more liveable densities (e.g., Paris at 100.0) and lower scores (dropping toward 0) for overcrowding extremes, while avoiding harsh zeros for any city. For instance, Paris's D_min yields PDS = 100 by definition, and Manila's high D pulls its score down to 21.4, reflecting amplified risks like pollution exposure (which can double above 20,000/km² per epidemiological models). Densities slightly below D_min yield scores very close to 100 due to the logarithmic compression, ensuring minimal penalization for compact but low-density forms. This adaptation ensures interpretable, bounded results (0–100) for cross-city comparisons, tuned to reward densities in the 2,000–10,000 range as "health-optimal" based on WHO guidelines.

Scores are then categorized using the following thresholds to provide actionable health interpretations:

- **100 (Perfect Score)**
  Represents the ideal balance of urban density. The city achieves optimal compactness, avoiding both overcrowding and sprawl. Density strongly supports accessibility and efficiency without generating health or space pressures.
- **Healthy (76–99)**
  Indicates densities within or close to the optimal range. Cities in this category balance compactness and space availability well. Health risks from density are minimal, though careful planning is needed to prevent future overcrowding or sprawl.
- **Moderate (51–75)**
  Represents densities that are workable but not ideal. Cities may be slightly too dense, creating localized crowding, or too sparse, leading to inefficient land use. These conditions are manageable but require monitoring to prevent further imbalance.
- **Poor (26–50)**
  Indicates densities that strain urban balance. Either population is too concentrated, creating overcrowding risks, or too dispersed, driving sprawl and inefficiency. Both extremes weaken livability by pushing density outside its healthy range.

- **Unhealthy (1–25)**
  Represents severely unbalanced densities. Extreme overcrowding or sprawl dominates, undermining livability. Public health, efficiency, and spatial equity are heavily compromised due to density being far outside the optimal zone.

The Population Density Score (PDS) is expressed on a 0–100 scale and divided into five categories to provide clear and actionable interpretations of urban density. This classification builds on the approach used in global indices such as the Environmental Performance Index (EPI), which translates complex data into ordinal categories for policy use, and UN-Habitat's City Prosperity Index (CPI), which employs performance bands like "weak," "moderate," and "strong" to simplify communication. In the PDS framework, scores of 1–25 are classified as Unhealthy, representing density extremes that create severe health and livability risks. Scores from 26–50 are considered Poor, indicating problematic density conditions where either overcrowding or under-density undermines well-being. The Moderate band (51–75) captures densities that are broadly tolerable but show growing strain on livability, while Healthy scores (76–99) reflect cities that have reached favorable density conditions, supporting balance between efficiency and risk. A Perfect score (100) represents the ideal balance of density, where risks are minimized, and urban form is optimally aligned with liveability. This five-tier system offers greater nuance than a simple three-band division, providing policymakers with a more precise tool to differentiate between cities that are nearing optimal density and those facing critical challenges, while remaining consistent with international best practices of using clear categorical thresholds for policy translation.

Scores were computed for seven global cities using 2023 data, with results aggregated at the city scale.

City	Population (2023)	Area km²	Urban Density	ULS	ULS_Category
Athens	3153386	717	4398	80.4	Healthy
Berlin	3769495	891	4230.6	81.4	Healthy
Cairo	22183000	606	36605.6	25.9	Unhealthy
Delhi	30291000	1484	20411.7	40.9	Poor
Istanbul	15701602	5343	2938.7	90.8	Healthy
Lagos	15600000	1171	13321.9	51.9	Moderate
Manila	1902590	43.7	43537.5	21.4	Unhealthy
New York	8467513	789	10732	57.5	Moderate
Paris	2165423	1054	2054.5	100	Very Healthy
São Paulo	12325232	1521	8103.4	64.7	Moderate

Figure : Population Density Score of Selected Global Cities Based on 2023 Population and Built-up Area

Justification

PDS links density to public health through evidence-based thresholds: moderate densities enhance walkability, efficiency, and equity, while extremes either severe overcrowding or very low sprawl are associated with negative health outcomes, including higher mortality and increased respiratory illness rates in overly dense cities (WHO, 2016; OECD, 2020). The logarithmic normalization ensures fair cross-city comparisons by compressing the skewed distribution of density values, consistent with OECD recommendations for normalized urban indicators. To make results more interpretable for policymakers, the PDS adopts a five-tier classification system. Scores of 1–25 are categorized as Unhealthy, indicating critical overcrowding or sprawl conditions that pose severe risks. Scores of 26–50 are labeled Poor, reflecting density levels that undermine livability due to significant stress on health and services. Moderate scores (51–75) represent tolerable but strained conditions, where density provides some benefits but risks are increasingly visible. Healthy scores (76–99) indicate densities that strike a favorable balance between efficiency and liveability, where risks remain low. A Perfect score (100) represents the optimal density condition, where population concentration is most compatible with sustainable urban health outcomes. This five-band framework improves upon simpler three-tier systems used in other indices by offering greater nuance and policy relevance, while still maintaining interpretability. It mirrors the categorization approaches of international benchmarks like the Environmental Performance Index (EPI) and the City Prosperity Index (CPI), which use ordinal bands to communicate complex data, but tailors the thresholds specifically to the unique health implications of urban density.

Future Refinements

The indicators developed in this framework provide a rigorous and transparent foundation for assessing urban health and livability, but there is substantial scope for improvement. Current formulations, for example, the Population Density Score (PDS), which applies a logarithmic normalization to urban density, ensure comparability across cities but rely on fixed thresholds and simplified assumptions. While global datasets such as WorldPop and the Copernicus GHSL ensure consistency, they may not fully capture fine-scale variations in urban form, neighborhood-level inequalities, or socio-environmental interactions. Additionally, uncertainties in input data and functional choices are not yet explicitly quantified.

Future refinements should transform these measures into a multidimensional framework that integrates density with environmental, infrastructural, and social indicators to more fully reflect urban health dynamics. Thresholds must evolve from fixed cut-offs toward adaptive, evidence-based benchmarks, calibrated to local and regional contexts for fairer comparisons. Embedding uncertainty analysis for example through error propagation or probabilistic modeling will improve transparency and interpretability of results. Longitudinal extensions should allow cities to track changes over time, turning static assessments into dynamic monitoring tools. Finally, incorporating scenario modeling (e.g., green infrastructure expansion, transport policy changes, density redistribution strategies) will enable policymakers to test the potential health and livability impacts of interventions before implementation, advancing the framework from diagnostic to predictive and prescriptive use.

WATER AND SANITATION SCORE (WSS)

Overview

The Water & Sanitation Score (WSS) is a composite measure (0–100 scale) developed to evaluate the extent and quality of urban water and sanitation services across global cities. It is grounded in the framework of SDG 6: Clean Water and Sanitation, drawing on three internationally recognized indicators: access to safe drinking water (W), access to sanitation facilities (S), and the proportion of wastewater safely treated (T). Each component is weighted to reflect its role in public health and infrastructure, with safe water prioritized most heavily.

Data for the index is drawn from validated UN custodianship sources — including the WHO/UNICEF Joint Monitoring Programme (JMP) for water and sanitation coverage, UN-Habitat and FAO AQUASTAT for wastewater treatment, and WRI Aqueduct for water risk assessments. These statistics are supported by Earth observation evidence from NASA (e.g., GRACE groundwater depletion, Earthdata imagery of polluted rivers, and SEDAC population grids), which provide independent verification of conditions on the ground.

By integrating official SDG statistics with NASA Earth observation datasets, the W&S Score provides a reliable and comparable tool for policymakers, researchers, and urban planners to assess service conditions, track inequalities, and prioritize investment toward achieving sustainable water and sanitation for all.

Data Sources

The WSS Score relies on validated international datasets and Earth observation evidence to measure urban water and sanitation conditions. Core statistics are drawn from the WHO/UNICEF Joint Monitoring Programme (JMP) for drinking water and sanitation coverage, and from UN-Habitat, FAO AQUASTAT, and UN-Water for wastewater treatment and water resource indicators. These official SDG 6 custodians provide harmonized data across countries, ensuring global comparability. To complement these, NASA Earth Observation datasets such as GRACE (groundwater depletion), Earthdata Worldview (surface water quality), and SEDAC (population and SDG grids) provide independent validation and spatial context for urban water challenges.

- WHO/UNICEF JMP supplies global data on safe drinking water (SDG 6.1.1) and sanitation services (SDG 6.2.1), standardized to reflect “safely managed” access.
- UN-Habitat and FAO AQUASTAT provide statistics on wastewater safely treated (SDG 6.3.1) and water stress (SDG 6.4.2), capturing infrastructure performance and sustainability of resources.
- NASA Earthdata and Earth Observatory offer EO-based indicators of water quality, detecting turbidity, algal blooms, and sewage plumes that signal untreated wastewater in urban rivers and coasts.
- NASA GRACE satellites monitor groundwater storage changes, highlighting depletion in water-stressed cities such as Delhi and São Paulo.
- NASA SEDAC (Socioeconomic Data and Applications Center) contributes population grids and SDG indicator layers, enabling exposure analysis and integration with urban water coverage.
- Copernicus GHSL complements the analysis by mapping urban settlement patterns, helping align sanitation needs with built-up density.

Methodology

The Water & Sanitation Score (WSS) is a composite measure (0–100 scale) designed to evaluate the performance of cities in providing essential water and sanitation services. It is based on three globally recognized SDG 6 indicators: access to safe drinking water (W, SDG 6.1.1), access to sanitation facilities (S, SDG 6.2.1), and the proportion of wastewater safely treated (T, SDG 6.3.1). These variables were chosen because they capture the critical dimensions of urban water security and public health.. The formula is expressed as**:**

$$\text{W\&S Score} = (0.40 \times W) + (0.35 \times S) + (0.25 \times T)$$

- ***W*** **= Access to Safe Drinking Water (SDG 6.1.1)**
    - **Definition:** Percentage of the population using *safely managed drinking water services*.
    - **Criteria:** Water must be on premises, available when needed, and free from contamination.
    - **Why Important:** Safe water is the most fundamental requirement for human survival and public health; lack of access leads to waterborne diseases and higher mortality risks.
    - **Sources:** WHO/UNICEF Joint Monitoring Programme (JMP); supported by NASA Earthdata and Earth Observatory for validation of water quality (e.g., river pollution, turbidity, chlorophyll-a).
- ***S*** **= Access to Sanitation Facilities (SDG 6.2.1)**

- **Definition:** Percentage of the population using *safely managed sanitation services*.
- **Criteria:** Improved sanitation facilities that are not shared with other households, where excreta are safely disposed of or treated.
- **Why Important:** Proper sanitation prevents the spread of infectious diseases, reduces contamination of water supplies, and improves urban health outcomes.
- **Sources:** WHO/UNICEF Joint Monitoring Programme (JMP); supported by NASA SEDAC population grids and Copernicus GHSL for identifying sanitation demand in dense settlements.

- ***T*** = **Wastewater Safely Treated (SDG 6.3.1)**
    - **Definition:** Proportion of domestic and industrial wastewater flows safely treated before discharge into the environment.
    - **Criteria:** Includes treatment at centralized plants or decentralized safe treatment systems.
    - **Why Important:** Untreated wastewater leads to river, groundwater, and coastal pollution, undermining both ecosystems and human health.
    - **Sources:** UN-Habitat, FAO AQUASTAT, and UN-Water; validated by NASA Earthdata Worldview (tracking sewage plumes and algal blooms) and EO Toolkit for Sustainable Cities.

The W&S Score representing Water & Sanitation allows for comparability among cities under a single, SDG-compatible framework that indicates success on SDG 6: Access to water and sanitation for all. The score is then categorized into five thresholds—At-Risk (0-25), Poor (26-50), Moderate (51-75), Good (76-99), and Excellent (100)—that allow for unambiguous interpretation to inform policymakers, urban planners, and academics. The W&S Score was rigorously calculated, using official UN data supplemented by multispectral image-based satellites (to enhance verifiability). This Water & Sanitation Score represents a trusted, transparent way for assessing urban water and sanitation conditions across the globe. The proposed thresholds transition standard scoring systems to a cumulative 0-100 (like the Human Development Index and Environmental Performance Index) while providing useful, qualitative intervals that prioritize communicability at the purpose and potential minimal technical complexity. Each threshold level represents action-oriented urgency: At-Risk carefully outlining immediate intervention periods and severity; Poor describing important gaps, and change probability; Moderate noting the entity has progressed, but continues to contend with access; Good matched to reasonably worked systems with small gaps; and Excellent entity as "model", in terms of the equitable implementation of support high quality systems of water and sanitation) and everlasting or sustainable access to water and sanitation. The W&S Scores were calculated for (seven) global cities with data from 2023-2023, compiled and applied at the city(s) scale, to help guide investment, policy and planning.

The descriptions for categories are as follows:

0–25 = At-Risk
The W&S Score indicates critically insufficient access to water and sanitation services. Cities in this range face severe public health risks, with inadequate coverage and poor wastewater management threatening population well-being. Immediate intervention, strong policy measures, and targeted investments are essential to protect residents and achieve SDG 6 targets.

26–50 = Poor
The W&S Score reflects substantial gaps in water and sanitation provision. Service reliability and coverage are inconsistent, placing populations at significant risk of waterborne diseases. Cities in this category require focused

improvements, infrastructure development, and governance enhancements to move toward equitable and sustainable access.

51–75 = Moderate

The W&S Score denotes partial progress toward adequate water and sanitation services. While coverage has improved, gaps remain in equity, quality, or sustainability of services. Cities in this range should continue planning and investing to ensure full SDG 6 compliance and reliable access for all residents.

76–99 = Good

The W&S Score reflects broadly functional and sustainable water and sanitation systems. Most residents have reliable access, and governance is effective, though small gaps may persist. Ongoing monitoring and incremental improvements are needed to maintain high-quality, SDG-aligned service delivery.

100 = Excellent

The W&S Score represents exemplary water and sanitation provision. Cities in this tier achieve full coverage, equitable access, and sustainable management, serving as models for SDG 6 implementation globally. These cities demonstrate high-quality governance, resilient infrastructure, and effective long-term planning for water and sanitation.

Scores were computed for seven global cities using 2023 data, with results aggregated at the city scale.

City / Country	Population (2023)	W (%)	S (%)	T (%)	W&S_Score	Category
Berlin / Germany	3,769,495	100	100	95	99	Well-Served
Delhi / India	30,291,000	40	82	60	60	Developing
Lagos / Nigeria	15,600,000	29	28	8	23	Critical
Manila / Philippines	19,025,900	48	63	68	58	Developing
New York / U.S.	8,467,513	97	99	90	96	Well-Served
Paris / France	2,166,423	100	99	91	98	Well-Served
São Paulo / Brazil	12,325,232	86	79	52	75	Developing

Figure: Water and Sanitation Score of Selected Global Cities in relation to their 2023 population.

Justification

The Water & Sanitation (W&S) Score was designed to provide a clear and balanced measure of how cities perform on critical dimensions of water access, sanitation coverage, and wastewater management. These three variables were chosen because they directly capture the essential components of SDG 6: ensuring that populations have safe and sufficient water, adequate sanitation, and environmentally responsible treatment of waste streams. Together, they represent both the human health perspective (household-level access) and the infrastructure perspective (system-level performance).

The decision to apply a weighted scoring system (40% water, 35% sanitation, 25% treatment) reflects the relative importance of each factor: safe water access is the most immediate requirement for survival, sanitation reduces disease transmission risks, and treatment ensures long-term environmental and public health sustainability. By combining these measures into a single composite score, the framework avoids focusing on one dimension at the expense of others, offering a holistic picture of service provision.

To aid interpretation, the continuous 0–100 score is categorized into three ranges: At-Risk (<60), Developing (60–84), and Well-Served (≥85). These bands were set using equal-interval scaling, a method commonly used in international reporting to simplify technical results into categories that are intuitive for policymakers and non-specialist audiences. The classification also reflects practical thresholds: cities below 60 generally face systemic risks to health and resilience, those between 60 and 84 have partial but uneven progress, and those above 85 demonstrate reliable, universal services.

This approach provides both comparability across cities and actionable insights for urban decision-makers. Rather than treating water, sanitation, and treatment as isolated issues, the W&S Score integrates them into a unified metric, making it easier to prioritize investment, monitor progress, and highlight urgent intervention needs in the global context of urban resilience.

Limitations

The W&S Score, while useful for comparing cities, has several limitations. Data availability is uneven, as many figures are modeled from national surveys and may miss intra-city inequalities, especially in informal settlements. Temporal gaps also exist since global datasets are not always updated annually, limiting real-time accuracy. The fixed weighting of water, sanitation, and treatment assumes equal relevance everywhere, though local priorities differ. Moreover, access indicators often capture infrastructure presence but not service quality or reliability, and wastewater treatment statistics may not reflect actual effectiveness. Broader climate and environmental stresses are only partially represented, and reducing complex realities into a single score risks oversimplification. Still, the W&S Score remains valuable as a clear, interpretable framework to guide policymakers and highlight priority areas for urban resilience and SDG 6 progress.

Future Improvements

The framework can be strengthened by incorporating inequality-sensitive measures (e.g., service gaps between districts), using Earth observation data for real-time monitoring of water quality and scarcity, and integrating climate resilience indicators to reflect future risks. Adjusting weightings based on regional priorities and improving the frequency of updates would further increase its accuracy and policy relevance.

URBAN ENVIRONMENTAL INTEGRATION SCORE (UEI)

Background

A submetric of the VITAL that quantitatively comprehends the status of how intimately a natural cover and environment could be found inside the cities. The foundation of the UEI metric is based on the recent standards suggested by Prof. Cecil Konijnendijk van den Bosch (Director of Nature Based Solutions Institute), called the 3-30-300 rule. For which it states that there should be at least **3 trees within 15m** of view. A city should consist of **30% natural canopy cover,** and finally that the residents should have access to a quality **green space within 300m** (Konijnendijk van den Bosch, 2021). United Nations Economic Commission for Europe, supports the agenda to have a greener space in urban areas, and also puts forward the 3-30-300 as a rule of thumb for urban forestry and urban greening. (United Nations Economic Commission for Europe, 2022). With recent developments in research and studies, the 3-30-300 rule gains more backup and sufficient evidence to use as a guideline for urban planning and city development that accounts for sustainability and health of residents.

A study in Philadelphia assessed the exposure-response functions in conjunction with projections of changes in canopy cover to assess the quantity of premature deaths that may be prevented through implementing the goal of 30% canopy cover in Philadelphia. It found that 403 overall premature deaths may be prevented in Philadelphia annually if the 30% goal is actually met (Kondo et al., 2020). On the other hand, a study from Denmark supports the 300m rule. The study found out that people living 1km away from a green space had a lower tendency to exercise, and also had higher chances of being obese as opposed to those living within 300m of green spaces (Toftager et al., 2011). A study in Barcelona found that meeting the 3-30-300 rule has a statistically significant impact resulting in fewer psychologist and psychiatric visits, indicating mental well-being of subjects (Nieuwenhuijsen et al., 2022).

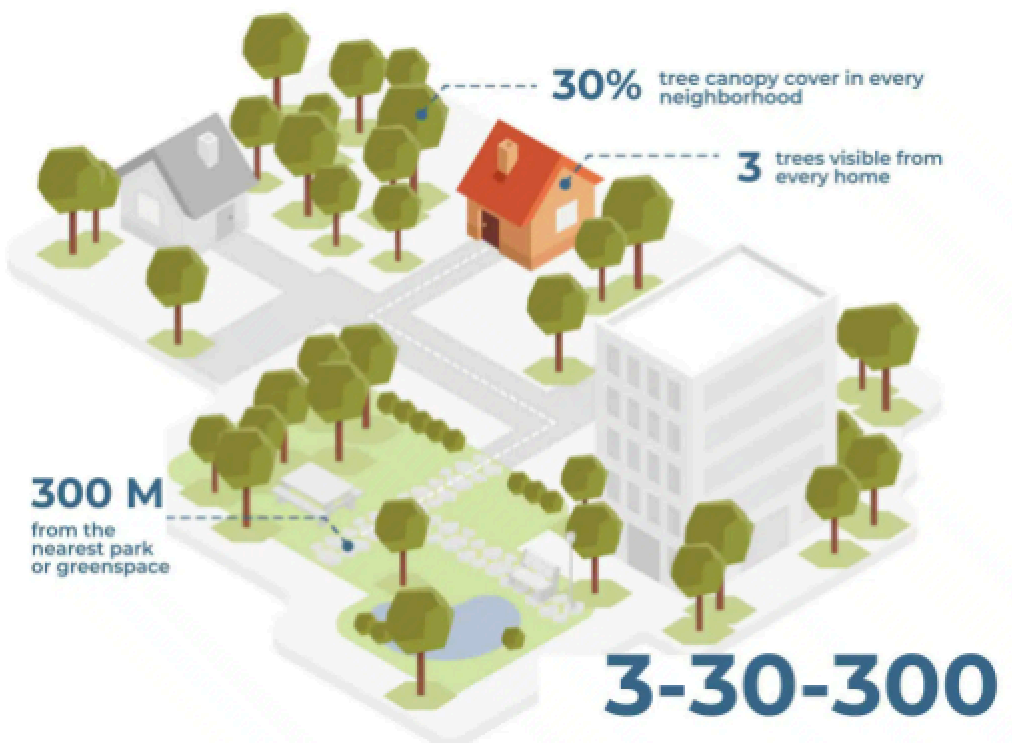


Image Source: https://planitgeo.com/library/urban-forestrys-new-benchmark-the-330300-rule

LCZs have an established interval percentage of how much pervious cover is estimated to exist in a specific area of a city. It also includes the types of pervious cover that could be found in each LCZ category, which may be sand, low plants, trees, etc. Using these available studies, we were able to identify the **LCZs which have green pervious covers (dense trees, scattered trees, and low plants) and at the same time sufficiently meets the 30% Pervious Surface Fraction.** LCZs that satisfy these requirements are LCZ 4 (Open high-rise), LCZ 5 (Open midrise), LCZ 6 (Open low-rise), LCZ 9 (Sparsely Built), LCZ A (Dense Trees), LCZ B (Scattered Trees), and LCZ C (Bushes and Scrubs)**.** We also identified the **LCZs that lack the former qualities**, and these are LCZs 1 (Compact High-rise), 2 (Compact mid-rise), 3 (Compact low-rise), 7 (Lightweight lowrise), 8 (Large lowrise), 14 (Low Plants), 15 (Bare Rock or Paved), and 16 (Bare soil or sand). (For reference, see figures 2 and 3)

Local climate zone (LCZ)	Sky view factor[a]	Aspect ratio[b]	Building surface fraction[c]	Impervious surface fraction[d]	Pervious surface fraction[e]	Height of roughness elements[f]	Terrain roughness class[g]
LCZ 1 *Compact high-rise*	0.2–0.4	> 2	40–60	40–60	< 10	> 25	8
LCZ 2 *Compact midrise*	0.3–0.6	0.75–2	40–70	30–50	< 20	10–25	6–7
LCZ 3 *Compact low-rise*	0.2–0.6	0.75–1.5	40–70	20–50	< 30	3–10	6
LCZ 4 *Open high-rise*	0.5–0.7	0.75–1.25	20–40	30–40	30–40	>25	7–8
LCZ 5 *Open midrise*	0.5–0.8	0.3–0.75	20–40	30–50	20–40	10–25	5–6
LCZ 6 *Open low-rise*	0.6–0.9	0.3–0.75	20–40	20–50	30–60	3–10	5–6
LCZ 7 *Lightweight low-rise*	0.2–0.5	1–2	60–90	< 20	<30	2–4	4–5
LCZ 8 *Large low-rise*	>0.7	0.1–0.3	30–50	40–50	<20	3–10	5
LCZ 9 *Sparsely built*	> 0.8	0.1–0.25	10–20	< 20	60–80	3–10	5–6
LCZ 10 *Heavy industry*	0.6–0.9	0.2–0.5	20–30	20–40	40–50	5–15	5–6
LCZ A *Dense trees*	<0.4	>1	<10	<10	>90	3–30	8

Figure 2: Table of Local Climate Zones and Percentage Characteristics

Based on the figure below, only LCZs 4, 5, 6, 9, 11, 12, 13 boast a sufficient amount or integration of trees and plants within cities. Low plants particularly grasses were removed from consideration as they provide minimal ecosystem services as they lack the urban heat mitigation, carbon sequestration, and cooling wherein trees, bushes, shrubs, and other plants excel at. Pavements and Bare Rock and Sand also unaccounted for reliable land cover, because of the same reason.

Figure 3: Descriptions and Illustrations of Local Climate Zone Characteristics
Source: https://essd.copernicus.org/articles/14/3835/2022/

Methodology of Urban Environmental Integration score

In the UEI metric score, we assessed the 30-300 portion of the rule, with the help of data from Local Climate Zones (LCZ). The first step was to extract the LCZ information of each city using a shapefile and Python's rasterio library, enabling us to work with pixels, each classed for an LCZ it belongs to. The scoring metric uses a simple linear relationship as the foundational rule of 3-30-300 is mainly a goal-oriented guideline for health and sustainability, unlike other metrics for which severity to health may not increase linearly and have a more complex relation.

30% Ideal Natural Cover Score

The LCZs that satisfy at least 30% green pervious cover is summed, and its ratio towards the total areas combined was calculated to obtain the percentage of the city that meets at least 30% green pervious cover.

$$NC30_{Rf} = \frac{\sum LCZ_{NC30}}{\#TotalAreas} * 100$$

NC30_Rf - Percent form of Relative Frequency of city areas with 30% Natural Cover
LCZ_NC30 - Local Climate Zone Categories that have 30% and above Natural Cover

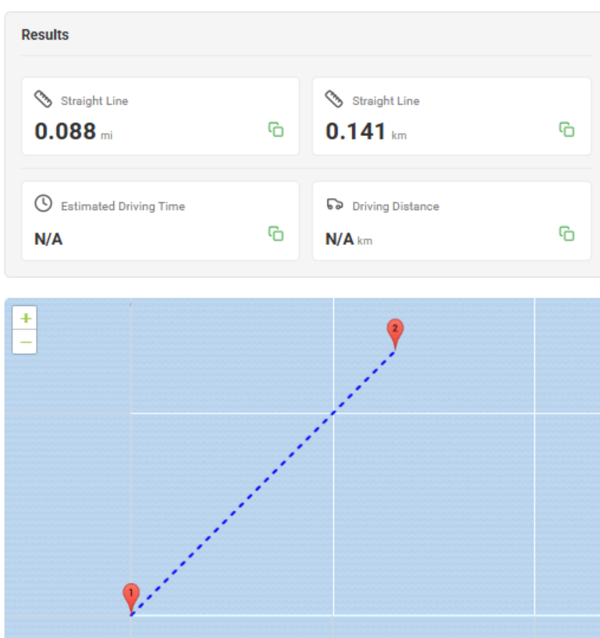
The ratio of the obtained percentage to 30% ideal standard was also assessed to review the city's score with 0% translating to a score of 0 and 30% translating to a score of a 100.

$$NC30_{score} = \frac{NC30_{Rf}}{30} * 100$$

Areas with access to Natural Cover within 300m

To accurately compute the distance of each pixel, it is required to know the Coordinate Reference System (CRS) used by rasterio. In the case of our data for UEI, the LCZ raster map has a CRS of EPSG:4326 where the pixel dimensions are:
Latitude: 0.000898315284119518 degrees
Longitude: 0.000898315284119518 degrees

The next process involves converting degrees into meters through Haversine's Formula, accounting the angular distance between two coordinates given a spherical Earth shape. The results yielded by using the EPSG:4326 pixel dimensions stated above are as follows:



Source Website: https://latlongdata.com/distance-calculator

The resulting distance is a diagonal distance, or in trigonometry a hypotenuse that is possible to convert into latitude and longitude distances in meters. The dimensions of pixels in the CRS are approximately equivalent to 100 m^2 as shown below.

$$Lat_m = 141sin(45) = 99.70m$$

$$Long_m = 141cos(45) = 99.70m$$

Assessing Proximity of Areas within 300m to a Sufficient Natural Cover

As we have established that 100m^2 is each pixel's equivalent distance, we could now measure that at least an LCZ with sufficient natural cover should be within 3 pixels away from a reference pixel. In order to successfully assess the proximity within 300m^2 range, the method used was distance_transform_edt from scipy.ndimage. The array of areas classified with the target LCZ category were then translated to boolean values. After, the distance transform computes the distance of True values (Compact Areas) to the False values (Areas with 30% Natural Cover) to check if compact areas at least have a convenient access to healthy areas of the city.

$$NC_{300m_{Rf}} = \frac{\sum NC_{300m}}{\#CompactAreas} * 100$$

$$UEI_{score} = \frac{NC30_{score} + NC_{300m_{Rf}}}{2} * 100$$

NC300m_Rf - The Percent Form of Relative Frequency of City Areas with 300m access to the Local Climate Zones with 30% Natural Cover.
NC300m - The Local Climate Zones that has 300m access to an area with 30% Natural Cover.

UEI Data Source

The Local Climate Zones data were extracted from a website managed by the Urban Climatology, Department of Geography, and Ruhr University Bochum, in Germany. The datasets utilized in their Local Climate Zone map were derived from pre-processed data from multiple earth observation datasets. The methodologies by our data source follows the published work of Demuzere, M., Kittner, J., Martilli, A., Mills, G., Moede, C., Stewart, I. D., van Vliet, J., and Bechtel, B. (2022). To properly bound and extract a city's LCZ data, a shapefile sourced from Database for Global Administrative Areas GADM was applied enabling the searching of polygon coordinate data of both state and city levels.

Scoring Descriptions

30% Ideal Natural Cover
0 - 20 Critical Environmental Deficit - City's natural cover needs immediate attention and care.

21 - 40 - Considerable Environmental Deficit - Natural Cover percentage of the city area is considerably lower than the 30% goal.

41 - 60 - Moderate Environmental Deficit - Natural Cover percentage of the city area meets approximately half of the healthy goal.

61 - 80 - Substantial Progress - Natural Cover percentage of the city area is significant but needs more improvement.

81 - 99 - Near Target Coverage - Natural Cover percentage of the city area nearly meets the required 30% Goal.

100 - Optimal Natural Cover - Natural Cover percentage of the city meets 30% goal, providing improved quality of health and life.

300m access to decent greeneries
0 - 20 - Severe Access Deficit - Barely any of the populated and dense areas has access to open spaces with decent greeneries.

21 - 40 - Limited Access - Some populated and dense areas have access to open spaces with decent greeneries.

41 - 60 - Partial Access - Approximately half of the dense areas have access to open spaces with decent greeneries.

61 - 80 - Broad Access - A significant majority of dense areas have access to open spaces with decent greeneries.

81 - 99 - Near-Universal Access - Almost every dense area has access to open spaces with decent greeneries.

100 - Universal Access - All of the dense areas have access to open spaces with decent greeneries.

Scores Obtained

Country	City	Areas With 30% Cover	Areas With 30% Cover RF	30% Ideal Cover Score	Access within 300m NatCov	Access within 300m NatCov RF	Total Compact Areas	Total Areas	UEI Score
Greece	Athens	938	18.98	63.27	753	18.8	4005	4943	41.04
Germany	Berlin	93674	64.05	100	10958	66.49	16480	146245	83.24
Egypt	Cairo	25040	62.85	100	2655	18.19	14596	39844	59.1
Turkey	Istanbul	253767	41.32	100	30598	23.47	130359	614155	61.74
Nigeria	Lagos	22136	33.32	100	9819	24.82	39562	66434	62.41
Philippines	Manila	222	6.03	20.1	340	9.82	3461	3683	14.96
India	Delhi	130173	75.77	100	24284	59.45	40849	171795	79.72
USA	New York	49716	48.72	100	17785	37.89	46942	102050	68.94
France	Paris	2705	16.96	56.53	2855	21.57	13238	15949	39.05
Brazil	Sao Paulo	77410	46.4	100	24456	31.2	78396	166822	65.6

In this table, it is important to note that each unit of area is 100m^2 based on the pixel resolution of the satellite image. Total Areas were utilized as a basis of fraction of natural cover. Meanwhile the ratio of Access within 300m NatCov to Total Compact Areas provided the data for scoring of compact areas with access to nature.

Significance

The UEI score gives equal weight to both the 300m access to the 30% cover areas, and also to the overall 30% ideal natural cover a city should ideally possess. UEI therefore illustrates the picture of not only the city's environmental status, but also whether nature is accessible to improve health and life of people in the city. Instead of taking into account strictly green spaces, the UEI assesses nearby LCZs that qualify with the percentage of nature having a significant beneficial impact on human health. Cities like Lagos, Nigeria excel in terms of 30% natural canopy, but are simply inaccessible and far from urbanized areas, attracting less people and serving less benefits. Even cities such as Berlin, Germany, considered to be one of the most sustainable and greenest cities in the world, only score decently towards accessibility of 30% natural cover. As urban planners develop cities further, the UEI score could provide a metric of nature accessibility, proving the need for a more strategic location of natural integration within cities.

Limitations

The full 3-30-300 rule currently poses challenges to measurement especially 3 trees within 15m is not measured or included with current technologies and satellites. The methodology used turned the 30-300 portion of the 3-30-300 rule into a continuous value, and must accept that there will be a 10% error. As mentioned from the background of the methodology, the UEI derives its 30% cover approximation from the Local Climate Zone categories that have the potential to meet the 30% green cover. Each of these categories have ranging values (e.g. 30% - 40%), implying that some underestimations may show in the program. The current data of LCZ uses a 100m pixel resolution which implies a favor on open areas with large amounts of tree or plant clusters. This limitation is evident in Berlin and Paris where in reality they possess slightly greater amounts of natural cover within cities but may be patched or not clustered resulting in invisibility through the satellite causing small errors in categorization of their LCZs. Compared to previous studies that limited their measurements to actual green spaces (parks, etc.), the current methodology focused on dense areas having access to open areas with sufficient and quality greeneries. If future innovators seek more accurate measurements in green cover, a higher resolution pixel (> 100m) would be needed to consider trees and plants that are unseen by 100m pixel dimension

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