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The dietary footprints and transition priorities of over 12,000 cities

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Abstract

Urban consumption plays a central role in driving global carbon emissions and is associated with a wide range of environmental pressures, including deforestation, water use, and biodiversity loss. As cities and networks of cities work to define and achieve quantitative sustainability goals, the lack of insight into their unique food footprints, shaped by each city's specific dietary patterns and demographic composition, remains a significant obstacle. Here we combine demographic, group-specific diet, and supply-chain environmental footprint data to estimate the dietary footprints in 12,683 cities across 159 countries.

We show that diet-related greenhouse gas emissions (GHGE) are highly concentrated in a small number of megacities. The 200 cities with the largest footprints account for approximately 15% of global population but nearly half of total global urban dietary emissions. Adoption of the EAT–Lancet 2.0 diet in the studied cities could modestly reduce total footprints (by 5–15%, depending on impact category). High-footprint cities have the greatest potential reductions from reducing meat and dairy consumption. However, these gains are largely matched by the potential rises in footprints from lower-income cities presently consuming below the EAT-Lancet recommended levels. Across transnational city networks (C40 Cities, Eurocities, and Milan Urban Food Policy Pact members) implementation of the EAT–Lancet 2.0 diet delivers substantial reductions 22–50% in GHGE, underscoring the policy relevance of city-level dietary footprinting.

Our results highlight the need for context-specific urban dietary strategies. The resulting database, MATILDA-City, provides a globally harmonised evidence base to benchmark, rank, and monitor city-level dietary footprints, supporting municipalities to coordinate actions toward sustainable food systems.

Introduction

Cities play a critical role in achieving ambitious sustainability goals, as key drivers of global resource consumption and emissions (1). Infrastructure decisions are critical to curtailing these impacts in the buildings and transport sectors (2, 3). Yet, dietary change is also a key pillar to urban sustainability. Unlike the lock-in of infrastructure, dietary patterns and their impacts can be influenced by short-term, large-scale policy interventions. Several transnational city networks have been established to this end. The C40 Good Food Cities initiative, 100 climate neutral cities mission of the EU, and the Milan Urban Food Policy Pact (signed by 330 cities) were set up to align and even surpass local food strategies with national and international sustainability goals. These include near-term goals for wide-scale adoption of a planetary health diet (e.g. Barcelona, New York, Milan), food waste reduction targets, and fiscal instruments to limit sugar-sweetened beverages. Despite these commitments, progress on these action plans remains hampered by data to benchmark, compare and rank city-level food consumption, impacts, strategies and goals (4, 5).

Data collection and modelling efforts designed to guide sustainable development routinely focus on consumption patterns and impacts at a national scale, overlooking the uneven contribution of urban

regions to anthropogenic environmental change. Where cities are the focus of concern, models typically support an aggregated or partial assessment of consumption activities. Early studies captured direct, production-based emissions of cities (6, 7). Although instructive, these approaches ignore the global impacts of urban consumption that extend beyond city borders and can account for around 50% of emissions-related impacts (8). Global, consumption-based footprinting analyses of cities have emerged in recent years in response to the growing need for cities to report direct and indirect emissions (9). These models have sought to use economic data to decompose national expenditure patterns by region, using household expenditure surveys (10) or spending data (11), to better capture supply-chain related environmental impacts of city consumption (12, 13). However, these are limited by coarse food categorisation and poorly reflect actual physical food intake, preventing actionable hotspotting of food consumption patterns and impacts across urban regions.

Bottom-up data collection on urban food consumption patterns offers another avenue for city-level dietary environmental footprinting. Such an approach relies on localised dietary recall surveys and urban assessment of food provisioning (14, 15). Whilst this provides superior detail of urban food habits, such data collection is not amenable to global comparison and remains impractical at a global scale due to time and resource constraints. Many cities lack funding to establish a comprehensive assessment of city-level consumption and monitoring against a wide suite of indicators (16). Among the G20, only around 40% of cities have adequate data to track climate pledges among, an issue that is more pronounced in low-income countries (17). Although national food intake surveys collect information on sub-regions, such information is either aggregated for privacy reasons or too incomplete to enable robust assessment of city-specific consumption patterns (18). Yet, by coupling information on population size and structure, food consumption patterns and impacts of cities can be derived, based on nationally-derived food consumption profiles of socio-demographic subgroups. We follow such an approach, to construct a global database for comparable, city-level dietary footprint estimates: MATILDA-City, building on MATILDA (Micro-Macro Assessment Tool to Identify Low-impact Dietary Actions), a global, consumer-level dietary footprinting tool (19).

The harmonisation of food consumption microdata, environmental impact information and demographic data provides a basis to estimate city-level footprints (20). Within this study, we couple MATILDA (19) with spatially-derived city population and economic data to estimate the food consumption patterns and environmental footprint of 12,683 cities by greenhouse gas emission (GHGE), water, and land footprint (see Materials and Methods). The resultant database, MATILDA-City, enables comparison, ranking and scenario modeling of dietary environmental footprints across different cities and can flexibly accommodate new city consumption or food supply data. We illustrate the usefulness of this tool by calculating the environmental gains of adopting the EAT-Lancet 2.0 diet across each city and broad transnational city networks, including C40 cities, EU climate cities and the Milan Urban Food Policy Pact (MUFPP).

Our analysis shows a highly uneven distribution of city dietary environmental footprints worldwide. The 200 largest cities account for nearly half of the total 5.16 Gt CO₂-eq of global city dietary emissions,

while megacities such as Jakarta, São Paulo, Guangzhou, and Tokyo, each exceed 70 Mt CO₂-eq. Across cities, animal-source foods dominate environmental pressures, with meat alone contributing 49% of dietary GHGE, 38% of water use, and 54% of land use. If the EAT-Lancet 2.0 diet were fully adopted, global city dietary greenhouse gas emissions would decrease by 14%, land use by 16%, and water use by 5%. These aggregate reductions arise because the EAT-Lancet diet leads to heterogeneous changes in diet-related environmental footprints across cities, with reductions in high-footprint cities but increases in other cities. Overall, 56% of cities experience increases in at least one environmental footprint indicator, resulting in a modest global net reduction. Within transnational city networks, adoption of the EAT-Lancet 2.0 diet yields net reductions in dietary environmental footprints, amounting to 22% in C40 Cities, 50% in Eurocities, and 30% across the Milan Urban Food Policy Pact members. The underlying database, MATILDA-City, provides a scalable database to support city-level decision support towards sustainable and equitable urban food systems.

Results

Our results indicate that urban diet-related greenhouse gas emissions (GHGE) are driven by a limited number of megacities. Globally, city-level diet-related GHG emissions total 5.16 Gt CO₂-eq per year (Fig. 1A). Asian cities contribute to nearly half of global dietary GHGE (51.4%), followed by South America (16.6%), Africa (11.9%), and Europe (10.7%) (Fig. 1B). As expected, total city-dietary GHGE show a strong positive correlation with total population size ($R^2 = 0.810$), indicating that larger cities generally have higher absolute emissions (Fig. 2A). The 200 most populous cities collectively account for 39.8% of the total urban population and 45.5% of the total GHGE across all cities. Collectively, the dietary GHGE from the 200 cities amount to 2.35 Gt CO₂-eq, comparable to diet-related emissions of Brazil (2.05 Gt CO₂-eq) (21). Among the 12,683 cities analysed, only four megacities exceed 70 Mt CO₂-eq - Jakarta (84.4 Mt CO₂-eq), São Paulo (84.1 Mt CO₂-eq), Guangzhou (81.9 Mt CO₂-eq), and Tokyo (73.5 Mt CO₂-eq), each comparable to the diet-related emissions of a small- to medium-sized country such as the Philippines (81.7 Mt CO₂-eq) or South Sudan (71.8 Mt CO₂-eq) (21). Cities with populations below 10 million contribute less than 5% of their national dietary GHGE, whereas several cities account for substantial shares of their respective national dietary GHGE footprints, such as Lima (9.9 million people, 45.9 Mt CO₂-eq, 59.5% of national total) and Moscow (15.6 million people, 45.9 Mt CO₂-eq, 23.8%). Regarding population distribution, most cities (12,234; 96.4%) represent less than 5% of their national population, whereas only 255 cities (2.0%) account for more than 10%.

City-level diet-related GHGE are unevenly distributed across food groups and cities. Meat (processed meats & unprocessed meats), dairy products, and refined grains account for the largest shares of city-level GHGE (Supplementary Fig. 1A). In high-emission cities such as Jakarta, São Paulo, and Guangzhou, meat alone accounts for over one-third of total dietary GHGE, while refined grains and dairy products together account for approximately one-quarter. In contrast, fruits, vegetables, and legumes contribute less than 10% on average to city-level GHGE and other impacts. Per-capita consumption patterns across cities (Supplementary Fig. 1B) show marked heterogeneity. Refined grains dominate diets in most cities (> 400 g/day), especially across Africa and Asia, whereas dairy intake varies widely, from low levels in

many African and Asian cities (about 120 g/day) to very high levels in Europe, North America, and Oceania (> 900 g/day). Meat consumption is particularly high in several European and North American cities. Cities with comparable population sizes exhibit markedly different dietary compositions and associated diet-related GHGE. For example, despite comparable total populations, Lima (9.9 million) and Paris (10.1 million) exhibit distinct dietary patterns and associated environmental impacts. In Lima, plant-based foods account for 59.6% of total dietary intake, while in Paris the corresponding share was 37.1%. Nevertheless, the total diet-related GHGE in Lima (45.9 Mt CO₂-eq) are approximately four times higher than those in Paris (15.4 Mt CO₂-eq) (Supplementary Fig. 1). Despite a higher plant-based share, total dietary GHGE in Lima are driven by higher emission intensities per unit of agricultural output, reflecting lower production efficiency.

City-level diet-related environmental impacts show substantial reductions when urban populations transition toward EAT-Lancet dietary patterns, with varying mitigation potential across GHGE, water use, and land use (Fig. 3). We estimate that full adoption of the EAT-Lancet 1.0 and 2.0 diets reduces total city-level dietary GHGE by 13.6% and 14.1%, respectively (approximately 0.7 Gt CO₂-eq, comparable to Mexico's total annual GHGE (22)) (Supplementary Fig. 2). For dietary water use, the same transitions lead to modest reductions of 5.6% and 4.8% relative to the baseline levels under the EAT-Lancet 1.0 and 2.0 diets, respectively. These savings roughly correspond to the entire dietary water footprint of Indonesia (230 km³) (23). Patterns for land use mirror those observed for GHGE, resulting in a 16.1% reduction in total city-level dietary land use under the EAT-Lancet 2.0 diet, equivalent to restoring an area of farmland roughly the size of India's cropland (156 Mha) (24). When the EAT-Lancet 2.0 diet is applied within specific transnational city networks, dietary environmental footprints decline by 22.3% across C40 member cities, 50.0% across Eurocities, and 29.8% across Milan Urban Food Policy Pact (MUFPP) cities.

Across all environmental indicators, animal-based foods drive most of the global reduction in city-level diet-related environmental impacts under the EAT-Lancet 2.0 diet (Supplementary Fig. 3). At baseline, meats (processed meat and unprocessed meat) are the largest contributors to city-level dietary GHGE (2.55 Gt CO₂-eq), water use (1,419 km³), and land use (479.8 Mha). Following full adoption of the EAT-Lancet 2.0 diet, meat-related GHGE decline by 1.15 Gt CO₂-eq (-45.3%), water use by 729 km³ (-51.4%), and land use by 236 Mha (-49.2%), relative to baseline levels. Eggs account for a smaller baseline footprint (0.18 Gt CO₂-eq, 123 km³, and 20.5 Mha) yet show comparable sector-specific impact reductions across GHGE, water use, and land use of 57.6%, 52.8%, and 54.0%, respectively. Seafood contributes 0.03 Gt CO₂-eq at baseline and decreases by 0.01 Gt CO₂-eq following adoption of the EAT-Lancet 2.0 diet, equivalent to a 39.9% reduction.

Although adoption of the EAT-Lancet 2.0 diet by cities leads to a net reduction in global diet-related environmental footprints, sustainability outcomes for individual cities are highly heterogeneous (Fig. 4A). Overall, 55.9% of cities show higher GHGE, 57.0% higher water use, and 56.4% higher land use under the EAT-Lancet 2.0 diet compared with baseline diets. In high-footprint cities such as São Paulo, Moscow, Guangzhou, Lima, and Tokyo (upper rows), total GHGE typically fall by one-third to two-thirds, driven by sharp declines in meat and dairy, partly offset by higher consumption of whole grains, legumes, nuts,

fruits and vegetables. By contrast, in several lower-footprint cities, particularly in South Asia, adoption of the EAT–Lancet 2.0 diet increases environmental pressures. In Dhaka and Delhi, where current diets are dominated by cereals and starchy staples with low intake of animal-source foods, GHGE almost double (89% increase in Dhaka; 108% increase in Delhi), accompanied by increases of 61–65% in water footprints and 64–92% increase in land footprints of these cities.

Discussion

This study offers a foundational assessment of dietary environmental footprints for over 12,000 cities, providing a new empirical basis for understanding how urban food consumption drives environmental pressures. Our findings have important implications for how cities can contribute to global sustainability transitions. We find that diet-related impacts are highly concentrated in a relatively small set of megacities. The top 50 cities drive more than a quarter of urban dietary environmental impacts (Fig. 1). Yet, over a quarter (28%) of these cities are not members of transnational food sustainability networks and fewer than half appear to have any city-level food plans or commitments to tackle these impacts (Supplementary Table 1), underscoring an urgent need for policy action on their dietary sustainability goals. The strong concentration of dietary footprints in a limited number of large metropolitan areas implies that targeted interventions in these cities could yield disproportionate global benefits. For example, our analysis for C40, Eurocities, and MUFPP shows that even partial adoption of sustainable reference diets within these networks can deliver notable aggregate reductions, with 9% of total dietary environmental impact reductions in dietary environmental impacts, despite covering only 2.5% of cities worldwide (Supplementary Fig. 2). Moreover, the variation in dietary patterns among similarly sized cities shows that population growth alone does not determine dietary environmental pressures; rather, the interaction of local food environments and supply chains shapes dietary footprints (25).

The considerable heterogeneity in city dietary footprints and responses to adoption of the EAT-Lancet 2.0 diet highlights the need to account for equity when promoting dietary transitions. We find that shifts towards the EAT-Lancet 2.0 diet can deliver meaningful aggregate reductions in GHGE and Land use, with smaller benefits for water use, in a subset of individual cities (44%) and across transnational city networks (Fig. 4, Supplementary Fig. 3). This is because high-footprint cities can realise substantial reductions by markedly lowering their intake of meat and dairy. However, in 56% of cities, adoption of the EAT-Lancet diet may lead to increased dietary environmental footprints across one or more environmental impacts. Specifically, cities in South Asia and parts of sub-Saharan Africa show substantial increases in GHGE, water use, and land use under the EAT-Lancet 2.0 diet, driven by their already low consumption of animal-based foods. Dietary recommendations designed for global health and sustainability objectives may not uniformly reduce environmental pressures within all contexts (26). Yet the substantial variation in dietary impacts among cities of comparable size shows that population alone does not dictate environmental pressure; rather, the interaction of urban food consumption patterns and supply-chain emission intensities also shapes city-level dietary sustainability (27, 28). This highlights the importance of aligning global dietary recommendations with region-specific nutritional needs and environmental contexts (29, 30).

Beyond identifying the scale and distribution of dietary environmental footprints, these results point to concrete policy levers that cities can deploy to influence food consumption patterns and their associated environmental impacts. Several C40 and MUFPP cities have increasingly used regulatory, fiscal, and procurement-based interventions to reshape local food environments (31, 32). Cities such as Milan and Barcelona have introduced measures including restrictions on high-sugar beverages, mandatory food-waste separation, and incentives for healthier retail environments (33), while Paris and London have advanced urban food strategies that integrate zoning rules for food retail, fiscal support for alternative proteins, and public information campaigns (34, 35). The heterogeneity of dietary footprints revealed in our analysis suggests that interventions must be tailored: high-impact cities may prioritise reducing red and processed meat consumption through procurement and pricing policies (36), whereas low-footprint cities may focus on improving nutritional adequacy and food access (37).

Regionalising dietary environmental footprints presents challenges for precise mapping of consumption patterns and production sources owing to the aggregated nature of food system data and footprint information. The accuracy of city-level food consumption estimates remains a major constraint of this study. Our model infers dietary patterns from population size, gender and age structure, national food intake patterns of sociodemographic subgroups, and city GDP as a proxy for energy intake, without capturing within-city heterogeneity in dietary habits. This approach overlooks regional, cultural, and socioeconomic differences that shape food choices and food access. While household budget surveys could provide income-based dietary differentiation, they often come at the expense of sectoral detail and spatial resolution. Future extensions could integrate alternative data sources such as food delivery platforms, restaurant menu datasets, and supermarket transactions, which can offer more spatially explicit information on consumption preferences (38). City-level dietary patterns have also been inferred from street-view analyses of obesogenic advertising (39) and studies of food deserts (40), which reveal spatial inequities in food access. Regionally disaggregated food intake surveys, facilitated by national statistical agencies, would substantially improve data accuracy while maintaining privacy safeguards. Using city GDP as a proxy for energy intake introduces additional uncertainty because it does not capture income inequality or related differences in calorie intake, food waste, and dietary composition (3). Finally, the geospatial datasets used to map urban populations vary in their reliance on census interpolation or building-density models, which may affect spatial accuracy, especially in megacities. For large metropolitan areas, bottom-up data integration is needed to better assess the implications of different input datasets for spatially explicit footprint estimates (41).

Several uncertainties also affect the estimation of production-side impacts associated with city-scale food consumption. Environmental impacts from livestock, irrigation, and land systems can vary by several-fold within large countries due to climate, technology, and management differences (42). The FABIO framework cannot capture differences between subnational production zones or identify specific sourcing regions for individual cities. However, we recognise that regionalised sourcing patterns and cross-border linkages can connect cities to production systems with varying levels of efficiency (43). Future work should prioritise resolving city-specific sourcing heterogeneity. Accessibility-based spatial proxies, such as road connectivity (44) or port proximity (45), may help distinguish city-level sourcing

patterns, but their empirical validity as predictors of import dependence remains limited (46). Furthermore, household-level food waste falls outside the MATILDA system boundaries, as the FABIO framework tracks environmental impacts only up to the point of food purchase. If post-consumer waste were incorporated, overall dietary GHGE, water use, and land use would rise—especially among younger, urban, and higher-income populations, who typically discard more food. Evidence indicates that the greatest losses occur for highly perishable plant-derived items, with waste rates commonly reaching 40–50% for fruits and vegetables, whereas animal-source foods are generally discarded at lower rates of around 20–30%. Nonetheless, because animal-based foods have substantially higher environmental intensities per kilogram, accounting for household food waste would raise the absolute magnitudes of impacts but would not alter the relative contributions of major food groups or the comparative patterns revealed by MATILDA-City.

These findings highlight both the responsibility and the opportunity for cities to drive global food-system transformations. As local governments increasingly translate national and global sustainability goals into urban policy, networks such as ICLEI (International Council for Local Environmental Initiatives), which represents more than 2,500 cities that identify food, water, and energy as core pillars of their transitions, illustrate the growing momentum for integrated urban action (47). MATILDA-City provides one such rapid appraisal database, delivering globally harmonized and spatially resolved estimates. Yet these model-based assessments are most effective when complemented by targeted bottom-up data collection, strengthened local monitoring capacity, and investment in food-system analytics to capture city-specific consumption patterns and inequities.

Materials and Methods

This study builds upon the MATILDA (Micro–Macro Assessment Tool to Identify Low-impact Dietary Actions) framework, a harmonised global modelling system that integrates dietary intake, supply-chain environmental footprinting, and population structure data (19). MATILDA is designed to bridge the micro-level detail of individual food consumption with the macro-level representation of global food production and trade. It combines three complementary datasets: the Global Dietary Database (GDD) (48), which provides harmonised intake data for 16 food and beverage groups across 36 socio-demographic subgroups (by age, sex, education, and urban/rural area) in 165 countries; the Food and Agriculture Biomass Input–Output model (FABIO) (49), which traces food-related supply chains across 187 regions and quantifies country-specific GHGE, water use, and land use; and GLOPOP-S, a synthetic global population dataset used to scale per-capita results to population-level estimates.

At its core, MATILDA establishes a concordance between the 16 GDD food groups and 72 primary commodity sectors in FABIO, enabling estimation of environmental footprints (GHGE, water use, and land use) associated with different levels of national food consumption in 165 countries. FABIO uses a Leontief demand-pull analysis to trace both direct and indirect environmental impacts linked to national food consumption, providing full supply-chain footprint of dietary patterns (50). The environmental impacts of food groups are calculated while accounting for product-level differences in food group

composition (e.g. the relative shares of apples and oranges in fruit consumption) to ensure that heterogeneous national food consumption patterns in each food group were represented. Intensity coefficients calculated in FABIO (e.g. m³ of water use per kg of food intake) are then linked with GDD subgroup dietary intakes (standardised to 2,000 kcal per capita per day) to estimate per-capita environmental footprints of demographic subgroups by food group. Outlier detection and interquartile range adjustments ensure stability across products with small trade volumes or extreme coefficients, as described in Taherzadeh and colleagues (19).

Finally, by multiplying per-capita footprints by subgroup population counts from GLOPOP-S or other external population datasets, MATILDA scales individual dietary impacts to total subgroup and national levels, capturing heterogeneity across 1,152 demographic–geographic combinations. Additional information on the model design and implementation is available in the Supplementary Material (Section 1 and 2).

Building on MATILDA, this study developed MATILDA-City, a spatially explicit extension of the modelling framework designed to assess urban dietary footprints. MATILDA-City integrates city-level demographic data with the MATILDA framework to quantify dietary environmental impacts across 12,683 cities worldwide. For each city, GDD-based dietary intake profiles are combined with age- and sex-resolved population distributions and country-specific FABIO coefficients to estimate GHGE, water use, and land-use footprints. The scalable nature of this model also helps contextualise city-level dietary footprints relative to national and international environmental targets (51).

City-level populations of different socio-demographic groups and GDP were obtained from publicly available geospatial datasets. Gridded data for population in 2025, disaggregated by age and sex bins, were obtained from WorldPop (52). Gridded GDP data for 2020 were obtained from Kummu et al. (2025) (53). We obtained city boundaries from the Global Urban Polygons and Points Dataset (54). This dataset contains a hierarchy of 123,034 urban settlements – 11% of these are urban centres, 75% are dense urban clusters, and 14% are semi-dense urban clusters. We restricted the analysis to 13,135 urban centres, i.e., top-tier cities, which together are inhabited by approximately 3.2 billion people. Gridded datasets were aggregated within each city polygon to obtain city-level totals (population by age, sex and GDP). We then excluded cities with missing boundary identifiers and retained only those located in countries covered by the MATILDA framework (165 countries), resulting in a harmonised dataset of 12,683 cities across 159 countries.

Energy intake was adjusted in two steps. First, energy-intake scaling was introduced to adjust GDD's 2,000 kcal reference values to realistic energy levels based on city-level economic status. We estimated a global log-linear relationship between national GDP per capita (PPP, constant 2021 USD) and per-capita calorie supply from the FAO food balance sheets and applied this relationship to downscaled gridded GDP data. The predicted energy intake for each city was then used to rescale all dietary intakes prior to environmental impact calculation. Second, dietary intakes were further rescaled using anthropometry-

based, age- and sex-specific energy intake estimates from Springmann (55), allowing energy intake to vary simultaneously across cities and demographic groups prior to environmental impact calculations.

We apply the EAT-Lancet reference diet to study the environmental impacts of cities shifting towards healthier and sustainable diets. The first version of the EAT-Lancet diet (1.0, published 2019) (56) recommends a daily intake of approximately 2,503 kcal, whereas the updated EAT-Lancet 2.0 (2025) (57) refines nutrient and environmental targets and is standardised to 2,395 kcal per day. Both guidelines promote predominantly plant-based diets rich in whole grains, fruits, vegetables, legumes, and nuts, and lower intakes of animal-source foods, added sugars, and refined grains. Since the EAT-Lancet diets do not specify quantities for coffee, tea, or refined grains, these food groups were held constant across all analyses to ensure comparability with current consumption.

The benchmarking framework compares six cases: (i) the baseline reflecting current urban diets; (ii) full adoption of EAT-Lancet 1.0; (iii) full adoption of EAT-Lancet 2.0; and (iv–vi) partial adoption where only selected transnational city networks transition toward the EAT-Lancet 2.0 pattern. These networks include C40 Cities (58), the Eurocities Network (59), and the Milan Urban Food Policy Pact (MUFPP) (60) –each comprising municipalities with explicit climate and food-system commitments. Under partial adoption, member cities adopt the EAT-Lancet 2.0 diet, while all other cities retain baseline consumption profiles.

Declarations

Data, Materials, and Software Availability

All datasets used in this study are publicly available. No proprietary or access-restricted data was used. All model inputs, intermediate datasets, and outputs are documented in the Supplementary Material, and the full methodological description is provided in the manuscript. Dietary intake data: Global Dietary Database (<https://globaldietarydatabase.org/>); Supply-chain environmental footprint data: Food and Agriculture Biomass Input–Output model (FABIO v1.2) (<https://doi.org/10.5281/zenodo.3551067>); Population and demographic data: WorldPop Global 1 km Population Grids (<https://doi.org/10.5258/SOTON/WP00647>); City boundary data: Global Urban Polygons and Points Dataset (GUPPD v1) (<https://doi.org/10.7927/BRQ1-XC29>); Economic data: Global Downscaled GDP per capita (1990–2022) (Kummu et al. 2025, Scientific Data (<https://doi.org/10.1038/s41597-025-04487-x>); World Bank World Development Indicators (GDP per capita, PPP)(worldbank.org/en/programs/icp/data). All computations were performed in R (v4.3) and Stata (v18).

CREDIT authorship

O.T., H.C., and S.J. designed the research. H.C., S.J., and O.T. performed the research. H.C., O.T., and S.J. analysed data. H.C. performed validation. H.C. and O.T. prepared the figures. O.T. led the research, and O.T., H.C., S.J. and D.D.M. wrote the paper.

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Figures

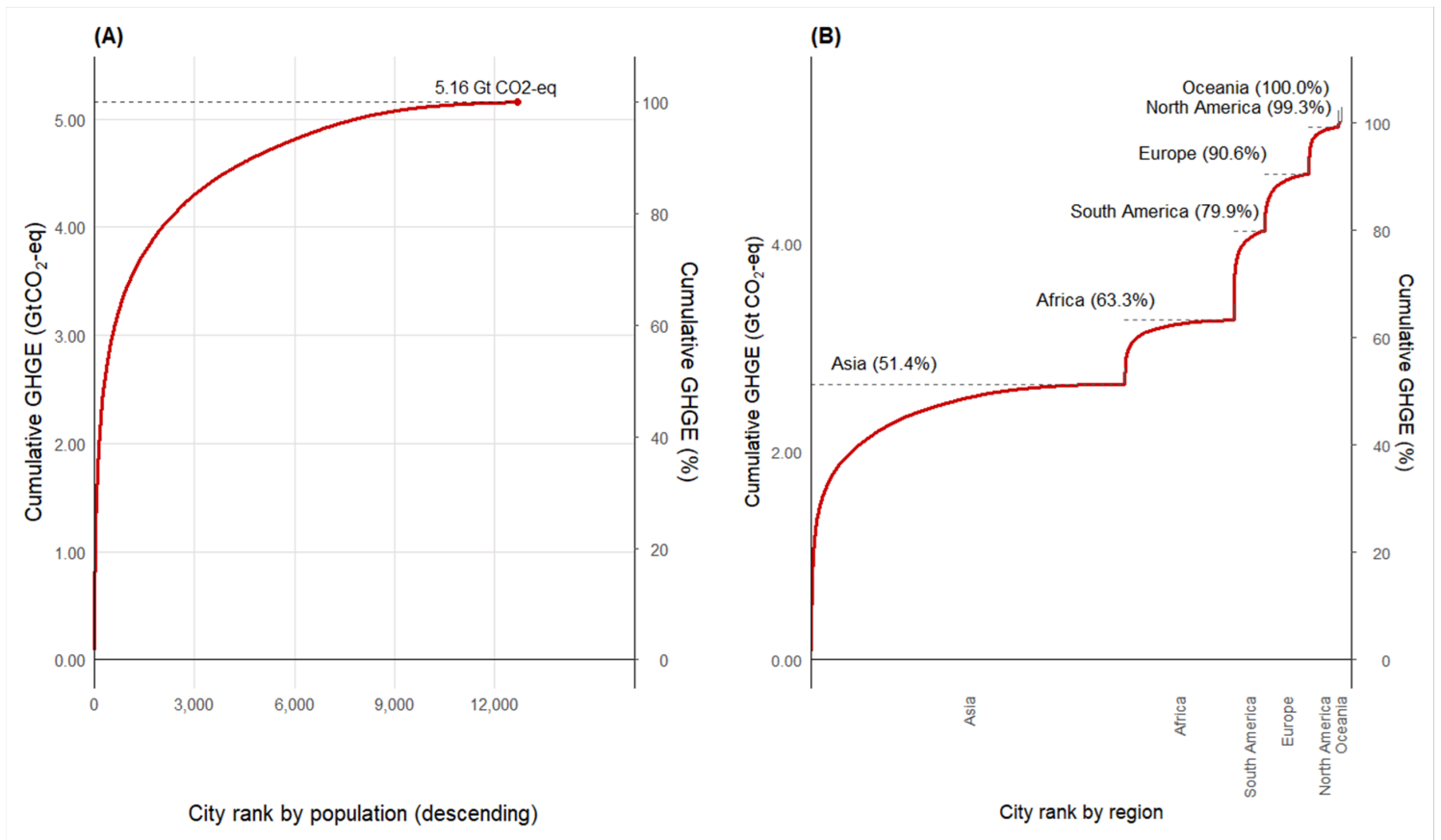


Figure 1

Cumulative city-level diet-related GHGE by population rank and world region

Panel (A) shows the cumulative distribution of total diet-related GHGE across all cities. Cities are ordered on the x-axis from largest to smallest by total population, and the y-axis shows the cumulative sum of city-level GHGE in Gt CO₂-equivalent. The right-hand y-axis expresses the corresponding percentage of city-level diet-related GHGE. Panel (B) presents the same cumulative GHGE curve, but the x-axis is organised by the world region (Asia, Africa, South America, Europe, North America, Oceania), with cities within each region sorted from largest to smallest by population size.

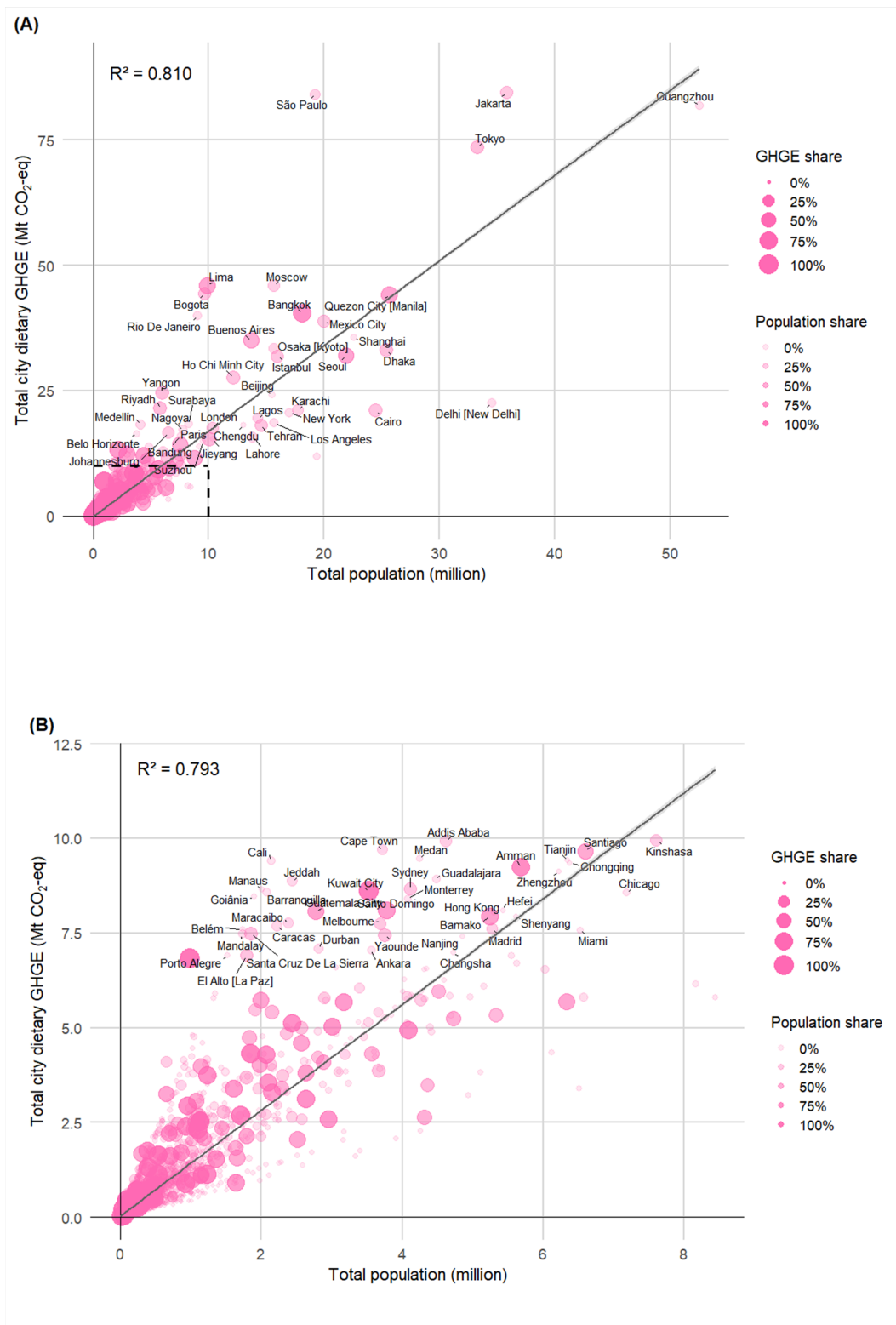


Figure 2

Relationship between city-level GHGE and total population across 12,683 cities worldwide.

Panel (A) shows the full distribution of cities showing the relationship between total population (million) and total dietary GHGE (Mt CO₂-eq). Each point represents one city ($n = 12,683$). The x-axis shows total population (million), the y-axis indicates total city-level GHGE (Mt CO₂-eq). Point size reflects the city's share of national dietary GHGE, as calculated by MATILDA (20) and point transparency corresponds to

its share of the national population. The dashed line represents the fitted linear regression between variables ($R^2 = 0.807$). Panel (B) shows the same relationship after excluding cities with total population > 10 million or total dietary GHGE > 10 Mt CO₂-eq (12,633 cities remaining), to highlight the trends among small- and medium-sized cities. Cities labelled fall within the top 40 cities ranked by total GHGE in each panel.

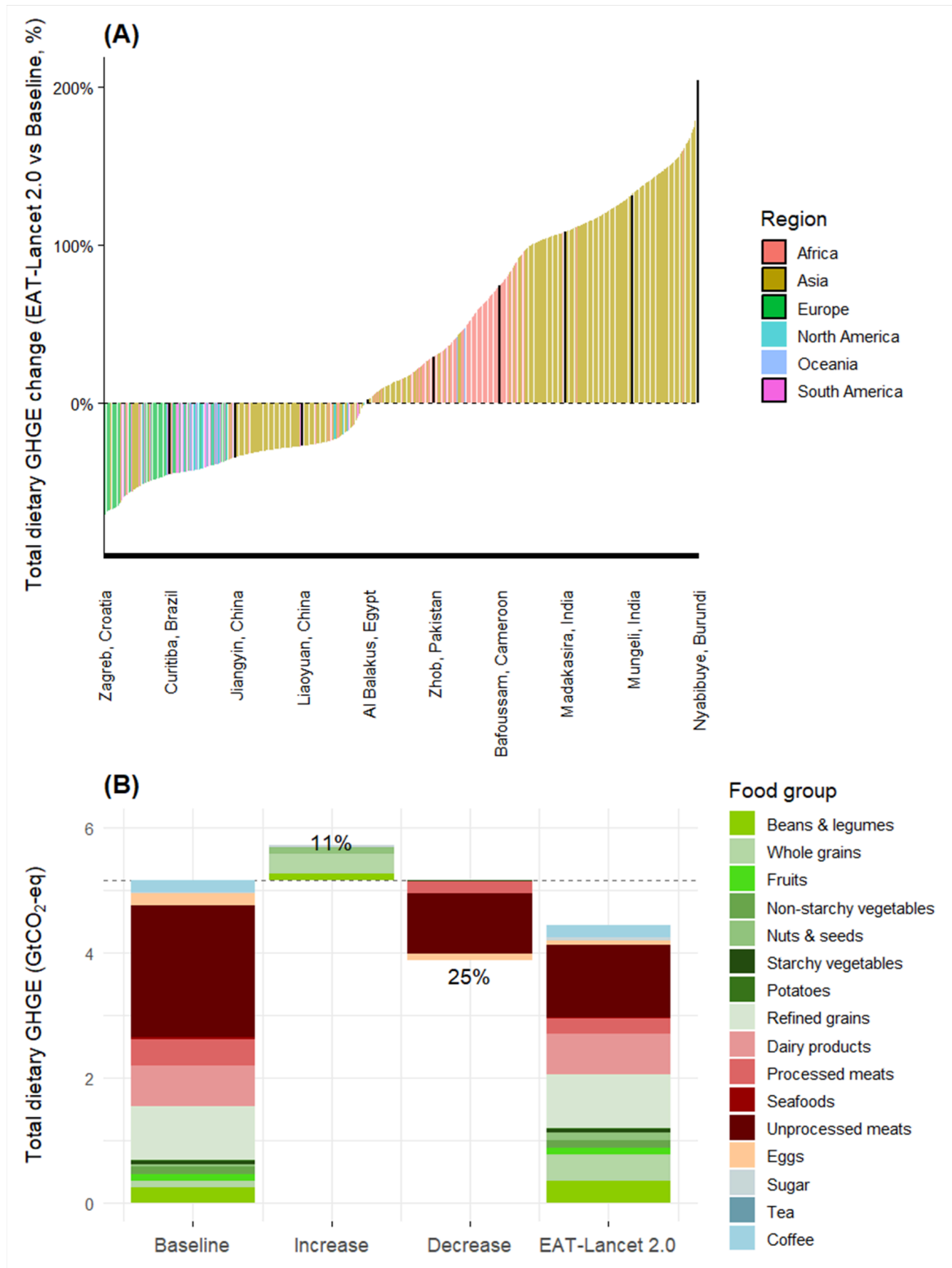


Figure 3

City-level changes in total dietary GHGE under the EAT-Lancet 2.0 diet

(A) Representative cities were ranked by percentage change in total dietary GHGE (Gt CO₂-eq), and the 10 labelled cities were selected at evenly spaced intervals across the lower and upper ends of the distribution. Total dietary GHGE were computed by aggregating food-group-specific emissions across all food groups, with EAT-Lancet 2.0 substitutions applied to plant-based foods, animal-source foods, and sugar, while food groups not specified in the EAT-Lancet recommendations were held constant. (B) The left bar represents baseline total GHGE, while the right bar shows total GHGE under EAT-Lancet 2.0. Middle bars illustrate the aggregated GHGE increases and decreases attributable to shifts in individual food groups, relative to the baseline. Positive and negative contributions are shown separately, stacked by food group.

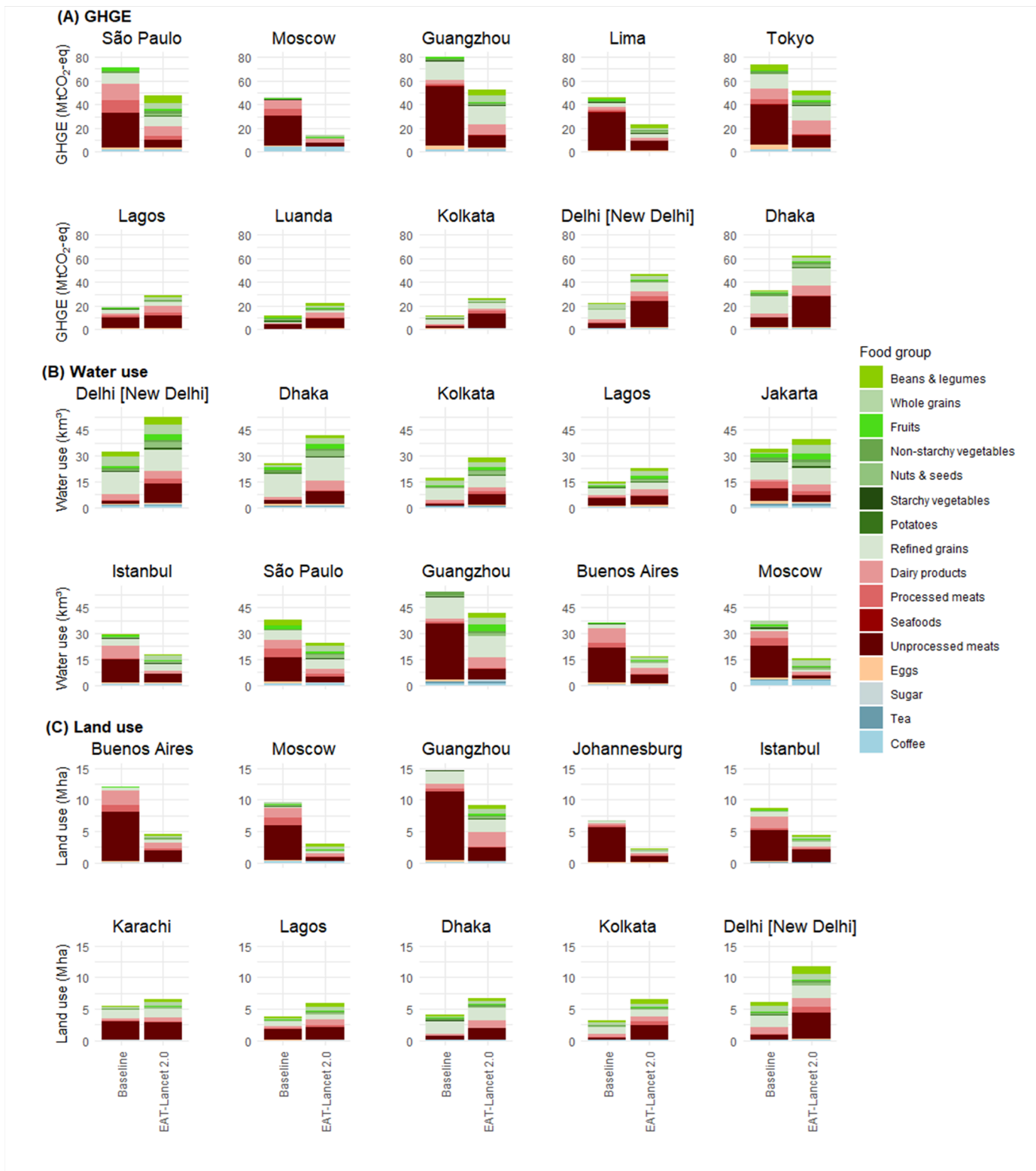


Figure 4

Comparison of dietary (A) GHGE, (B) Water use, and (C) Land use between the Baseline and EAT-Lancet 2.0 diet across representative cities.

Panel (A) presents stacked bar charts of absolute changes in total diet-related greenhouse gas emissions (GHGE; Mt CO₂-eq/year) for selected cities, comparing current dietary patterns (Baseline) with

the EAT–Lancet 2.0 diet. Panel (B) shows corresponding plots for diet-related water use (km^3/year), and Panel (C) for land use (Mha/year). For each indicator, the upper row displays the five cities with the largest absolute reductions in environmental footprints following adoption of the EAT–Lancet 2.0 diet, while the lower row displays the five cities with the smallest absolute reductions (i.e., lowest absolute changes). Within each bar, total city-level changes are decomposed into contributions from 16 food groups.

Supplementary Files

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- [SupplementaryMaterial.docx](#)