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Supplementary appendix 1

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The impact of urban configuration types on urban heat islands, air pollution, CO² emissions and mortality in Europe: a data science approach

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Supplementary material

A) European cities dataset.

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A) **European cities dataset.**

Our analysis focused on European cities listed in the Urban Audit dataset 2018 (1), which follows the city definition by the Organization for Economic Cooperation and Development - European Commission (OECD-EC), based on population density and local administrative boundaries (2). The original dataset encompasses 980 cities across 31 European countries (EU27, United Kingdom (UK), Norway, Switzerland and Iceland). We excluded Saint Denis (Réunion) and Fort-de-France (Martinique) due to their location outside of the European study area. Since the City of London is primarily an economic hub rather than a residential area (with only 8,600 inhabitants in 2021), we opted to include Greater London instead and excluded the 32 London boroughs encompassed within the Greater London area to avoid double-counting (3). Overall, we considered 946 European cities for the analysis. We collected all data at 250m x 250m grid cell resolution based on the Global Human Settlement Layer (GHSL) population dataset for 2015 (4), following the same data collection procedure as in our previous studies (5–8). Given that the GHSL had population misallocations into non-residential areas and we were interested in describing populated areas in terms of urban configuration and exposures, we adjusted the GHSL layer to include only grid cells overlapping with residential areas from the Urban Atlas and redistributed the misallocated population into the remaining grid cells proportionally based on the GHSL population density $(6,7)$. In total, our dataset included $n = 825,148$ grid cells.

B) **Division of cities into rings.**

Figure S1. *An example of the division of the cities into rings is shown for Barcelona, Spain (left panel) and Brussel, Belgium (right panel).*

C) **Local Climate Zones (LCZs) classification.**

We retrieved the LCZ classification developed by Demuzere and colleagues (9,10) at 100m resolution for Europe. We overlaid the LCZ layer with our 250m grid cell layer and estimated the proportion of area corresponding to each LCZ for each of the grid cells. We excluded grid cells that had more than 80% of their area not covered by the LCZ layer ($n = 1,208$).

Figure S2. *Description of Local Climate Zones (LCZs) categories from Stewart & Oke, 2012.*

Figure S3. *Descriptive boxplots of LCZs data for all cities by ring. The proportion of each LCZ in each ring is shown. * Outliers are kept in the plots in order to show the complete distribution of the data that was employed in the UMAP analysis.*

Table S1. *Descriptive of LCZs data for all cities by ring.*

D) **Open Street Map (OSM) road classification.**

To evaluate the street design, we retrieved the density of distinct road typologies from the OSM database (11). We included road types as follows: motorized roads (formed by "motorway" and "trunk"), primary roads, secondary roads, tertiary roads, residential roads (formed by "unclassified", "residential" and "living streets"), pedestrian zones and cycleways (**Table S2**). For each grid cell, we calculated the length in meters of each road type. Given inconsistencies in OSM data and overrepresentation of specific road types in some of the cities, we excluded from the analysis grids with values above the 99.5th percentile of each category to avoid outliers in the dataset.

Table S2. *Description of OSM road categories.*

OSM road typologies by ring

Figure S4. *Descriptive boxplots of OSM road typologies for all cities by ring. The mean length per grid cell in meters for each ring is shown. * Outliers are kept in the plots in order to show the complete distribution of the data that was employed in the UMAP analysis.*

Table S3. *Descriptive of OSM road typologies for all cities by ring.*

E) **Motorized traffic flows.**

Figure S5. *Descriptive boxplot of traffic volume for all cities by ring.*

Table S4. *Descriptive of traffic volume for all cities by ring.*

F) **Surface Urban Heat Island (SUHI).**

We estimated the SUHI as the difference between the mean summer rural Land Surface Temperature (LST) and the median summer LST recorded in each urban grid cell. Data was retrieved from Landsat-8 images for 2015 (12) at 30 × 30m resolution, with data acquisition time varying between 9 and 11 am for Europe. We implemented a cleanup process for clouds and other potential quality issues. Specifically, we employed the 'QA_PIXEL' band: Pixel quality attributes generated from the CFMASK algorithm. This allows us to filter out pixels affected by clouds, snow, or shadows (cirrus, snow, and shadows) in all images, irrespective of whether they are in urban or rural areas. To define the surrounding rural area, we took a buffer zone of 6 kilometers surrounding each city, to ensure sufficient coverage, and defined the rural area based on Corine Land Cover agricultural, forest and natural areas categories (13). Specifically, the categories included were: non-irrigated arable land, permanently irrigated land, rice fields, vineyards, fruit trees and berry plantations, olive groves, pastures, annual crops associated with permanent crops, complex cultivation patterns, land principally occupied by agriculture with significant areas of natural vegetation, agroforestry areas, broad-leaved forest, coniferous forest, mixed forest, natural grasslands, moors and heartland, sclerophyllous vegetation and transitional woodland-shrub. We filtered out blue spaces to avoid underestimating the average rural LST (14) and excluded the CLC green urban areas category to prevent the inclusion of urban parks from neighboring cities in the measurement of surrounding greenness.

Figure S6. *Descriptive boxplot of SUHI for all cities by ring.*

Table S5. *Descriptive of SUHI for all cities by ring.*

G) **Tropospheric Nitrogen Dioxide (NO2).**

Tropospheric $NO₂$ is a short-lived tracer to map the footprint of predominantly anthropogenic emissions from combustion processes. Natural contributions are confined to lightning (15) and microbial processes in soils (16). Therefore, it has proven to be a suitable tracer to delineate urban pollution islands and pollution hot spots (17–20). In this study, data from TROPOMI, the sensor aboard the Sentinel-5 Precursor satellite as part of the Copernicus Space Infrastructure, was used to obtain observations of tropospheric NO₂ (21). Specifically, the Level 2 tropospheric NO₂ data product (Version 1.2) using the algorithm developed by van Geffen et al., (2020) and provided by the European Space Agency (ESA) was exploited (22). The nominal spatial resolution of the observations (pixels) was 3.5 x 7.5 km² and was improved to 3.5 x 5.5 km² on August 6, 2019. The tropospheric NO₂ vertical column densities were retrieved with a conservative quality flag greater than 75. In a next step, all Level 2 products over Europe from 1st January 2019 to 31st December 2019 were oversampled onto a regular grid of 0.0025° x 0.0025° spatial resolution, which corresponds to ~100 to 200m depending on the latitude, following Müller et al., (2022) (18). By means of the temporal aggregation and the rigorous tiling approach of the pixels, the spatial resolution could be increased for persistent emission sources and anthropogenic NO₂ footprints. The resulting yearly mean can be considered a robust estimate to delineate the NO₂ footprints of the European cities. The year 2019 was chosen as the most recent year not influenced by any COVID-19 measures or effects. The data has proven to be feasible to analyze the shape of urban pollution islands of megacities (19), smaller cities with complex terrain (20) and emission hot spots for the contiguous United States (23) and Germany (18). Due to the physical limitations of the measurements, intra-urban hot spots cannot fully be resolved. Thus, we consider the data to represent urban background conditions. However, the observational data is not influenced by any chemical-transport modeling, assumptions on emissions, machine learning or geostatistical modelling.

Figure S7. *Descriptive boxplot of tropospheric NO² for all cities by ring.*

Table S6. *Descriptive of tropospheric NO² for all cities by ring.*

H) **CO² emissions.**

We retrieved CO_2 emissions data from the Open-source Data Inventory for Anthropogenic CO_2 (ODIAC) (24), which provides CO_2 emissions from fossil-fuel combustion at 1 x 1 km resolution for 2019. In this dataset, national emissions are spatialized based on satellite night-time light data and power plant location and profiles (24). To estimate the per capita emissions, we overlaid the $CO₂$ emissions layer with the 250m grid cell layer and distributed the $CO₂$ emissions proportionally based on the intersecting area of the 250m grid cells with the 1 km grid cells. For each 250m grid cell we calculated the CO₂ emissions as follows: Grid cell emissions (250m) = Intersection area * Total CO₂ emissions (1 km) / Total area CO₂ grid (1 km). Afterwards, to consider that each 250m grid cell might intersect with more than one 1 km CO₂ grid, we did an aggregate sum by the 250m grid cells to obtain the total CO₂ emissions at 250m resolution. We divided the emissions between the population in each 250m grid cell to obtain the $CO₂$ per capita emissions in metric tons.

Figure S8. *Descriptive boxplot of CO² per capita emissions for all cities by ring.*

Table S7. *Descriptive of CO² per capita emissions for all cities by ring.*

I) **Main analysis.**

To identify and characterize distinct urban configuration types, we applied the Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP), followed by the k-means clustering algorithm. UMAP is a novel non-linear dimension reduction algorithm able to learn the manifold structure of large input datasets and produce a low-dimensional embedding that preserves the basic topological structure of the manifold (25). UMAP was chosen for this analysis because it outperforms previous dimension reduction algorithms, such as t-SNE, in terms of speed and better preservation of the data's global structure, which potentially results in more meaningful inter-cluster relations (25).

i) Variables correlation.

We used LCZs and OSM variables from each of the five rings for each city as input data for the UMAP algorithm. For establishing the relative strength of the correlations in our dataset and in order to prevent a distorted embedding, we evaluated the distribution of correlations (**Figure S9**). We defined as outliers correlation values greater than r = 0.55 (**Figure S10**) and established it as exclusion criteria for conducting UMAP. Accordingly, we excluded the pedestrian and residential roads categories from OSM as both variables presented correlations equal to or above r = 0.55 with the Compact Midrise and Low Plants variables, respectively. In addition, we excluded LCZs categories with null values at percentile 75% (i.e. open highrise, compact lowrise, heavy industry, bush scrubs, rock paved and soil sand) to avoid distortions of the embedding (25,26) (**Figure S3, Table S1**).

Correlation plot of urban configuration variables

Figure S9. *Correlation plot of urban configuration variables considered for the analysis.*

Figure S10. Distribution of correlations in our dataset.

ii) UMAP and k-means parameter optimization.

The choice of UMAP parameters (i.e. *n_neighbors and min_dist*) is crucial and allows to balance between the local and global structure of the data in the final projection (27). A lower value of *n_neighbors* pushes the UMAP algorithm to focus more on the local structure, while *min_dist* controls how tightly points are clustered together, with lower values resulting in higher clustering (27). For this study, we opted for *n_neighbors* = 15 and *min_dist* = 0 as UMAP parameters. These choices emphasize local data relationships while maintaining a connection with the broader structure. The choice of the *n_neighbors* parameter was further validated using the trustworthiness score for values between 0 and 30 (28) (**Figure S11**). To select the optimal number of clusters for the k-means algorithm, we applied the Elbow method and set the number at $k = 4$ (**Figure S11**).

Figure S11. *Trustworthiness score plot to validate the choice of the n_neighbors parameter for the UMAP algorithm (left panel) and Elbow method plot to identify the optimal* number of clusters for the k-means clustering algorithm (right panel). * A trustworthiness score above 0.8 represents a good preservation of the local data structure in the low*dimensional space.*

iii) Results.

Figure S12. Geographic location of each urban configuration type. The geographic location of all urban configuration types was generally widespread, with Compact-High Density cities prevailing in Southern and Eastern Europe, Open Lowrise-Medium Density and Open Lowrise-Low Density in Western Europe and the UK and Green-Low Density cities in Northern Europe and the Netherlands.

Table S8. Dunn's test results for motorized traffic flows and the SUHI intensity.

Table S9. Dunn's test results for the NO₂ exposure and CO₂ per capita emissions.

J) **Validation of the NO² exposure and CO² emissions variables.**

i) CO₂ per capita emission from CAMS.

To verify the CO₂ metric, we additionally explored the CO₂ emissions reported in the state-of-the-art Copernicus Atmosphere Monitoring Service (CAMS) regional inventory (version 7) for the residential and transport sectors (29). These sectors were chosen to better align with the ODIAC dataset. Since the CO₂ per capita emissions were extracted for residential grid cells, excluding industrial and port areas and their associated emissions, it was considered that focusing on residential and transport emissions would more accurately reflect the emission sources captured by ODIAC in our dataset. CAMS emissions were available at 0.1 x 0.05º resolution for the years 2000-2021 (30). We overlaid these emissions with our city boundaries and extracted the total emissions for each city. Per capita emissions were then calculated by dividing the total emissions by the total city population.

Figure S13. *CO² per capita emissions from the CAMS database for the residential sector (left panel) and the transport sector (right panel) by urban configuration type.*

Table S10. *CO² per capita emissions from CAMS by urban configuration types.*

Table S11. *Dunn´s test results for CO² per capita emission from CAMS database (residential sector).*

Table S12. *Dunn´s test result for CO² per capita emissions from CAMS database (transport sector).*

ii) NO₂ exposure.

To validate the NO₂ proxy, we employed NO₂ measurements from official monitoring stations, available through the European Air Quality e-Reporting system (31). We extracted annual mean values for 2019 from background stations located in urban and suburban areas, considering only stations with ≥ 75% data coverage. We overlaid the station coordinates with our city boundaries to identify the stations within each city and then calculated the mean NO₂ levels from all stations for each city. Data was available for 516 cities.

Figure S14. *Mean NO² concentration by urban configuration type.*

Table S13*. NO² concentration by urban configuration type.*

Table S14. *Dunn´s test results for NO² concentration.*

K) **Sensitivity analyses.**

i) Exclusion of Mediterranean cities.

Table S15. *List of Mediterranean cities.*

Figure S15. *Mean SUHI by ring for Mediterranean and non-Mediterranean cities.*

Table S16. *Kruskal-Wallis test results for SUHI differences in Mediterranean vs. non-Mediterranean cities.*

** A non-parametric test was performed because the data did not comply with the homogeneity of variance assumption.*

Table S17. *Percentage of cities corresponding to each of the biomes for each urban configuration type.*

Figure S16. *SUHI intensity by urban configuration type excluding the Mediterranean cities. The mean and 95% CIs are shown.*

Table S18. *SUHI intensity by urban configuration type excluding the Mediterranean cities.*

Table S19. *Dunn's test results for the SUHI intensity excluding the Mediterranean cities.*

ii) Alternative SUHI estimation.

We explored an alternative approach to calculate the SUHI intensity, namely the Simplified Urban Extent (SUE) algorithm developed by Chakraborty and Lee (32). In this approach, the SUHI is defined as the LST difference between urban and non-urban land uses within the same urban extent, rather than the LST difference with the adjacent rural area. Additionally, the dataset estimates are adjusted for elevation, by masking out rural pixels that have an elevation difference greater than 50m with the urban pixels. This definition allows us to isolate the influence of extrinsic factors that may affect rural area's LST, such as peri urban areas, elevation, proximity to water bodies, and climatological factors; however, this has limitations in providing an accurate measure of the excess heat resulting from anthropogenic modification of natural landscapes as it takes as reference green urban areas, which are predominantly non-natural (i.e. artificial) landscapes. Note that there are other differences between these and the main estimates, including the different resolutions (Landsat at 30m native resolution versus the 1000m native resolution of the MODIS (Moderate Resolution Imaging Spectroradiometer) LST estimates used for the SUE algorithm), different return periods (every 16 days for Landsat versus daily for MODIS), and differences in view angles (much wider range of view angles for MODIS compared to Landsat), all of which would impact the degree of spatial variability within cities.

Figure S16. *Mean SUHI by ring considering an alternative approach for SUHI estimation.*

Figure S17. *SUHI intensity by urban configuration type using an alternative approach for SUHI estimation. The mean and 95% CIs are shown.*

Table S20. *SUHI intensity by urban configuration type using an alternative approach for SUHI estimation.*

Table S21. *Dunn's test results for the SUHI intensity using an alternative approach for SUHI estimation.*

L) **Mortality rates.**

i) Natural-cause mortality.

Natural-cause mortality rates were retrieved at the city level from our previous studies on the health impacts of environmental exposures in European cities, estimated based on data from the Eurostat city database for 2015 (6,7) . Briefly, we retrieved the population and all-cause mortality distribution in 5-year age groups (for adults aged 20 and older) and excluded the proportion of external deaths in each age group (identified by ICD10 codes V01-Y89) from all-cause mortality counts to obtain age-specific naturalcause mortality rates. Afterwards, the age-specific mortality rates were employed to estimate the age-standardized mortality based on the European standard population (33).

Table S22. Dunn's test results for the age-standardized natural-cause mortality rates.

ii) Attributable mortality.

Figure S18. PM2.5, NO² and lack of green space age-standardized attributable mortality rates by urban configuration type.

Table S23. PM_{2.5}, NO₂ and lack of green space age-standardized attributable mortality rates by urban configuration type.

** NDVI: Normalized Difference Vegetation Index*

*** Data from Khomenko et al., 2021, Barboza et al., 2021.*

Table S24. Dunn's test results for the PM_{2.5}, NO₂ and lack of green space age-standardized attributable mortality rates.

REFERENCES

- 1. Eurostat. Urban Audit [Internet]. 2018. Available from: https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statisticalunits/urban-audit
- 2. Dijkstra L, Poelman H. Cities in Europe. The new OECD-EC definition. [Internet]. 2012. Available from: https://ec.europa.eu/regional_policy/en/information/publications/regional-focus/2012/cities-in-europe-the-new-oecd-ec-definition
- 3. Office for National Statistics. How the population changed in the City of London: Census 2021 [Internet]. 2022. Available from: https://www.ons.gov.uk/visualisations/censuspopulationchange/E09000001/
- 4. European Commission. Global Human Settlement [Internet]. 2019. Available from: https://ghsl.jrc.ec.europa.eu/data.php
- 5. Iungman T, Cirach M, Marando F, Barboza EP, Khomenko S, Masselot P, et al. Cooling cities through urban green infrastructure: a health impact assessment of European cities. Lancet. 2023;401(10376):577–89.
- 6. Pereira-Barboza E, Cirach M, Khomenko S, Iungman T, Mueller N, Barrera-Gómez J, et al. Green space and mortality in European cities: a health impact assessment study. Lancet Planet Heal. 2021;5(10):e718–30.
- 7. Khomenko S, Cirach M, Pereira-Barboza E, Mueller N, Barrera-Gómez J, Rojas-Rueda D, et al. Premature mortality due to air pollution in European cities: a health impact assessment. Lancet Planet Heal. 2021;5(3):e121–34.
- 8. Khomenko S, Cirach M, Barrera-Gómez J, Pereira-Barboza E, Iungman T, Mueller N, et al. Impact of road traffic noise on annoyance and preventable mortality in European cities: A health impact assessment. Environ Int. 2022;162:107160.
- 9. Demuzere M, Bechtel B, Middel A, Mills G. Mapping Europe into local climate zones. PLoS One. 2019;14(4):e0214474.
- 10. Demuzere M, Bechtel B, Middel A, Mills G. European LCZ map [Internet]. 2020. Available from: 10.6084/m9.figshare.13322450
- 11. OpenStreetMap contributors. Planet OSM [Internet]. 2015. Available from: https://www.openstreetmap.org/
- 12. U.S. Geological Survey. Landsat-8, Collection 2, Level-2 [Internet]. 2023. Available from: https://www.usgs.gov/landsat-missions/landsat-data-access
- 13. Copernicus Land Monitoring Service. Corine Land Cover (CLC) 2018 (Version 2020_20u1) [Internet]. 2018. Available from: https://land.copernicus.eu/pan-european/corine-land-cover
- 14. Copernicus. Climate variables for cities in Europe from 2008 to 2017 [Internet]. 2019. Available from: https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-urban-climate-cities?tab=overview
- 15. Pérez-Invernón FJ, Huntrieser H, Erbertseder T, Loyola D, Valks P, Liu S, et al. Quantification of lightning-produced NOx over the Pyrenees and the Ebro Valley by using different TROPOMI-NO2 and cloud research products. Atmos Meas Tech. 2022;15(11):3329–51.
- 16. Lu X, Ye X, Zhou M, Zhao Y, Weng H, Kong H, et al. The underappreciated role of agricultural soil nitrogen oxide emissions in ozone pollution regulation in North China. Nat Commun. 2021;12:5021.
- 17. Voigt C, Lelieveld J, Schlager H, Schneider J, Curtius J, Meerkötter R, et al. Cleaner Skies during the COVID-19 Lockdown. Bull Am Meteorol Soc. 2022;103(8):E1796–E1827.
- 18. Müller I, Erbertseder T, Taubenböck H. Tropospheric NO2: Explorative analyses of spatial variability and impact factors. Remote Sens Environ. 2022;270(2):112839.
- 19. Erbertseder T, Hannes Taubenböck TE, Gilardi L, Paeth H, Marconcini M, Dech S. Earth Observation-based analysis of NO2 pollution and settlement growth in megacities. In: 2023 Joint Urban Remote Sensing Event (JURSE) [Internet]. 2023. Available from: 10.1109/JURSE57346.2023.10144190
- 20. Samad A, Kiseleva O, Holst CC, Wegener R, Kossmann M, Meusel G, et al. Meteorological and air quality measurements in a city region with complex terrain: influence of meteorological phenomena on urban climate. Meteorol Zeitschrift. 2023;
- 21. Veefkind JP, Aben I, McMullan K, Förster H, Vries J de, Otter G, et al. TROPOMI on the ESA Sentinel-5 Precursor: A GMES mission for global observations of the atmospheric composition for climate, air quality and ozone layer applications. Remote Sens Environ. 2012;120:70–83.
- 22. Geffen J van, Boersma KF, Eskes H, Sneep M, Linden M ter, Zara M, et al. S5P TROPOMI NO2 slant column retrieval: method, stability, uncertainties and comparisons with OMI. Atmos Meas Tech. 2020;13(3):1315–35.
- 23. Goldberg DL, Anenberg SC, Kerr GH, Mohegh A, Lu Z, Streets DG. TROPOMI NO2 in the United States: A Detailed Look at the Annual Averages, Weekly Cycles, Effects of Temperature, and Correlation With Surface NO2Concentrations. Earth's Futur. 2021;9(4):e2020EF001665.
- 24. Oda T, Maksyutov S, Andres RJ. The Open-source Data Inventory for Anthropogenic CO2, version 2016 (ODIAC2016): a global monthly fossil fuel CO2 gridded emissions data product for tracer transport simulations and surface flux inversions. Earth Syst Sci Data. 2018;10:87–107.
- 25. McInnes L, Healy J, Melville J. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction [Internet]. 2018. Available from: https://umap-learn.readthedocs.io/en/latest/index.html
- 26. McInnes L, Healy J, Melville J. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. 2020; Available from: http://arxiv.org/abs/1802.03426
- 27. Coenen A, Adam P. Understanding UMAP [Internet]. 2023. Available from: https://pair-code.github.io/understanding-umap/
- 28. Amazon Web Services Labs. On the Validation of UMAP [Internet]. 2022. Available from: https://github.com/awslabs/amazondenseclus/blob/main/notebooks/Validation For UMAP.ipynb
- 29. Kuenen J, Dellaert S, Visschedijk A, Jalkanen JP, Super I, Denier Van Der Gon H. CAMS-REG-v4: a state-of-the-art high-resolution European emission inventory for air quality modelling. Earth Syst Sci Data. 2022;14(2):491–515.
- 30. ECCAD. Emissions of atmospheric Compounds and Compilation of Ancillary Data [Internet]. 2022. Available from: https://eccad.aeris-data.fr/
- 31. European Environment Agency. Air Quality e-Reporting (AQ e-Reporting) [Internet]. 2022. Available from: https://www.eea.europa.eu/en/datahub/datahubitem-view/3b390c9c-f321-490a-b25a-ae93b2ed80c1
- 32. Chakraborty T, Lee X. A simplified urban-extent algorithm to characterize surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. Int J Appl Earth Obs Geoinf. 2019;74:269–80.
- 33. Eurostat. Revision of the European Standard Population. Report of Eurostat's task force. [Internet]. 2013. Available from: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-13-028