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Full length article



A Europe-wide characterization of the external exposome: A spatio-temporal analysis

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ABSTRACT

Background: Harmonised data on external environmental exposures are essential for multi-cohort exposome studies. This paper describes the development of fine-spatial resolution models and resulting exposure maps for 33 major exposome factors—including physical–chemical, built, social, and food environments—across Europe from 2000 to 2020, and examines their spatial and temporal interrelations.

Methods: New fine spatial resolution Europe-wide models were developed for annual/monthly average air pollution, daily temperature, and annual-average road-traffic noise, combined with post-processing of existing data on green, blue, and grey spaces (imperviousness), walkability, light-at-night, and urbanicity. Exposure metrics relevant for epidemiological studies were developed for all exposome factors, with correlations calculated at European and country levels. Stability and trends over time were assessed for 18 factors.

Results: At the European level, most environmental factors showed weak correlations ($R < 0.4$), except NO_2 , which showed moderate to strong correlations with built environment factors. Country-level correlations varied. Annual average exposure surfaces were stable over time, with strong correlations between early and late time

Abbreviations: NO_2 , Nitrogen dioxide; $\text{PM}_{2.5}$, Fine particles with an aerodynamic diameter of less than 2.5 μm ; PM_{10} , Fine particles with an aerodynamic diameter of less than 10 μm ; O_3 , Ozone; L_{day} , A-weighted long-term average sound level determined over all the 12hr day periods of a year; L_{evening} , A-weighted long-term average sound level determined over all the 4hr evening periods of a year; L_{night} , A-weighted long-term average sound level determined over all the 8 hr night periods of a year; L_{den} , Long-term average day, evening, night sound levels with a respective 5dB and 10dB penalty for the evening and night period, determined over all 24hr days in a year; ERA5, fifth generation European Centre for Medium-Range Weather Forecast (ECMWF) atmospheric reanalysis of the global climate; LAN, Light-At-Night; CMPD, Cardio-Metabolic and Pulmonary Diseases; END, Environmental Noise Directive; CNOSSOS-EU, Common NOISE aSSessment MethODs; RF, Random Forest; OSM, OpenStreetMap; LST, Land Surface Temperature; NDVI, Normalised Difference Vegetation Index; MSAVI, Modified Soil-Adjusted Vegetation Index; DMSP, Defense Meteorological Satellite Program; DEM, Digital Elevation Model; GHS, Global Human Settlement; GHSL, Global Human Settlement Layer; EUSILC, European Union Statistics on Income and Living Conditions; SES, Socio Economic Status; RMSE, Root Mean Square Error; LAEA, Lambert Azimuthal Equal Area.

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points for all factors except O₃ (R = 0.66). Trends indicated decreases in air pollution and increases in temperature, green space, and imperviousness, while trends in light-at-night and O₃ were mixed across Europe.

Conclusions: This comprehensive analysis of the temporal and spatial relationships between external exposome factors across a large geographical area show low to moderate correlations between exposome factors. Annual average exposure surfaces were also stable over time across Europe. These findings support both the utility of multi-exposure epidemiological analyses, and that any modest temporal misalignment between exposure assessment and follow-up period of health studies is not critical.

The data described in his paper are openly available to researchers.

1. Introduction

The environment and human health nexus have been extensively studied, with substantial evidence demonstrating, for instance, adverse effects of air pollution for various health outcomes (Brunekreef and Holgate, 2002; WHO, 2016a). Similarly, adverse health effects have been attributed to noise (Welch et al., 2023; Sørensen et al., 2024), high and low ambient temperature (Bunker et al., 2016), lack of residential green or limited access to green space (WHO, 2016b; Barboza et al., 2021), and light-at-night (LAN) (Bozejko et al., 2023). However, these environmental stressors do not occur independently, but rather are concurrent exposures individuals encounter throughout the day, year and their life course. Consequently, complex correlations between different environmental exposures are often observed (Ohanyan et al., 2022; Beulens et al., 2022; Liu et al., 2023).

Exposome, defined as the totality of environment to which an individual is exposed from conception onwards (Wild, 2005), allows the estimation of the joint health effect of environmental factors (ecosystems, lifestyle, social and physical-chemical) that is of interest. The external exposome can be defined as the exposures assessed before entering the body (Turner et al., 2017). To date, an increasing number of exposome studies have been undertaken linking a broad range of external exposome factors with health (Ohanyan et al., 2022; Maitre et al., 2018; Agier et al., 2019; de Bont et al., 2023; Nobile et al., 2024).

To analyze joint effects of the external exposome, epidemiological studies in multiple countries are especially useful. The Exposomics and Helix projects, for example, have pioneered exposome research in Europe (Vineis et al., 2017; Vrijheid et al., 2014). These studies encountered several challenges in elucidating health effects when considering the external exposome. One major challenge is the availability of exposure data and maps with sufficient spatial and temporal coverage across Europe, as illustrated by a recent study reporting on city-level external exposome data for 2017–2020 for 10 European cities (Tagliaferro et al., 2024). While local or national environmental models exist, integrating these into pan-European multi-cohort studies is complex because the epidemiological findings can depend on the underlying exposure model, exposure distributions and their interrelationships. A second challenge is the correlation between different exposure factors. Ignoring these correlations, or relying on single-exposure studies, can lead to imprecise conclusions about health effects. Multicollinearity, if ignored, can lead to unstable effect estimates, and make it difficult to separate the effects of individual exposures in multi-exposure models (Agier et al., 2016; Weisskopf et al., 2018). A third challenge is temporal trends in external exposures, potentially leading to temporal misalignment if exposure maps do not match the follow-up period of epidemiological studies, e.g. because often only recent exposure models are available (Strak et al., 2021). For air pollutants, several studies have documented stability of spatial exposure contrasts across time (i.e. years), but mostly for specific countries and pollutants (Eeftens et al., 2011; Gulliver et al., 2016; de Hoogh et al., 2018). There is some evidence in the Netherlands to suggest that walkability is relatively stable over time (Timmermans et al., 2021) while the food environment is subject to change (Pinho et al., 2020). Less is known about stability of other environmental stressors and their interrelations.

The EXPANSE project (EXposome Powered tools for healthy living in

urbAN Settings), as a whole, investigates the relationship between the urban components of the exposome and cardio-metabolic and pulmonary diseases (CMPD) (Vlaanderen et al., 2021). The project includes health data from a variety of administrative, children and adult cohorts encompassing over 25 million individuals across Europe. As a foundational part of the project, we developed a comprehensive geographical database of external exposome factors for Europe, spanning 2000–2020, to capture spatial and temporal variations. We developed new models for several exposures, including air pollution, temperature and noise (Bussalleu et al., 2024; Shen et al., 2022; Shen et al., 2024; Shen et al., 2024). A critical requirement was that datasets needed to be harmonised, to facilitate pan-European comparisons and health analyses and to meet the epidemiological needs in terms of temporal (as far back as the year 2000) and spatial resolution.

In this exposure paper we: 1) describe the external exposome factors created in the EXPANSE project, including newly developed models for exposures where existing models or measurements were inadequate, 2) investigate the correlations between the external exposome factors and 3) assess spatial and temporal stability of these factors. Analyses were conducted at two geographic scales: Europe-wide and country level. In this paper we therefore detail different external exposome factors that can be used in epidemiological studies.

2. Material and methods

We selected the known and suspected risk factors for CMPD in the external exposome, including air pollution, noise, temperature, lack of green space (or greenness), lack of blue space, grey space (or imperviousness), light-at-night, walkability, degree of urban and the social and food environment (Vlaanderen et al., 2021; Rajagopalan et al., 2024). Our objective was to develop exposure models and maps of these factors at a fine spatial resolution, at different time points, as far back as the year 2000. A key requirement was to develop harmonised maps across Europe, given that EXPANSE cohorts are spread across different parts of Europe. Because existing models and monitoring data were insufficient for our purposes, we developed new models for air pollution, temperature, road traffic noise (referred to as noise) and walkability. For green, blue and grey space, light-at-night and imperviousness, for which data or models of sufficient quality were available, we leveraged the existing remote-sensing data and land use maps to develop Europe-wide exposure surfaces.

2.1. Study area

The exposure maps we generated, described below, were calculated for the whole of Europe (EU27 (excluding Malta, Republic of Cyprus) plus the United Kingdom, Norway, Switzerland, Serbia, Albania and North Macedonia), unless otherwise indicated. We used the ETRS89-LAEA projection (ESPG:3035) in all our GIS analyses. Fig. 1 shows the spatial and temporal resolutions of the different environmental exposures. For air pollution, temperature, green space, imperviousness (or grey space) and light-at-night, exposure maps for multiple years were developed.

2.2. External exposome factors

Table S1 shows the full list of external exposome factors (n = 33) developed and/or obtained in this study. Here we briefly summarize the data.

2.2.1. Physico-chemical environment

Air pollution. Air pollution models do exist for Europe but not at the required extent (section 2.1) nor spatial and temporal resolution. Therefore, new models were developed, building on previous work in the ELAPSE (Effects of Low-Level Air Pollution: A Study in Europe) project that created hybrid land use regression (LUR) models for Western Europe only for 2010. The ELAPSE models combined routine monitoring, satellite observations, chemical-transport modelling and fine spatial resolution traffic and land use predictors (de Hoogh et al., 2018). In EXPANSE we developed models predicting monthly and annual average concentrations (2000–2019) for ambient nitrogen dioxide (NO₂), fine particles with an aerodynamic diameter of less than 2.5 μm (PM_{2.5}), fine particles with an aerodynamic diameter of less than 10 μm (PM₁₀) and ozone (O₃) at a fine spatial scale (25x25m) (Shen et al., 2022; Shen et al., 2024). Compared to ELAPSE, we modelled individual years over a 20-year period; improved the spatial resolution (100 x 100 m to 25 x 25 m); increased spatial coverage (more countries); and allowed for variations in the relationships between predictors and concentrations across Europe and across time.

The development of the annual models is described in detail elsewhere (Shen et al., 2022). In brief, air pollution concentrations measured at routine monitoring sites from the AIRBASE database were used to calibrate and validate the models, and a range of spatial and spatio-temporal predictor variables were used to help explain the variation in these measurements. Geographical weighted regression (GWR) outperformed supervised linear regression and random forest explaining on average 0.66, 0.77, 0.62 and 0.58 of the spatial variation (R²) respectively for NO₂, PM₁₀, PM_{2.5} and O₃ (five-fold hold-out-validation). Monthly models were developed to allow evaluation of medium-term exposure metrics such as seasonal averages. The development of monthly models followed a similar methodology as the annual models (Shen et al., 2024), with five-fold cross validation yielding moderate to good performances (R²: 0.31–0.66 for NO₂, 0.40–0.79 for O₃, 0.40–0.78

for PM₁₀, 0.46–0.87 for PM_{2.5}). For the analysis presented here, we focus on the annual air pollution models as these are the main exposure metrics applied in epidemiological analyses of long-term exposure.

Noise. Road traffic noise data across Europe is available through the strategic noise maps required by the Environmental Noise Directive (END). These data, however, have large spatial gaps, being mandatory only for urban agglomerations with population > 100,000 and around major roads (more than 3 million vehicles per year), and historically is not fully harmonised across Europe (Khomenko et al., 2022). Also, the END requires reporting only above 55 dB Lden (50 dB Lnight), and in 5 dB intervals thus lacking estimation at lower levels. To harmonise noise modelling across our study area, the CNOSSOS-EU (Common Noise aSSessment MethODs) framework was employed for modelling noise indicators including Laeq16, Lday, Levening, Lnight, and Lden (in dB) (Kephalopoulos et al., 2014).

The implementation of CNOSSOS-EU by Morley et al. (Morley et al., 2015), applied in EXPANSE to create the EU noise map, is a simplified sound propagation model developed for Europe-wide noise mapping requiring a range of input data including a detailed road network, traffic intensity, land use and building data. Traffic intensity is a crucial input variable for road noise modelling. However, due to a lack of freely available traffic flow data across Europe, we first developed a geo-statistical random forest (RF) model capable of estimating traffic flow for the year 2019 for all roads in Europe based upon traffic counts in multiple European countries (Shen et al., 2024). We subsequently modelled the following noise metrics: Lden, Lday, Lnight, Leve and Laeq16 at the maximum exposed building façade for all buildings from OpenStreetMap for the year 2019. We evaluated the performance of our EU noise model in the United Kingdom, Switzerland, the Netherlands and Stockholm (Sweden), by comparing our noise estimates with estimates from respective national noise propagation models (i.e. current gold standard). For Lden, for example, the comparison yielded moderate correlations for Switzerland, the Netherlands and the United Kingdom (Pearson’s correlation = 0.52–0.77) and a lower correlation in Stockholm County (Pearson’s correlation = 0.39) (Shen et al., 2025).

Temperature. Long-term daily data on minimum, maximum, and mean temperature is essential for studying the health impacts of cold spells and heatwaves. These data are globally available from ERA5 (the fifth

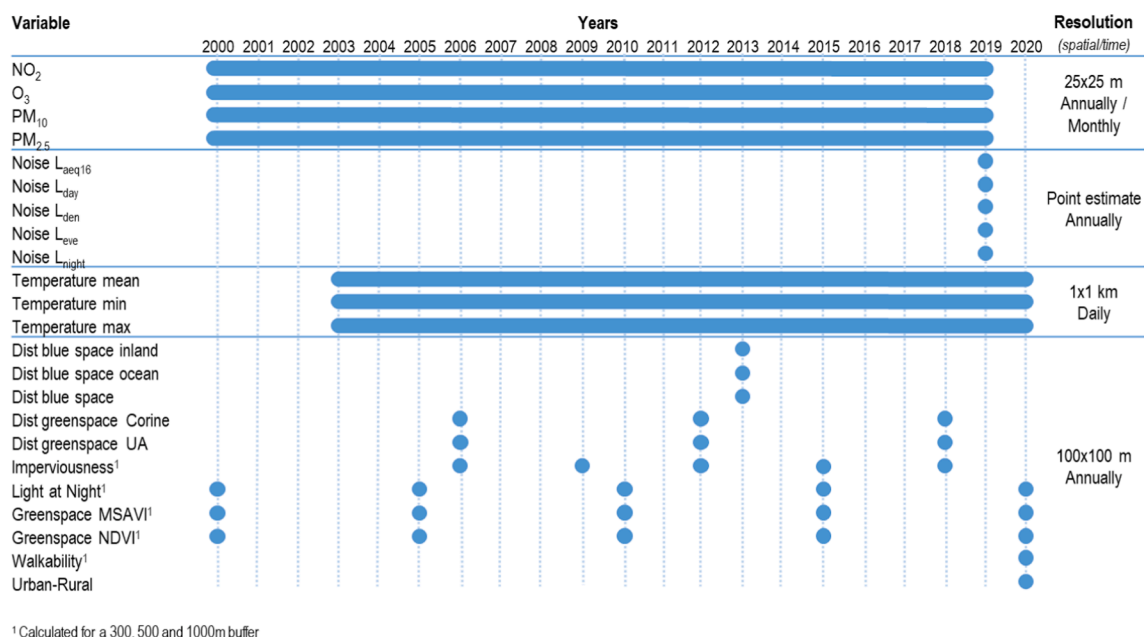


Fig. 1. Temporal and spatial resolution of the 33 external exposome factors (some factors were calculated for buffer sizes 300, 500 and 1000 m, indicated with ¹).

generation ECMWF atmospheric reanalysis of the global climate) but the resolution (10x10 km) is too coarse to detect within-city variability needed for epidemiological analyses. Time series studies typically rely on weather station measurements, often situated outside urban areas, failing to account for higher urban temperatures and the urban heat island effect. Therefore, we aimed to model daily minimum, maximum and mean ambient temperature at a finer resolution of 1x1 km for Europe between 2003 and 2020 (Bussalleu et al., 2024). Ambient temperature (Ta) was modelled using random forest with Ta measurements, collected from global, regional and local ground monitoring networks, as the dependent variable. Predictor variables included Land Surface Temperature (LST), for which missing values were imputed during pre-processing, CORINE Land-Cover classes (CLC), impervious surface density, Normalised Difference Vegetation Index (NDVI), latitude and longitude, population density, and meteorological variables (from ECMWF ERA5). Models explained on average 0.96 (R^2) of the variability in minimum, maximum and mean daily Ta measurements (in degrees Celsius) (using 5-fold cross-validation) with a RMSE of 1.2, 1.8 and 1.6 °C respectively for mean, min and max Ta.

2.2.2. Built environment

The majority of built environment data (greenness, imperviousness or grey space, artificial light-at-night, degree of urban indicator) were obtained from existing data sources and resampled to the necessary spatial and temporal resolution. The remaining factors (distance to green and blue spaces and walkability) were newly calculated within GIS. Supplement S2 gives a detailed description of the built environment data, with a short summary per variable below.

Green space.

- Normalised difference vegetation index (NDVI) satellite imagery data were collected for the years 2000, 2005, 2010, 2015, and 2020 using MODIS product (MOD13Q1) and processed using Google Earth Engine to obtain the annual surfaces at 250 x 250 m resolution for the study area. In each year, all valid individual images were used. A raster dataset was then generated with the mean, standard deviation, and median value per pixel. The process included removing water features using a high-resolution water mask layer (Joint Research Centre Global Surface Water) (Pekel et al., 2016) and a quality filter to remove non-valid pixels. The surfaces were resampled to 100 x 100 m after which a focal statistics process was performed to create surfaces representing the mean for the surrounding 300 m, 500 m, and 1000 m (radius) around each pixel. These buffer sizes were selected to cover commonly used metrics in epidemiological studies of surrounding greenness.
- The modified soil-adjusted vegetation index (MSAVI) was used to address some limitations of NDVI in areas with a high proportion of exposed soil surfaces, e.g. with high percentage of bare soil, scarce vegetation, or low chlorophyll content in plants. Qi et al. (Qi et al., 1994) developed the MSAVI by calculating a soil brightness correction factor thus minimizing the effect of background soil. Imagery data were extracted from the same MODIS data source and years as NDVI. The same process described for NDVI was used to compute the mean for the surrounding 300 m, 500 m, and 1000 m (radius) around each pixel.
- Distance to the nearest green space indicator was created using the main European datasets freely available in Europe: CORINE and Urban Atlas. To map publicly accessible green spaces, we combined green land cover types including green urban areas (parks) and sport and leisure facilities together with agricultural areas and forest and semi-natural areas. For each version (2000, 2006, 2012, and 2018 for CORINE and 2006, 2012, and 2018 for Urban Atlas), we created a

100 x 100 m European surface with the Euclidean distance from each pixel centroid to the nearest green space, defined by the relevant classes from the respective datasets.

Blue space. Three metrics were determined to depict exposure to blue space: 1) distance to the sea-shore, 2) distance to the nearest inland water feature, and 3) distance to the nearest blue space by taking the minimum of metric 1) and 2). All calculations were from the 100 x 100 m pixel centroid to the relevant feature. The EU-Hydro dataset was used to characterize the blue spaces indicators (COPERNICUS, 2019). Distance to blue space was calculated for one time point (2013) as we did not expect to see major changes in the spatial distribution of blue space over time.

Grey space. Impervious surface maps (expressed as a percentage of soil sealing per area unit, i.e. grey space) were generated, using the imperviousness degree layer from the Copernicus Land Surface Monitoring Service for the years 2000, 2005, 2010, 2015, and 2020 at a 100 x 100 m resolution. Impervious areas are characterized by the substitution of the original (semi-) natural land cover or water surface with an artificial, often impenetrable or sealed cover. Similar to greenness, a resampling analysis using a focal statistics process was performed to calculate the mean degree of imperviousness within 300 m, 500 m, and 1000 m (radius) around each pixel.

Light-at-night. Light-at-night (LAN) was characterized using DMSP (Defense Meteorological Satellite Program) for the years 2000, 2005, and 2010 and VIIRS (Version 1 VIIRS Day/Night Band Night-time Lights) for the years 2015 and 2020. Following the previously described computation procedures, a focal statistics process was applied to compute averages within 300 m, 500 m, and 1000 m (radius) around each pixel.

Walkability. A walkability index, a tool to assess how walkable neighbourhoods or cities are, was created and customised for Europe following the approach of previous indexes developed specifically for the US (Frank et al., 2010) and more recently for the Netherlands (Lam et al., 2022). These studies identified key predictor variables which were found to correlate with walking, of which the following were included in our index: street connectivity density, slope, population density, pedestrian street density, accessibility to public transport, food retail density, NDVI and distance to green space. For each indicator we calculated 100 x 100 m resolution surfaces with the average value within 300 m, 500 m, and 1000 m (radius) using focal statistics. Global population density was obtained from the 250 x 250 m dataset for 2015 (Schiavina et al., 2023). Slope was derived from the EU-DEM dataset at 25 x 25 m resolution. We used Open Street Map (OSM) to retrieve the street network and derive the connectivity and pedestrian variables. For connectivity, we retrieved the street intersection nodes from the street network and then rasterized them to create a 100 x 100 m surface with intersection density per pixel, as a connectivity indicator. For pedestrian street density, we first selected the relevant street categories (see Supplement S2) and then rasterized each street category into 10 x 10 m binary rasters (1 if a pixel contained a street, 0 otherwise). We then applied a resample method to obtain 100 x 100 m surfaces with the aggregated number of streets for each pixel. Similarly, we extracted the public transport stations for metro, bus, train and tram and derived the related surfaces with the station density per 100 x 100 m pixel. Food retail density was also obtained from OSM to produce a 100 x 100 m surface with the average value within 800 m around each pixel. We conducted several exploratory analyses to test each indicator's completeness and robustness, and performed correlation analysis between indicators at different scales (i.e. city, country, Europe) and different urban configurations (i.e. rural vs. urban). We also performed a comparison against an existing walkability index finding moderate

correlations (R 0.5) (Walkability Score Netherlands version 1.0 (Wagtendonk and Lakerveld, 2019)).

All the surfaces were normalized as z-scores to be able to combine them into a single index using the following algorithm:

$$\text{Walkability} = z(\text{population density}) + 0.5 * z(\text{street connectivity}) + 0.5 * z(\text{pedestrian street density}) - z(\text{slope}) - z(\text{distance to green spaces}) + z(\text{food stores density}) + z(\text{NDVI}) + z(\text{public transport station density})$$

Weights were set to 1 for all indicators except street connectivity and pedestrian street density for which we set the weights to 0.5 as these indicators are related and represent similar/complementary street design configurations. Equal weighting is commonly used in walkability studies, as it is not (yet) known what factors are more important nor whether the importance is different across regions. Z scoring is done to standardise units and allow averaging.

Degree of urban. A degree of urban indicator was created based on the Global Human Settlement (GHS) population grid from the Global Human Settlement Layer (GHSL) (Schiavina et al., 2022). A focal mean within 1500 m (square window) was applied to create a 100 x 100 m population density surface. The degree of urban indicator was calculated on a continuous scale, with low to high scores indicating rural to urban. We did not set a threshold for differentiating when a pixel is either urban or rural, as this depends on the local setting and is therefore potentially different across Europe.

2.3. Food environment

No European datasets characterizing the geographical food environment (e.g., availability food retailers within an area) existed in 2020. We therefore set out to construct the following indicators using Open Street Map (OSM) data (Pinho et al., 2023). We extracted points of interest (POIs) from OSM labelled as fast-food outlets, supermarkets and restaurants and separately calculated the counts within 800 m buffers around randomly selected residential addresses. We tested the quality of the OSM data in five European regions (the Randstad (Netherlands), Barcelona (Spain), Basel (Switzerland), Greater Athens (Greece) and Łódź (Poland)) by comparing them with Google Street View (GSV) images and found that although the agreement was poor for individual points of interest, OSM data were able to broadly explain the spatial variation of the food environment using the count of selected food retailers as indicator in three of the five regions (i.e. Randstad, Barcelona and Basel) (Pinho et al., 2023). As we could not validate other regions we do not support using OSM data beyond the Randstad, Basel, and Barcelona at this time. Also, in these three regions, only restaurant density, fast food restaurant density and supermarket density were deemed of sufficient quality.

2.4. Social environment

Harmonised data characterising the social environment in which individuals live is not currently available at a meaningful small area or neighbourhood European-wide level. By social environment, we refer to a number of dimensions including the material, socio-economic and socio-demographic characteristics of the neighbourhood. This includes the social composition of the neighbourhood (average socio-economic level (education, income, occupation), proportion of single-parent families, immigrants), the crime rate, the safety of the neighbourhood and the availability of public services (e.g. schools). In EXPANSE we evaluated European Union Statistics on Income and Living Conditions (EUSILC) data for harmonisation of social factors across Europe and identified other data sources with social variables reflecting the living conditions of people in their neighbourhood. However, we found a lack of consistent, publicly available social data at the neighbourhood level.

Due to these limitations, it was not feasible within the project timeframe to develop a harmonized area level socioeconomic status (SES) and/or deprivation variable for Europe.

2.5. Statistical analyses

2.5.1. Geographical level of analysis

To investigate the relationships between exposures and their stability over time, we generated a random dataset of 120,264 building facades points across Europe (Fig. S1). The selection was stratified by population density within NUTS1 region (First-level Classification of Territorial Units for Statistics), using the 100x100 m population estimates for year 2020 from the GHSL (Schiavina et al., 2023). These random points represented a stratified selection of the location of the European population and was used in that capacity to investigate the correlation between and the spatial and temporal stability of the exposures.

2.5.2. Correlations between exposures

The correlation between all the different exposures was investigated for the most recent year of each, using: 2019 for the four air pollutants (NO₂, PM_{2.5}, PM₁₀ and O₃), temperature and noise; and 2020 for NDVI, MSAVI, imperviousness, light-at-night, and degree of urban. Exposures were extracted at the random points and the following correlations were calculated: Pearson's R at both the European and country level, and Spearman's rank correlation at the European level. The correlation matrix was visualized using a correlogram. The analysis at the European level could obscure differences in exposure both between and within countries. Thus with the analysis at the country level, we wanted to assess how exposures are correlated within countries. This is important as most health studies do not exploit European-wide exposure contrasts (Strak et al., 2021; Stafoggia et al., 2022), but are analyzed at a national or sub-national level. The analysis also addressed heterogeneity of within-country correlations. For the purpose of this assessment, we defined Pearson's correlation coefficients (R) as weak (R < 0.4), moderate (>0.4–0.6), moderately strong (>0.6–0.8), strong (> 0.8–0.9) and very strong (>0.9).

2.5.3. Stability in time

Stability of the spatial structure for exposure surfaces was explored for the four air pollutants (NO₂, PM_{2.5}, PM₁₀ and O₃), temperature, NDVI, MSAVI, imperviousness and light-at-night by comparing two time points. These exposures were extracted at the random points, and correlations calculated for 2000 vs. 2019/20 and 2015 vs. 2019/20 at the European and country level. We reported Pearson's R. For the air pollutants and temperature we also assessed stability of the exposure surfaces for intermediate time points.

2.5.4. Trends in exposures over time

To evaluate the time trends, we used the whole raster datasets, not the 120,000 random points. For the air pollutants (NO₂, O₃, PM₁₀ and PM_{2.5}), greenspace (MSAVI and NDVI), mean temperature, light-at-night and imperviousness, we were able to investigate trends in time by calculating the mean and population weighted mean (mean_{pw}) of selected exposures by country, and across Europe. The mean_{pw} of exposure X was calculated using Equation (1).

$$\text{Mean}_{pw}X = \frac{\sum (X_i \times \text{Pop}_i)}{\sum (\text{Pop}_i)} \quad (1)$$

where X_i is the value of the stressor X at pixel i, Pop_i is the sum of population at pixel i. In addition to the Mean and Mean_{pw} we calculated the delta ($\Delta = X_t - X_{t+1}$) and relative delta or percentage change ($\Delta / X_t \times 100$) over the different time periods.

For the selected exposures, Mean and Mean_{pw} were derived for 2000, 2010 and 2019/20 (depending on the exposure), with deltas calculated for the period 2000–2019/20. The population data used for the

population weighting was extracted from GHSL database at an approximately 100 m resolution for the years 2000, 2010 and 2020 (European Commission, 2023). For the exposure surfaces in years not covered, the closest year was used (e.g. the 2019 NO₂ surface was matched with population data from 2020).

For illustration purposes we mapped spatial variations of 12 of the 18 exposure factors across Europe resampled all exposure surfaces to a 5 km hexagonal grid. This included annual average concentrations for all 4 air pollutants, the annual mean temperature, light-at-night, NDVI, MSAVI, distance to green space (CORINE) and blue spaces, imperviousness and degree of urban. It was not possible to map noise across Europe as these were only modelled at the facades of buildings and not on raster.

Similarly, distance to green space using Urban Atlas was not mapped as this data is restricted to urban areas only. Instead of the 5 km hexagonal grid, walkability was mapped at its original resolution for a selection of cities.

Statistical analyses were carried out in R version 4.1 and maps were created using ArcGIS Pro 3.1.3.

3. Results

All results, mapped in 5 km hexagonal grids for illustrative purposes, show large variability in levels across Europe, both between and within countries (Fig. 2 and S2). Some factors are primarily driven by

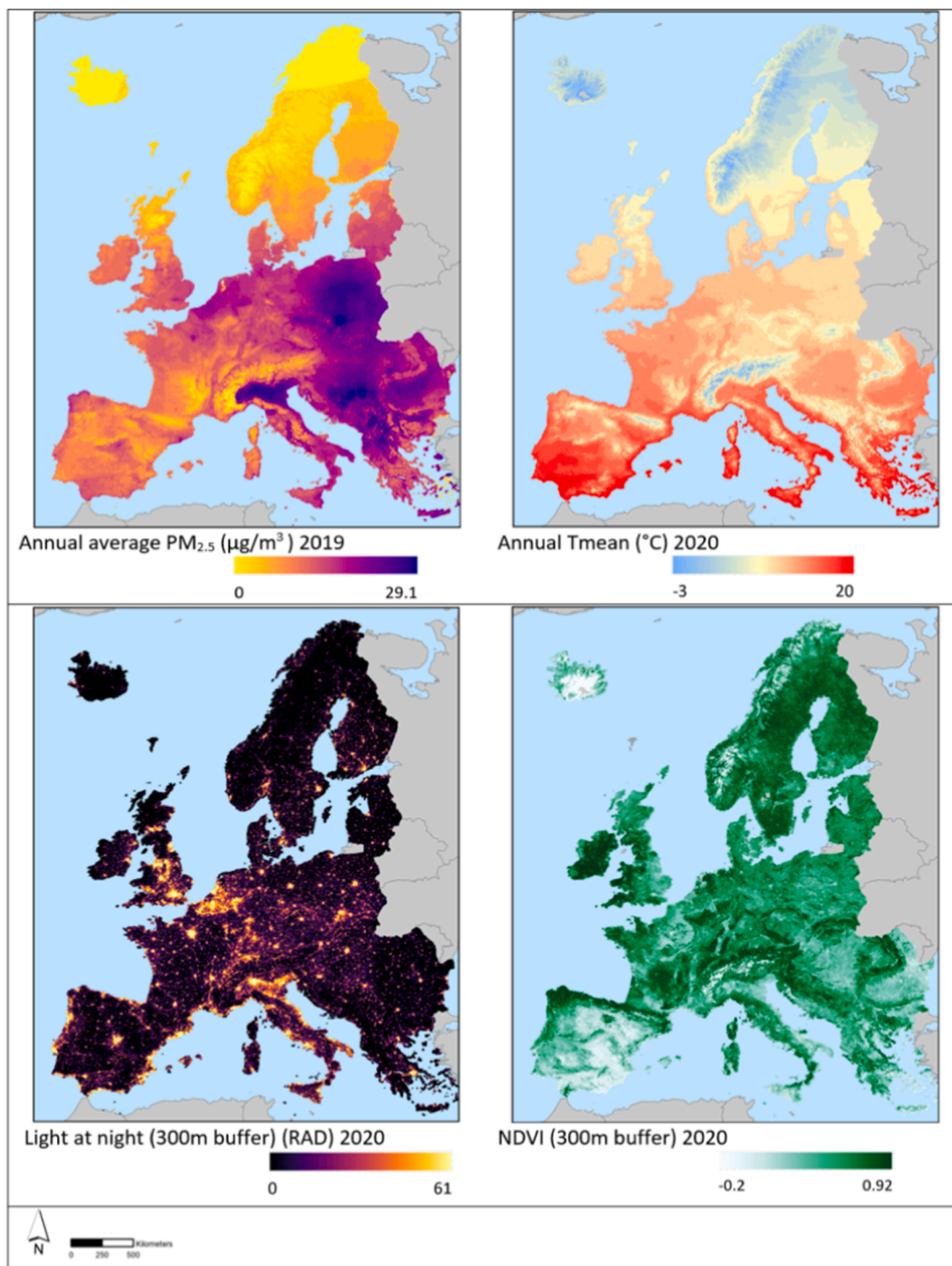


Fig. 2. Maps of environmental factors with clockwise form the top left: annual average PM_{2.5}, annual mean temperature, light-at-night and NDVI.

urbanisation, like NO₂, light-at-night and imperviousness, where major cities and larger regions (e.g. Po-valley, Netherlands-Germany region) experience high exposure levels. Factors like temperature, NDVI and O₃ show a more regional pattern across Europe. All air pollutants have a north-south gradient with particularly elevated PM concentrations in Eastern Europe (Fig. 2 and S2). For several factors, patterns related to

altitude are present.

Relationships between External Exposome factors across Europe

3.1. Correlations between factors over space

Correlations between the 33 exposures calculated for 2019/2020 at

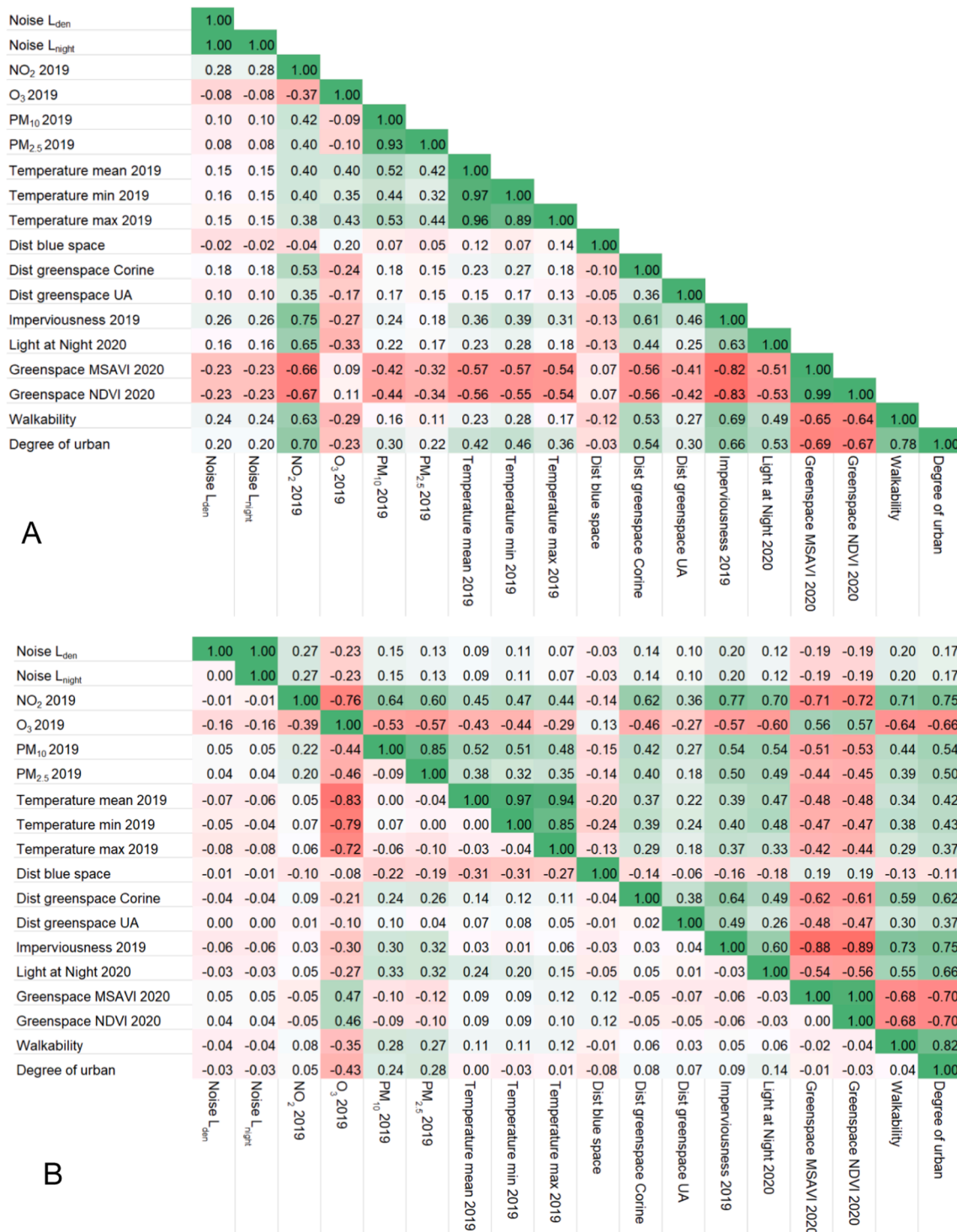


Fig. 3. A) Pearson correlations at 120,264 points across Europe between 18 external exposome factors for the year 2019/2020; Pearson correlation coloured from -0.83 (red) to white (0) to + 1 (green). B) Top right: median of country-specific Pearson correlation coefficients; bottom left: difference between the country-specific median and the Europe-wide Pearson correlation between 18 external exposome factors for the latest time period (2019/2020) for 120,264 random points across Europe; coloured from -0.89 (red) to 0 (white) to 1 (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the ~ 120,000 random points across Europe differed depending on pollutant (Fig. S3). All the noise metrics were very strongly correlated with each other ($R > 0.99$), resulting in identical correlations with the other exposure factors. This pattern was also observed within other environmental factors: Temperature (Tmean, Tmax and Tmin; $R > 0.88$); green space (MSAVI all buffers and NDVI all buffers; $R > 0.94$), light-at-night (all buffers; $R > 0.89$), imperviousness (all buffers; $R > 0.88$) and walkability (all buffers; $R > 0.96$). Air pollution exposures were weakly to moderately correlated with each other ($R -0.37-0.42$), except for PM_{2.5} and PM₁₀, which showed a strong correlation ($R 0.93$).

We reduced the dataset for subsequent analysis to 18 factors from the original 33, by using only the 300 m buffer for exposures with multiple buffer sizes (see correlogram in Fig. 3a correlogram). Despite the high correlations, we retained the following exposures because they are frequently used in epidemiological analyses: Lnight and Lden for noise and PM_{2.5} and PM₁₀ (also because they show slightly different correlations with other exposures). For blue space, we only selected the shortest distance to any water feature. The Spearman correlation corresponds well to the Pearson's R (Fig. S4).

Across Europe (Fig. 3a), apart from PM_{2.5} and PM₁₀ ($R 0.93$), we observed weak correlations between NO₂ and the PMs ($R \sim 0.40$), NO₂ and O₃ ($R -0.37$) and O₃ and PMs ($R \sim -0.10$). Correlations between groups of environmental factors were mixed. There were weak correlations between all noise metrics and other external exposure factors ($R -0.23 - 0.28$). The four air pollutants had a weak to moderate correlation with the three temperature factors ($R = 0.32 - 0.53$). Among the four air pollutants, NO₂ tended to have moderate to moderately strong negative and positive correlations with other external exposure factors (e.g. imperviousness $R 0.75$; light-at-night $R 0.65$; MSAVI, NDVI $R -0.67$; Walkability. $R 0.63$). The other pollutants had weak relationships, with O₃ always having the opposite sign compared with NO₂ and PM. The degree of urban indicator had a moderately strong positive correlation with NO₂, walkability and imperviousness and a moderately strong negative correlation with the greenness indicators NDVI and MSAVI.

The correlations between exposures across the whole of Europe obscured the heterogeneity in variations between some exposures by country and were affected by between country contrasts. The median of within-country correlations between exposure factors was similar to the correlations across Europe for most combinations (Fig. 3a and 3b). Correlations between O₃ and temperature changed from positive correlations ($R 0.35 - 0.43$) across the whole of Europe to negative within-country median correlations ($R -0.43 - -0.29$). Furthermore, correlations between PM_{2.5}, PM₁₀, NO₂ and O₃ were stronger within countries than across Europe.

The difference between the Europe-wide Pearson correlation and the median and standard deviation (SD) of the country-specific Pearson R's (Fig. S5) shows that the largest difference was observed between O₃ and temperature. O₃ and temperature showed a positive correlation Europe-wide but a negative country-specific correlation (Fig. S6) in most countries (difference $R -0.83 - -0.72$ and SD 0.36). For example the UK, Switzerland and Romania were among the countries showing a negative correlation. O₃ and the green space measures NDVI and MSAVI showed a moderate positive correlation in most countries (median $R 0.56$), while a weak correlation Europe-wide ($R 0.10$). In Fig. S6 this is further illustrated by looking at the extremes in country-wide correlations. Spain was the only country with a negative correlation ($R -0.14$) between O₃ and MSAVI/NDVI. In contrast, Latvia, Ireland and Hungary all had correlations greater than 0.8. Although correlations between the majority of built environment factors and air pollutants were similar at the country and Europe-wide level, there were exceptions. For example, correlations between the PMs and imperviousness and light-at-night were stronger at the country level. The correlation of noise metrics with other factors was quite stable with standard deviations of correlations all < 0.10 . Similarly, correlations between most of the built environment factors (distance to green spaces; impervious surface; LAN,

MSAVI, NDVI and Walkability) showed equal stability ($STDV < 0.11$). Correlation patterns between these factors were indeed similar at both the European and country scales (Figs. 3a and S6).

At the country level some factor combinations showed an absence or presence of heterogeneity in correlations across Europe. For example, NO₂ vs. Lden and Walkability vs. NDVI, show almost no variability across Europe and are all consistently positive or negative (Fig. S7). Other combinations displayed variability, also in the direction of association. O₃ vs. Tmean, for example, had a negative correlation in most Western and Eastern European countries, and positive correlations in some South and North European countries.

3.2. Stability of exposure over time

Correlations at the ~ 120,000 random points across Europe revealed robust stability at the European level for most factors with temporally resolved surfaces (Fig. 4 and Fig. S8). Strong to very strong correlations were observed between early (2000) and late years (2020–2019) for all factors at the European level, except of O₃, which correlated moderately strong ($R 0.66$). For the factors air pollution and temperature stability was also strong within the periods of 2000–2019 and 2005–2019 respectively (Table S3; $R > 0.84$, except for O₃ $R 0.68-0.91$). This trend was also reflected at the country level, where most countries exhibited $R > 0.8$ for all factors. There were some exceptions notably for O₃, PM₁₀ and PM_{2.5} in some countries. For example, O₃ and PM₁₀ in Slovakia showed weak correlations between 2000 and 2019 ($R 0.39$ and 0.41 respectively) and PM_{2.5} in the Netherlands also showed a weaker correlation ($R 0.45$) (Fig. 4 and Fig. S8).

3.3. Trends in exposure over time

Changes over time for those exposures modelled for multiple years for Europe as a whole and by country were assessed using populations weighted exposure estimates.

3.3.1. Air pollution

Generally, population weighted air pollution concentrations have declined from 2000 to 2019 across Europe (Figs. 5 and 6) with all countries exhibiting a negative change for NO₂, PM₁₀ and PM_{2.5}. However, the rate of decline in population weighted NO₂, PM₁₀ and PM_{2.5} concentrations differs per country, with in general smaller decreases in Eastern vs. Western Europe (Fig. 6, Table S2). The picture for O₃ is more complicated with, for example, the Netherlands, Belgium and Spain showing an increase of $11 \mu\text{g}/\text{m}^3$ and countries in the East of Europe showing a decrease of $7 \mu\text{g}/\text{m}^3$.

The decline in NO₂ concentrations was more pronounced between 2010 and 2019 compared to 2000–2010, with some countries showing an increase in levels in the 2000–2010 (median change in population weighted NO₂ 2000–2010 = $-0.8 \mu\text{g}/\text{m}^3$; 2010–2019 = $-4.1 \mu\text{g}/\text{m}^3$). For the whole of Europe, the change in population weighted NO₂ was $-1.5 \mu\text{g}/\text{m}^3$ in the earlier versus $-6.5 \mu\text{g}/\text{m}^3$ in the latter period.

Like NO₂, levels of PM_{2.5} also reduced across Europe between 2000 and 2019 with the largest decrease in the period 2010–2019 with a reduction of $-4.4 \mu\text{g}/\text{m}^3$ in population weighted PM_{2.5} across Europe. Compared to NO₂, PM_{2.5} exhibited a different spatial pattern across Europe with Eastern European countries showing the highest population weighted PM_{2.5} concentrations with North Macedonia, Serbia and Bosnia and Herzegovina being the three most polluted countries with 22, 21.1 and $21 \mu\text{g}/\text{m}^3$ respectively in 2019 (Table S2).

Population weighted O₃ concentrations were highest in Southeast Europe in 2000. Albania, Greece, Montenegro, Bosnia and Herzegovina and North Macedonia were all in the top four in the ranking with population weighted O₃ concentrations greater than $75 \mu\text{g}/\text{m}^3$. In all these countries O₃ concentrations reduced between -5 to -10% , whereas in other countries an increase was observed, strongest so in Spain in 2019 ($77 \mu\text{g}/\text{m}^3$), followed by the Netherlands and Belgium seeing a large

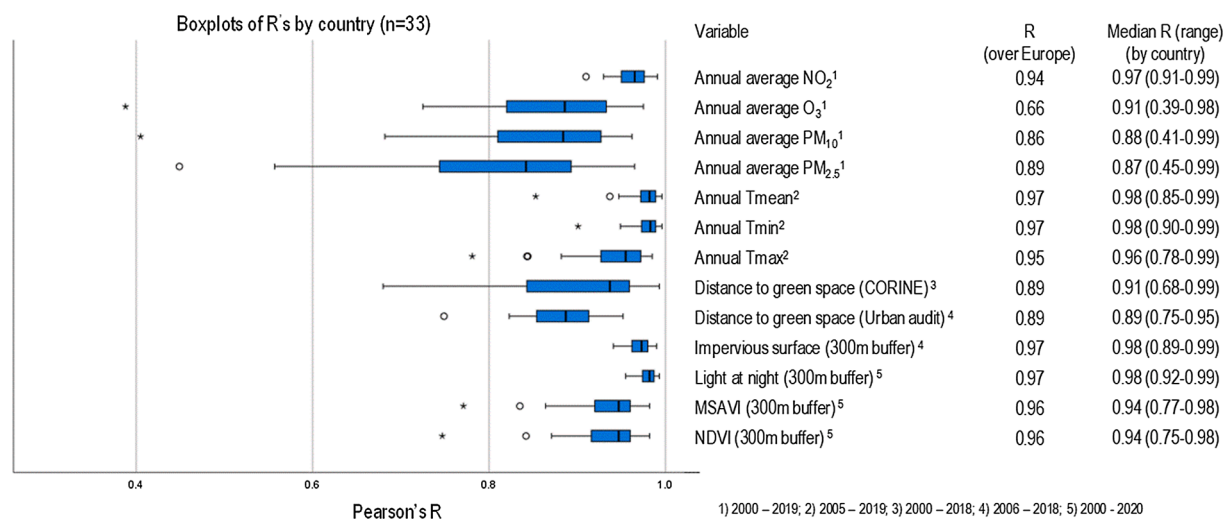


Fig. 4. Stability over time – correlations (Pearson's R) between the exposures for the same variable at two time points (from- and to-year shown in footnote) showing the Pearson's R across all random points in Europe and boxplots of R by country. Boxplots show the median (bold line), interquartile range (blue box) plus whiskers showing minimum and maximum within 1.5 times the IQR plus outliers points outside 1.5 times the IQR. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

percentage increase (+12 %).

Large reductions in multiple air pollution concentrations were observed in some countries between 2000 and 2019. Spain and Portugal, for example, show a reduction of more than 8 µg/m³ for NO₂, 15 µg/m³ for PM₁₀ and 7 µg/m³ for PM_{2.5} (Table S2).

3.3.2. Temperature

Between 2005 and 2020, the mean temperature increased across Europe (Fig. 5, Table S2), with a population weighted temperature rise of 0.6 °C. However, the magnitude of this increase varied by country, ranging from almost no change in Ireland (−0.1 °C) and Iceland (+0.1 °C) to an increase of more than 2 °C in Lithuania, Montenegro, Estonia and Latvia. Absolute population weighted temperatures in the Baltic States were low (between 8 and 9 °C) compared to the rest of Europe.

3.3.3. Built environment

A small increase was observed in the greenness indicators MSAVI and NDVI between 2000 and 2020. In terms of percentage change there was substantial heterogeneity, with Hungary and Bulgaria exhibiting more than a 16 % increase and Luxembourg the only country with a decrease of 3 %. More substantial increases were observed for imperviousness, ranging from 0.7 to 11.4 % for all countries (Table S2), indicating an increase in urban sprawl between 2000 and 2020.

Light-at-night did not show a clear trend and varied substantially between countries. With large increases in for example Albania (87 %) and decreases of around 7 % in Denmark, the Netherlands, Belgium and Slovakia.

4. Discussion

Harmonised spatial and time-varying pan-European data on environmental stressors are essential for several reasons: 1) to analyse exposure patterns across time and space in Europe, 2) to investigate the interrelationships between environmental factors across Europe, and 3) to conduct multi-site studies across Europe for understanding the singular and combined associations of these exposures with health outcomes.

4.1. Correlations between factors

We found mostly weak to moderate correlations between different

exposure factors. At the European level we observed weak correlations between NO₂, the PMs and O₃. Noise correlated weakly with all external exposome factors, while air pollution correlated moderately with temperature. Of the air pollutants, NO₂ was stronger correlated with the built environment factors. At the country level, correlations were similar for most combinations, except those involving O₃ and temperature.

Several studies compared different environmental exposure factors, often at the city, regional or country level or within one or multiple cohorts, with even fewer studies including cohorts from different countries. Studies have compared air pollution with: 1) road traffic noise (Fecht et al., 2016; Nieuwenhuijsen et al., 2017); 2) road traffic noise and NDVI (Klompaker et al., 2019); 3) temperature (Zhao et al., 2024); 4) road traffic noise, NDVI and temperature (Chen et al., 2024); 5) road traffic noise, NDVI, blue and green space and walkability (Maitre et al., 2022); and 6) NDVI and walkability (de Bont et al., 2023; Doiron et al., 2020). A detailed discussion of findings in other studies, focusing on between-domain relationships, is available in Supplement text S3.

The findings of these studies are generally consistent with our results, with stronger correlations within domains of exposure than between exposure domains. For example, weak positive correlations were found between road traffic noise and NO₂ and PM_{2.5}, and weak negative correlations between noise and O₃. Correlations between temperature exposures and other environmental exposures tended to be weak.

The generally modest correlations between exposures of different domains can be explained by different contributing sources or features of sources. Even the correlation between noise and air pollution is moderate, though motorized traffic is an important shared source of both stressors. Traffic speed and road surface both affect air pollution and noise in different directions.

Implications

In multi-cohort studies in multiple countries, epidemiologists often perform harmonised analysis per cohort and then meta-analyse effect estimates (Strak et al., 2021; Stafoggia et al., 2022). The rationale for a country-specific analysis may be that data cannot be pooled due to data protection issues. Concerns about unmeasured confounding have also led to within-country analyses (Strak et al., 2021). In such a setting, the within-country correlations (Fig. 3b) are relevant for interpretation of the epidemiological results. The generally weak to modest but significant correlations suggest that single exposure models may be confounded by other correlated environmental stressors. The generally modest correlations that we found suggest that with appropriate

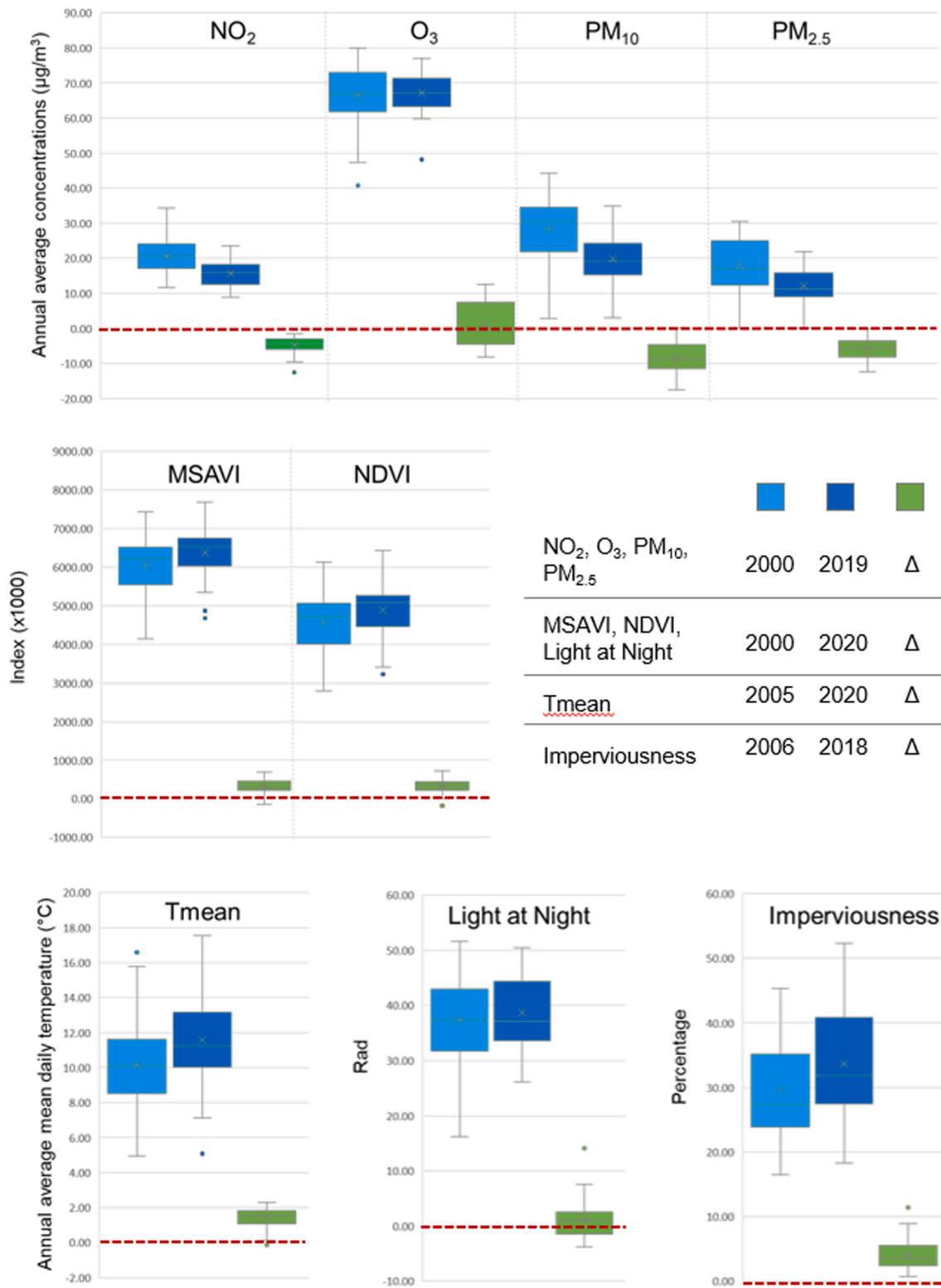


Fig. 5. Change over time for NO₂, O₃, PM₁₀, PM_{2.5}, MSAVI, NDVI, temperature, light-at-night and imperviousness summarizing data from 34 European countries. In each of the figures, the first two boxplots show the population weighted concentrations for 2000 or 2005 (light blue) and 2019 or 2020 (see legend) (dark blue). The last box plot (green) in each of the figures shows the change (delta) in population weighted concentration between 2000/2005 and 2019/2020. Boxplots show the mean (X), median line and first and third quartile boxes plus whiskers showing minimum and maximum within 1.5 times the IQR plus outliers points outside 1.5 times the IQR. The null line is indicated by the red dotted line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

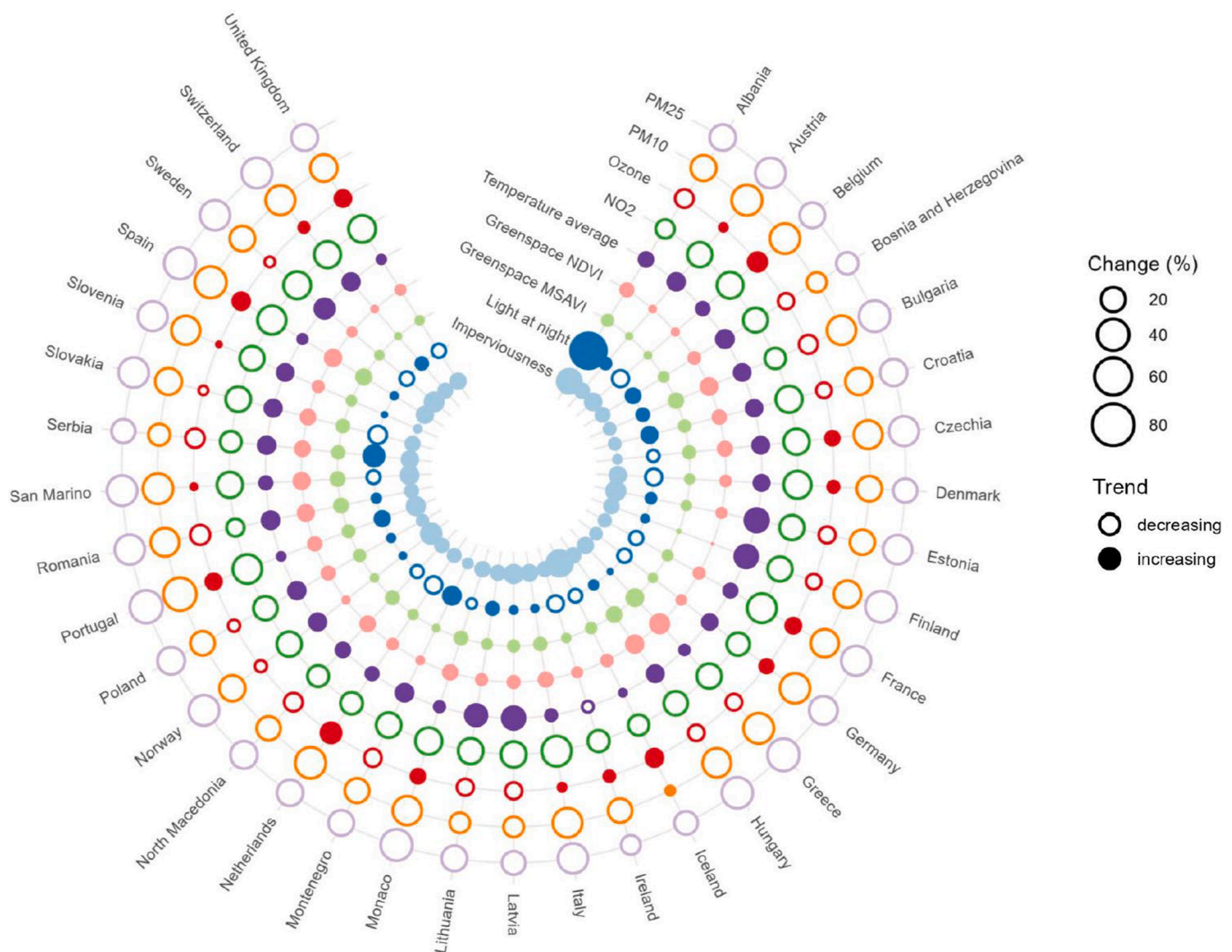


Fig. 6. Radial plot of changes over time between time points per country for PM_{2.5}, PM₁₀, Ozone, NO₂, Temperature average (2000 to 2019), NDVI, MSAVI, Light-at-night and Imperviousness (2000 to 2020). The size of the circle indicates the absolute change in percentage, an open circle indicates a decreasing trend, a closed circle indicates an increasing trend.

statistical methods, independent and joint effects can be estimated in epidemiological studies (Agier et al., 2016).

Note, however, that models used to predict different exposure factors often rely on similar predictors (e.g. predictor ‘land use’ used in noise, air pollution and temperature models), or use an exposure as a predictor (e.g. exposure ‘imperviousness’ used in air pollution and temperature models). As a result, the correlation patterns derived from these models may be different than the correlations in the underlying measurement data, as suggested by previous research (Beelen et al., 2014; Eeftens et al., 2012; Boogaard et al., 2009). This makes that comparing multi-variable models may be challenging and that inference should be done with care.

4.2. Stability over time

Previous studies have documented stability of measured and modelled air pollution surfaces over periods of at least 10 years in Europe and North America (Eeftens et al., 2011; de Hoogh et al., 2018; Cesaroni et al., 2012; Gulliver et al., 2013). de Hoogh et al. (de Hoogh et al., 2019) evaluated the spatial structure of modelled air pollution surfaces using Hybrid/LUR method for NO₂ (2010 with 2005 and 2000) and PM_{2.5} (2010 with 2013). They found very strong correlations between the NO₂ surface for 2010 and the 2005 and 2000 NO₂ surfaces

(R₂ > 0.91) across the whole of Europe and between the 2010 and 2013 PM_{2.5} surfaces (R₂ = 0.88). These are very similar as our findings (NO₂: R₂ = 0.89; PM_{2.5}: R₂ = 0.80 comparing 2000 – 2019). Our study documents very high correlations for a period of 20 years in a wide range of European countries.

Our results show robust stability of spatial contrast for most environment factors for which we had exposure data for multiple time points. Few other studies have evaluated this issue beyond air pollution. Our findings for green space are in line with an analysis within the pooled cohort of the ELAPSE study (Bereziartua et al., 2022) and studies in Barcelona and Canada (Nieuwenhuijsen et al., 2018; Villeneuve et al., 2012). The spatial stability is explained by the relative stability in the location of dominant sources (major roads, industrial area) in the study area between 2000 and 2020. In areas with strong infrastructural developments or change in industrial activity, spatial patterns may be less stable.

Implications

The stability of spatial contrasts suggests that using a single time point in exposure assessments may be sufficient to detect associations with health even when exposures are temporally misaligned with the follow-up period of the cohort. Nevertheless, due to increasing and decreasing trends in exposures over time, the estimated effect per unit of

exposure is influenced by these temporal trends, especially if the contrast in exposure may change (e.g. if concentrations in more polluted areas decrease more rapidly than in less polluted areas).

4.3. Trends in exposure over time

A comprehensive analysis of time trends in air pollution concentrations in rural environments across Europe was conducted by Aas et al. (Aas et al., 2024) between 2000 and 2019 using measured data at rural monitoring stations. They reported annual reductions of 2.4 % for PM_{2.5} and 1.7 % for NO₂. Chen et al. (Chen et al., 2024) reported trends for NO₂, O₃, PM₁₀ and PM_{2.5} between 2000 and 2019 using measured data at background stations reporting annual reductions of 2.4 % (NO₂), 2.3 % (PM_{2.5}) and 2.7 % (PM₁₀). For O₃ an increase of 0.2 % was found. Our data shows similar annual changes (reductions of 1.3 % for NO₂, 1.8 % for PM_{2.5} and PM₁₀ and an increase of 0.4 % for O₃) noting that our data is using a population weighted mean compared to a rural environment mean used by Aas et al. (Aas et al., 2024).

We observe a modest increase of 0.6 °C across Europe between 2005 and 2020. However, when looking at the country-level, the change varies more, between -0.1 and 2.3 °C. The increases are in line with an observed temperature increase globally which is attributed to global warming (IPCC IPCC. Climate Change, 2021).

A study of Verhoeven and Dedoussi (Verhoeven and Dedoussi, 2022) assessed the trend across Europe in NDVI-derived land cover classes between 2000 and 2019 and observed that forest land cover increased, whilst agricultural and shrubs and herbaceous vegetation showed the opposite trend. We observed a modest increase in NDVI and MSAVI across Europe, showing some heterogeneity at the country level. We were not able to distinguish trends between different green land cover classes.

A study by Bennie et al. (Bennie et al., 2014) showed that although night time light pollution in Europe between 1995 and 2010 overall increased, some countries, including Sweden, Denmark and Belgium, contain areas where a decline was detected. In our assessment we observe a decrease in light-at-night for the same countries.

Implications

For most of the exposure factors we assessed, we show that trends in time follow the same direction (e.g. decrease in air pollution, increase in temperature, increase in greenness and imperviousness surfaces) at both the European and the national scale. However, the magnitude of change in population weighted exposures per country (Fig. 6 and Table S2) differs between time periods.

4.4. Limitations

We were not able to develop harmonised exposure data for the food and social environment. Sufficient quality OSM data to characterize the food environment was only available for the three regions we were able to evaluate (Randstad in the Netherlands, Barcelona and Basel). More work needs to be done to improve the OSM data in regard to identifying and updating these types of food environment, and other data sources, like Google or Bing, could be harnessed. There are datasets available that depict the food environment at the local scale, such as the commercial LOCATUS database in the Netherlands or the General Classification of Economic Activities (NOGA) in Switzerland (Pinho et al., 2023), and potential local administrative data sources such as business registries. Mapping the social environment, using area level socioeconomic position or deprivation indexes, on a small/reasonable geographical scale has proved too complex on a European scale. Social data, such as education, employment and income, is very widely held and accessible within countries, most often in the national language of the country concerned, which makes it difficult to access. In addition, the social data collected between countries is not the same and is aggregated on very different spatial scales. All this hampers the

development of a harmonised index of socioeconomic position or deprivation at European level. There are initiatives to develop harmonised indices of disadvantage in Europe, but this only concerns a few European countries. There is a need to facilitate access to social data across Europe on a small spatial scale, and to work towards harmonising key factors or deriving social factors from pan-European data sources.

This was the first pan-European noise modeling effort aimed at producing harmonised exposures. However, we were not able to conduct a historical exposure assessment for noise, due to the lack of historical input data specifically road data and traffic volumes. Vienneau et al. (Vienneau et al., 2024), however documented high correlations (R 0.91) in modelled road traffic noise levels between 2001 and 2010 at residential locations in Switzerland, thereby indicating that noise may be stable over time as well.

A study by Huss et al. (Huss et al., 2019) found that satellite-based measurements of light-at-night did not correlate with indoor bedroom illuminance levels, suggesting that satellite data may not accurately reflect personal indoor light exposure during evening and nighttime hours. In contrast, for other environmental exposures such as air pollution, noise, and heat, significant relationships between outdoor and indoor levels have been documented (Foraster et al., 2014; Meier et al., 2015; Nguyen et al., 2014). However, factors like building characteristics and individual activity patterns can influence these relationships, potentially leading to exposure misclassification.

The external exposome encompasses a wide range of exposures, such as pesticides and other chemicals, microplastics, ultrafine particulates, ionizing and non-ionizing radiation, which we were unable to assess during this project. The primary reason for this was the lack of harmonized European-wide data necessary for modelling these exposures at the required fine spatial and temporal scale. Future efforts should prioritize extending the number of pan-European exposure surfaces for key determinants. The potential benefit of optimizing existing models may be smaller compared to the gains from focusing on new exposures. This importantly points to the need for harmonized exposure assessment from the start.

Observed correlations between modelled exposures were not only driven by the exposures themselves but also by the underlying model structures as they 1) share similar predictor variables or 2) in some models they serve as input information to estimate other exposures.

4.5. Utility of EXPANSE data

Harmonised spatial and time-varying pan European data on environmental stressors is important as to:

1) **study exposure patterns in time and space across Europe;** We showed patterns over time and between countries. This data can be used to identify where interventions should take place. From an epidemiological perspective, the fact that previous analyses did not use time-varying exposures may not have been a major issue *per se*, though it would influence the estimated risk per unit of exposure. Trend analyses showed that, although some environmental conditions appear to be improving, this improvement is not consistent across all regions of Europe. Specifically, the Balkans seemed to experience slower improvement, and in some cases, environmental conditions were deteriorating.

2) **investigate the interrelationship between environmental factors;** overall, the correlations were weak, which allows the application of most multivariable exposure-health models. However, some correlations were influenced by underlying data structures, which should be acknowledged when interpreting these models. Additionally, correlations varied between countries and when pooled across Europe, complicating the interpretation of Europe-wide analyses, especially when the direction of the correlation changed. For example, a positive correlation may appear across Europe due to country-level differences, but within most countries, the same factors may be negatively correlated.

3) **understand their association with health effects**; Though not reported here, the EXPANSE data is designed for and can be used for analyzing health effects. Further, the validity of many of these models (e.g. temperature, air pollution) has been well-documented. Our maps enable time-varying analyses, mixture modelling, and joint effect estimation. As the interpretation of the models could be challenging, given that varying correlations across Europe may lead to uncontrolled confounding in the analyses, it seems advisable to also perform country-specific analyses. The EXPANSE data can also be used to investigate gender and/or socio-economics status differences in exposures at different geographical scales.

4) **perform health impact assessments of combined environmental stressors**; These data can be applied for health impact assessment studies across the Europe. However, it is crucial to use effect estimates based on the same exposure measures. By making the EXPANSE resources open, we facilitate both health analyses and their use in health impact assessments. Notably, for example, the new standardized noise estimates represent a major step forward in integrated analyses of noise and air pollution.

5. Conclusions

To our knowledge, this is one of the most comprehensive analyses of the temporal and spatial relationships between external exposure factors across a large geographical area. Most factors show low to moderate correlations, supporting the need for multi-exposure analyses in exposure health analyses.

We found substantial spatial stability of exposure surfaces over time across Europe, supporting that modest temporal misalignment between exposure model and follow-up period of the health study is not critical. Also, that we did not model every year for the environmental factors known to change less over time, is not likely to be problematic. We also showed that air pollutant levels have declined while temperatures have risen over the study period, which should be considered in epidemiological analyses.

The data described in this paper are available to researchers via the Exposome maps platform (<https://exposome.nl/tools/exposome-maps.html>).

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CRedit authorship contribution statement

Kees de Hoogh: Writing – review & editing, Writing – original draft, Visualization, Methodology, Supervision, Investigation, Formal analysis, Conceptualization. **Gerard Hoek**: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Benjamin Flückiger**: Writing – review & editing, Visualization, Formal analysis, Data curation. **Alonso Bussalleu**: Writing – review & editing, Visualization, Data curation. **Danielle Vienneau**: Writing – review & editing, Writing – original draft, Methodology. **Ayoung Jeong**: Writing – review & editing, Methodology. **Nicole Probst-Hensch**: Writing – review & editing, Resources, Methodology. **Maria Gabriela M. de Pinho**: Writing – review & editing, Data curation. **Joreintje D. Mackenbach**: Writing – review & editing, Data curation. **Jeroen Lakerveld**: Writing – review & editing, Data curation. **Joline WJ Beulens**: Writing – review & editing, Resources, Data curation. **Raphaele Castagné**: Writing – review & editing, Data curation. **Cyrille Delpierre**: Writing – review & editing, Resources, Data curation. **Michelle Kelly-Irving**: Writing – review & editing, Data curation. **Youchen Shen**: Writing – review & editing, Visualization, Data curation. **Anke Huss**: Writing – review & editing, Methodology. **Payam Davdand**: Writing – review & editing, Methodology, Data

curation. **Marta Cirach Pradas**: Writing – review & editing, Data curation. **Mark Nieuwenhuijsen**: Writing – review & editing, Resources, Data curation. **Jelle Vlaanderen**: Writing – review & editing, Resources, Methodology, Funding acquisition. **Roel Vermeulen**: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envint.2025.109542>.

Data availability

Data will be made available on request.

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