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Environmental exposure assessment in the German National Cohort (NAKO)

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A B S T R A C T

We aimed to assess the exposure to multiple environmental indicators and compare the spatial variation across participants of the German National Cohort (NAKO) to lay the foundation for health analyses.

We collected highly resolved German-wide data to capture the following environmental drivers: urbanisation by population density; outdoor air pollution by particulate matter ($PM_{2.5}$), nitrogen dioxide (NO_2), ozone; road traffic noise; meteorology by air temperature, relative humidity; and the built environment by greenspace and land cover. All assessed exposures were assigned to the NAKO participants based on their baseline residential addresses.

The NAKO study regions ranged from highly urbanised areas (Berlin, Hamburg) to rural regions (Neubrandenburg). This large variation is reflected in the individual environmental exposures at the place of residence. In 2019, annual $PM_{2.5}$ and NO_2 levels ranged from 6.0 to 14.6 and 3.7–33.6 μg/m^3, respectively. Annual mean air temperature ranged between 7.8 and 12.7 °C. Noise data was available for a subset of urban residents (22 %), of which 42 % fell into the lowest and 1.8 % into the highest category of Lden 55–59 and Lden >75 dB (A), respectively. Greenspace also showed considerable differences (Normalised Difference Vegetation Index between 0.08 and 0.84). Spearman correlation was moderate to high within the different exposure groups, but mostly low to moderate between the groups.

For the first time, a comprehensive population-based dataset with high quality environmental indicators is available for the whole of Germany. Expanding the database by adding innovative indicators such as light pollution, walkability, biodiversity as well as contextual socioeconomic factors will further increase its usefulness for science and public health.

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1. Introduction

The World Health Organization estimates that a considerable part of the global disease burden is attributable to environmental factors (Global Burden of Disease (GBD) Risk Factors Collaborators, 2024; Prüss-Ustün et al.). Outdoor air pollution alone is ranked the number one leading risk factor worldwide for attributable morbidity and number two for global mortality, only surpassed by high blood pressure (Health Effects Institute). Furthermore, non-optimal temperature is ranked number ten for mortality (Health Effects Institute).

Environmental risk factors encompass a range of exposures, including air pollution, ambient noise, water and soil pollution, adverse meteorological conditions, and characteristics of the built environment that negatively affect health such as lack of greenspace and biodiversity. These factors are associated with various adverse health outcomes, ranging from respiratory diseases, cardiovascular and metabolic conditions, mental and neurological conditions, infectious diseases, birth outcomes, and cancers (Johannessen et al., 2023; Klompmaker et al., 2021; Herder et al., 2023; Fuller et al., 2022). The severity of conditions caused by environmental exposures also varies from subclinical changes unobserved by the exposed to subtle symptoms, development of new manifest disease, disease exacerbations, increased medication, hospital admissions, all the way to increased mortality (Thurston et al., 2017).

A comprehensive assessment of environmental factors is essential for understanding etiological pathways, assessing causality, detecting synergies and interactions in epidemiological research and to inform political actions and public health interventions (Clougherty and Kubzansky, 2009). For example, recent studies show that air pollution can exacerbate the health effects of temperature extremes and vice versa (Rai et al., 2023; Stafoggia et al., 2023). Elevated temperatures exacerbate the formation of ground-level ozone (O_3), amplifying respiratory distress and cardiovascular complications (Vicedo-Cabrera et al., 2023; Bloomer et al., 2009). The built environment can intensify the adverse effects of heat by contributing to the so-called heat island effect (Heaviside et al., 2017; Oke, 1973). Noise pollution, a ubiquitous urban stressor that shares road traffic as one of the main sources with air pollution, interacts with both air pollution and the type of the built environment as well as with the availability of greenspace. Ambient noise exposure can increase the physiological stress response, potentially exacerbating the health impacts of air pollution (World Health Organization (WHO), 2018).

Assessing environmental exposures is inherently challenging, because many environmental factors, such as air pollution, noise, and air temperature, exhibit high spatial and temporal variability on different geographical and temporal scales. Methodological limitations, including the need for sophisticated monitoring equipment, long time series of measurements, spatial heterogeneity, and the influence of individual behaviours as well as socioeconomic position and neighbourhood on personal exposure, contribute to the complexity. Moreover, the assessment of long-term exposures often requires expensive and time-consuming modelling approaches (Chen et al., 2019; Hoek, 2017). For epidemiological studies, a high degree of harmonisation between study areas and study periods is essential, allowing pooled assessment of large cohort data (Brunekreef et al.; Chen et al., 2023).

Several long-standing German cohort studies such as KORA (Holle et al., 2005), Heinz Nixdorf Recall study (Schmermund et al., 2002), or SALIA (Schikowski et al., 2010) have contributed substantially to the understanding of the link between environmental exposures and health. While most earlier analyses focused on single exposures (Schikowski et al., 2010; Hoffmann et al., 2007; Peters et al., 1997), in recent years also the interplay has become the focus of attention (Herder et al., 2023; Ogurtsova et al., 2023; Niedermayer et al., 2024; Fuks et al., 2019). However, with baseline recruitment between 1985 and 2003, the cohorts suffer from loss-to-follow up and healthy survivor bias. They were also limited to specific study regions partly lacking significant spatial variation in the exposures. Furthermore, with around 300 to 5000 participants in the analyses (depending on the waves and outcomes under investigation), the power is partly limited, especially with regard to subgroup analyses. In 2014, the German National Cohort (NAKO), the largest population-based epidemiological cohort study in Germany to date, was incepted and has enrolled more than 200,000 adult participants in 18 study centres (Peters et al., 2022). The NAKO aims to investigate the determinants of health and disease in the adult population. To this end, a deep characterisation of individual-level risk factors related to lifestyle and socioeconomic factors, and health variables including biomarkers and omics, has taken place at the baseline examination and during follow-up visits. To this wealth of data, we added individual exposure to environmental factors at the place of residence of the participants. We specifically focused on air pollution, ambient road traffic noise, air temperature and relative humidity, and characteristics of the built environment because of their known high health relevance (Prüss-Ustün et al.). Moreover, this selection of exposures allows the focus to shift from single to multi-exposure approaches, as previous studies have shown that these exposure mixtures are specific to urban living environments and may have interactive and synergistic joint health effects (Herder et al., 2023; Chen et al., 2024; Klompmaker et al., 2019; Dimakopoulou et al., 2024). In this article, we describe the methods applied to comprehensively characterise the environmental exposures within the NAKO cohort and present descriptive results of long-term exposures for the full study population and as well as stratified by study centre and degree of urbanisation.

2. Methods

2.1. Study population

The NAKO baseline examination was conducted between 2014 and 2019 in 18 study centres across Germany (Peters et al., 2022). Age and sex-stratified random samples of the general population were drawn from compulsory registries of residents within 16 study regions ranging from highly urbanised areas (Berlin, Hamburg) with up to 4,123 inhabitants/km^2 to rural regions (Neubrandenburg) with 732 inhabitants/km^2. The final study population consisted of 205,414 men and women aged 19–74 years. The participants were not required to still live in the study regions during baseline examination, when also the residence information was updated. Since up to several years could lie between the random sampling and baseline assessment, participants could have already moved out of the study regions.

2.2. Environmental exposures - data gathering, processing, cleaning and quality control

An overview of the environmental exposures together with the respective data sources, the specific indicators, and temporal and spatial resolution is given in Table 1. Data gathering and processing is described in detail in the following paragraphs. Since all data were collected from published sources, we refer to the respective references (below and Table 1) for specific data cleaning and quality control aspects. We visually investigated implausible values, missing data or extreme outliers by generating maps of all parameters.

2.2.1. Urbanisation

Degree of Urbanisation was gathered from Eurostat which classifies the European local administrative units (LAU; for Germany the municipalities) into three categories: cities (densely populated areas), towns and suburbs (intermediate density areas), and rural areas (thinly populated areas) (EUROSTAT, 2020). We downloaded the source dataset 2020 which is based on the population grid from 2018 (JRC2018) and administrative boundaries from 2020 (LAU2 2020). In addition, we obtained population density at a 5 km × 5 km, 1 km × 1 km and 100 m × 100 m grid from a private company (WIGeoGIS GmbH) for 2018 reflecting the smaller and larger neighbourhood.

2.2.2. Air pollution

Air pollution data was collected from two different sources. First, we gathered spatially high-resolution data from the ELAPSE (Effects of Low-Level Air Pollution: A Study in Europe) project which centrally modelled annual mean concentrations of particulate matter with a diameter below 2.5 µm ($PM_{2.5}$), nitrogen dioxide (NO_2), warm season (April to September) O_3 and the absorbance of $PM_{2.5}$ ($PM_{2.5}$abs) by land use regression (LUR) models for Western Europe for the year 2010 (de Hoogh et al., 2018). The model was developed by regressing routine monitoring data from the AirBase network of the European Environmental Agency on satellite observations, chemical transport model estimates, land use, and road data and validated the models with 5-fold cross-validation. The models were then applied to a 100 m × 100 m grid to compile concentration maps. Second, hourly air quality data with a spatial resolution of approximately 2 km × 2 km was obtained from the Federal Environment Agency (UBA) (Umweltbundesamt). The UBA compiled Germany-wide maps using optimal interpolation to combine air quality measurements with simulated fields of the chemical transport model REM-CALGRID (Nordmann et al., 2020). We gathered all hourly maps for particulate matter with a diameter below 10 µm (PM_{10}), $PM_{2.5}$, NO_2, and O_3 for the years 2014–19 and calculated daily (for O_3 the daily maximum 8-h mean following ELAPSE) and annual means (for O_3 the warm season mean following ELAPSE).

2.2.3. Noise

We used a noise map for Germany with a resolution of 10 m × 10 m that delineates five day-evening-night level (Lden) noise classes (55: 55–59 dB(A), 60: 60–64 dB(A), 65: 65–69 dB(A), 70: 70–74 dB(A), 75: ≥ 75 dB(A)) (Staab et al., 2024). Missing data was coded as 40 dB(A) for the areas covered by the Environmental Noise Directive (END) obligation 2002/49/EG Article 3 section k (Directive, 2002), and as missing (NA) for the remaining grid cells. The original data was derived from the strategic road traffic noise maps for Germany for the reference year 2017 from the central European Environment Information and Observation Network (EIONET) data repository of the European Environment Agency (European Environment Agency (EEA)a). Since each reporting unit is responsible for the compilation of the respective map, 84 separate files were available for urban agglomerations with more than 100,000 inhabitants or affected areas along major roads with more than 3 million vehicle passages a year. The 84 separate data files therefore had to be substantially processed, harmonised, corrected for topological errors and aggregated to the final dataset (Staab et al., 2024).

2.2.4. Meteorology

Daily near-surface mean, minimum and maximum air temperature on a 1 km × 1 km grid was estimated using a three-stage spatiotemporal model since the year 2000 (Nikolaou et al., 2022). Thereby, ground-based air temperature measurements were combined with satellite-based land surface temperature (LST) and spatial predictors. In the first stage, a linear mixed effects model with daily random intercepts and slopes was developed on the combinations of days and grid cells with both air temperature measurements and LST data available to calibrate their strong relationship, also considering various spatial predictors. In the second stage, the first-stage model was applied to the days and grid cells without air temperature measurements but with available LST data to predict air temperature for these combinations. To achieve full air temperature coverage for all days and grid cells, the second-stage temperature predictions were regressed against thin-plate spline interpolated temperature values in the third stage. Diurnal temperature range (T_{range}) was then calculated as the difference of the daily maximum and minimum air temperature. All temperature indicators are also available as seasonal and annual averages since the year 2000. Based on the air temperature predictions, ground-based relative humidity measurements and further modelled and satellite-derived spatiotemporal predictors, daily mean relative humidity and the standard deviation were modelled using a random forest approach and are available also on a 1 km × 1 km grid since the year 2000 (Nikolaou et al., 2023). Both the temperature and relative humidity models are continuously updated and are currently available until 2023.

2.2.5. Built environment

As indicator for greenspace, we collected satellite information on the normalised difference vegetation index (NDVI) which is calculated as the difference of the reflected radiation in the visible red and in the near infrared divided by the sum of the two. It ranges from −1 to 1, with values close to −1 indicating water, values close to 0 indicating areas without living vegetation, and values close to 1 indicating dense green vegetation (Johannessen et al., 2023). We gathered NDVI data from two sources with different temporal resolutions. Monthly NDVI data on a 1 km × 1 km grid were available from the NASA Terra Moderate

Table 1
Overview of environmental exposures and specific indicators individually assigned to residential addresses of NAKO participants.

Indicator	Specific indicators	Statistic	Temporal resolution	Spatial resolution	Provenance
Urbanisation	Degree of urbanisation	Three categories (cities, towns and suburbs, rural areas)	Reference year (2018)	Municipality level	EUROSTAT (EUROSTAT, 2020)
	Population density	N/km^2	Reference year (2018)	5 km × 5 km 1 km × 1 km 100 m × 100 m	WiGeoGIS GmbH
Air pollution	$PM_{2.5}$, $PM_{2.5}$abs, NO_2, O_3	Mean	Annual; O_3: warm season (2010)	100 m × 100 m	ELAPSE (de Hoogh et al., 2018)
	PM_{10}, $PM_{2.5}$, NO_2, O_3	Mean; O_3: daily maximum 8-h mean	Daily to annual; O_3: warm season (2014–19)	1 km × 1 km	UBA (Nordmann et al., 2020)
Noise	Ambient road traffic noise day-evening-night levels (Lden)	Mean in buffer: 10 m, 100 m	Annual (2017)	10 m × 10 m	EIONET (European Environment Agency (EEA)a)
Meteorology	Air temperature	Mean, min, max, diurnal range	Daily, seasonal, annual (2014–19)	1 km × 1 km	HMGU (Nikolaou et al., 2022)
	Relative humidity	Mean, SD	Daily, seasonal, annual (2014–19)	1 km × 1 km	HMGU (Nikolaou et al., 2023)
Built environment	Greenspace: Normalised Difference Vegetation Index (NDVI)	Focal mean: 300 m, 1 km	Bi-annual (2015–17)	10 m × 10 m	German Aerospace Center (Weigand et al., 2020)
	Greenspace: Normalised Difference Vegetation Index (NDVI)	Mean	Monthly to vegetation period (2014–19)	1 km × 1 km	MODIS (Didan, 2015)
	Land cover	Focal mean: 300 m, 1 km	Bi-annual (2015–17)	10 m × 10 m	German Aerospace Center (Weigand et al., 2020)

$PM_{2.5}$: particulate matter with an aerodynamic diameter ≤2.5 µm; $PM_{2.5}$abs: $PM_{2.5}$ absorbance; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter with an aerodynamic diameter ≤10 µm; SD: Standard deviation; UBA: Federal Environment Agency.

Resolution Imaging Spectroradiometer (MODIS) (Didan, 2015). We calculated annual vegetation period means by averaging the months between March and October. To exclude water pixels, we masked the data using a mask layer (MOD44W). Remaining negative values were set to missing for both NDVI measures. The German Aerospace Center provided long-term values at a 10 m × 10 m resolution averaging all Sentinel-2 images collected between June 27, 2015 and September 29, 2017 with a cloud cover lower than 60 % (Weigand et al., 2020). Additionally, we obtained land cover data from the German Aerospace Center, matching the same temporal and spatial resolution (Weigand et al., 2020). From the original seven land cover types (artificial land, open soil, high seasonal vegetation, high perennial vegetation, low seasonal vegetation, low perennial vegetation and water), we combined the four vegetation categories into one.

2.3. Procedure for linkage of environmental data with health data to secure data protection

The NAKO independent trust centre at the University Medicine of Greifswald administrates the person identifying data like the addresses. It performed the geocoding of participants' residential sampling and baseline addresses using a proprietary algorithm (Appendix A, Supplementary Methods). Only the geocodes together with a specific pseudonym (ID-EDU) were securely transferred once to the NAKO environmental data unit (EDU) located at Helmholtz Munich (Fig. 1). The EDU assigned the environmental exposures to the geocoded addresses. For subsequent epidemiological analyses, only the assigned exposure values are linked to the respective health information. For each data application, the data transfer unit submits the ID-EDU with an application-specific pseudonym (ID-A) to the EDU. The EDU combines the requested environmental data replacing ID-EDU with ID-A and hands it back for linkage with the health data. In future, we also intend to integrate a selection of the environmental variables such as the annual averages into the research database at the data integration centre.

2.4. Harmonisation and assignment of environmental exposures to participants' addresses

Before the actual assignment, all exposure maps were harmonised and in case reprojected into an INSPIRE (Infrastructure for Spatial Information in the European Community) (European Commision (EC), 2019) conform joint projection (EPSG:3035, ETRS89-extended/LAEA Europe) which is the recommended standard for Europe (European Commission). The respective reference grids were downloaded from the German Federal Agency for Cartography and Geodesy (© GeoBasis-DE/BKG (2018)). Since the original UBA air pollution data was issued in two different spatial resolutions (until 2016: ~1.7 km x ~2.3 km; from 2017 on: 2.4 km × 2.4 km), we applied bilinear resampling to the 24 h-mean concentrations to achieve a consistent INSPIRE conform spatial resolution of 1 km × 1 km for the whole study period.

For most of the exposure maps, we assigned the values of the corresponding grid cells the participants' geocodes were located in using the extract() function from the R package raster (raster, 2024). For the spatially highly resolved noise data, we calculated the mean noise levels in buffers of 10 and 100 m around the geocodes to derive area-weighted mean noise levels on a continuous scale. Beforehand, grid cells without data (coded as 40 dB(A) or NA) were set to 40 dB(A) as lower limit of detection. Similarly, for the spatially highly resolved greenspace and land cover data from the German Aerospace Center, we calculated surrounding focal means of 300 m and 1 km to capture the built environment in the neighbourhood of the place of residence. The degree of urbanisation was assigned based on the municipality identification number.

2.5. Description of the multi-exposure environment

We generated maps for all environmental exposures to visualise the spatiotemporal patterns across Germany. To describe the participants' individual exposure to the environmental indicators, we calculated descriptive statistics and compiled boxplots, the latter also stratified by study centre and degree of urbanisation. Moreover, we calculated Spearman correlation coefficients to investigate the interplay between the multiple environmental exposures.

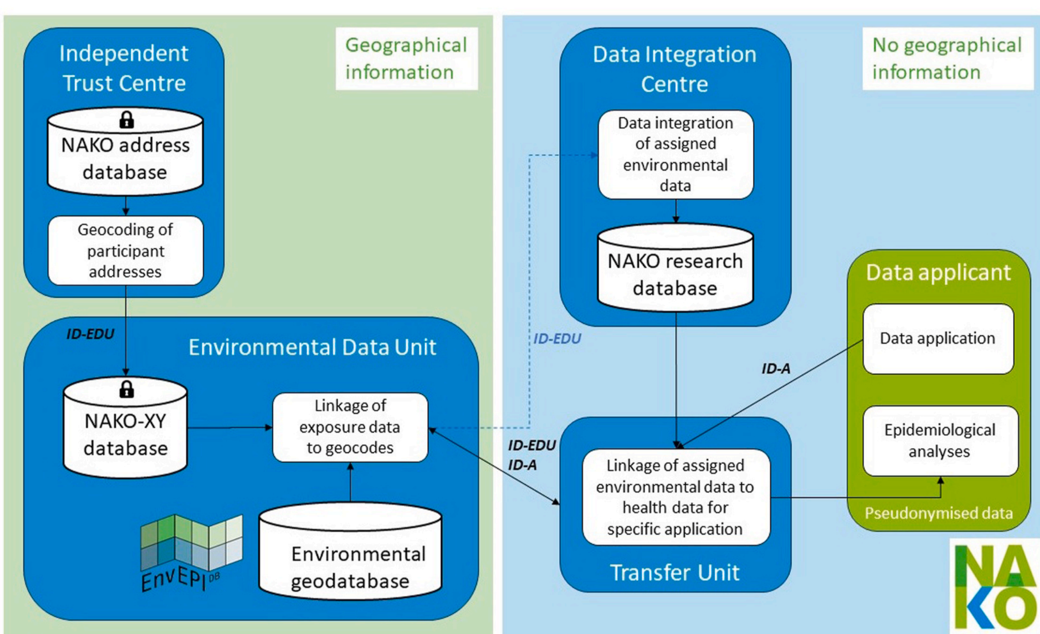

Fig. 1. Procedure to link environmental data to NAKO participants and secure data protection of individual address information. The blue dashed arrow visualises an intended workflow that is not yet established. ID-A: application-specific pseudonym; ID-EDU: geocode-specific pseudonym. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3. Results

3.1. Distribution of residential addresses

From the originally recruited 205,414 participants, 362 participants had revoked their informed consent completely, resulting in 205,053 participants by the end of the baseline recruitment in October 2019 (Peters et al., 2022). Further revocations (N = 307) and addresses that could not be geocoded (N = 4) reduced the number of participants included in this analysis to 204,742. Of these, 6,940 participants changed their address between random sampling and baseline examination, of which 5,310 participants moved more than 1 km, 1,487 moved more than 10 km, and 234 moved more than 100 km away. Fig. 2 visualises the number of participants for these two time periods per grid cell of a 5 km × 5 km raster laid over Germany. The distributions clearly demonstrate that almost all participants lived in the study regions during recruitment, whereas several moved out and spread across Germany between sampling and baseline examination. A detailed overview of the number of participants per study centre (where the examination took place) and study region (where the participants lived at the date of baseline examination) showed that 819 participants no longer lived in one of the study centre regions and 53 participants travelled to another study centre for the examination (Appendix B, Supplemental Table S1). The following descriptive analyses refer to the participants' residences at baseline examination.

3.2. Degree of urbanisation

The study regions were categorised as either urban (Hamburg, Bremen, Berlin, Hannover, Münster, Essen, Leipzig, Düsseldorf, Mannheim), or as a mixture of mostly suburban and rural areas (Neubrandenburg), or a mixture of all three categories (Kiel, Halle, Saarbrücken, Regensburg, Augsburg, Freiburg) (Fig. 3). Accordingly, 71 % of the participants resided in urban areas (N = 146,616), 16 % in suburban areas (N = 32,203), and 13 % in rural areas (N = 25,848). This variation is also reflected in the population density ranging from 16 to 300,378 inhabitants per 5 km × 5 km grid cell (Table 2 and Supplemental Fig. S1) and the individually assigned environmental exposures.

3.3. Air pollution

The spatially highly resolved ELAPSE models showed a larger variation with generally higher 2010 annual average $PM_{2.5}$, NO_2 and O_3 levels ranging from 9.0 to 23.9, 4.7–78.1 and 46.2–102.6 μg/m^3, respectively, compared to the less spatially-resolved UBA models (2014

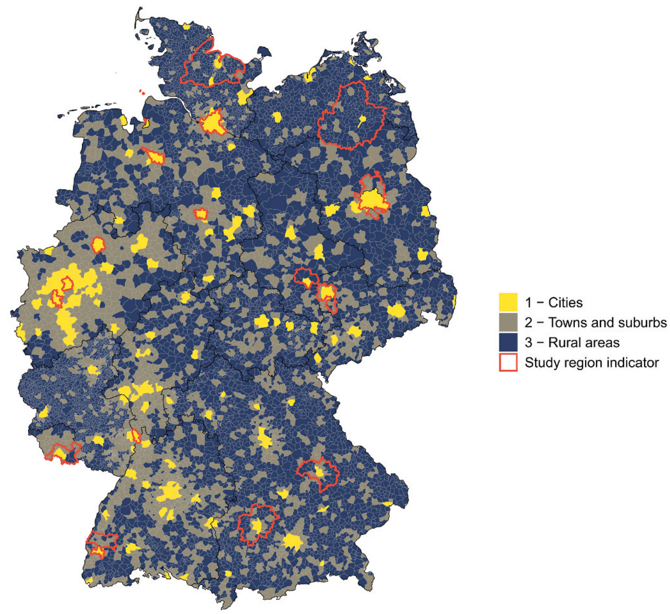

Fig. 3. Degree of Urbanisation (DEGURBA) based on source dataset from EUROSTAT, 2020 across Germany.

annual average $PM_{2.5}$, NO_2 and O_3 ranging from 6.5 to 20.5, 4.3–35.7 and 65.5–96.5 μg/m^3, Table 2 and Supplemental Figs. S2 and S3). The improvement in air quality over the years was further seen when comparing the UBA estimates for 2014 and 2019 with median $PM_{2.5}$ and NO_2 concentrations decreasing from 14.2 to 17.8 to 10.2 and 15.6 μg/m^3, respectively, except for O_3 which increased from 82.3 to 87.9 μg/m^3 (Table 2 and Supplemental Fig. S3). Nevertheless, in 2019, 100 % and 82 % of the participants were still exposed to concentrations above the WHO recommendations of 5 μg/m^3 for $PM_{2.5}$ and 10 μg/m^3 for NO_2 (Supplemental Fig. S4) (World Health Organization WHO, 2021). A comparison of the concentrations by degree of urbanisation and study region showed highest levels for urban and lowest for rural areas, and a large heterogeneity across the study regions in terms of levels and ranges (Supplemental Figs. S5–S8).

3.4. Noise

As a result of the strategic noise mapping only being required for selected exposed areas, data was primarily available for participants

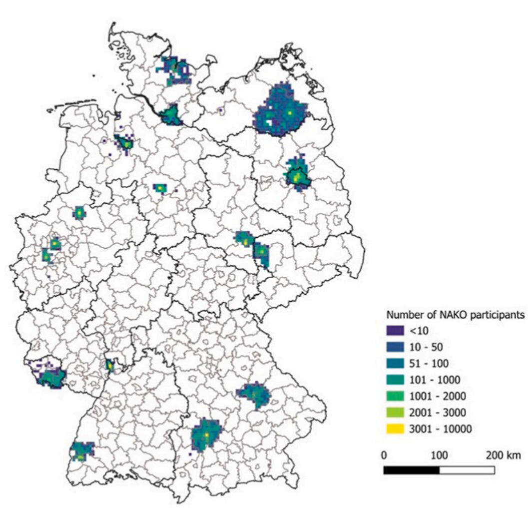

Fig. 2. Distribution of residential addresses from NAKO participants at random sampling (left) and baseline examination (right) per 5 km grid.

Table 2
Distribution of environmental exposures at baseline residences of NAKO participants (N = 204,742).

Indicator	Year	Missing								
		N (%)	Mean	SD	Min	5 %	Median	95 %	Max	IQR
Urbanisation										
P_{dens} 5 km (N)	2018	0 (0)	68,940	68,574	16	1,686	45,734	230,394	300,378	90,009
P_{dens} 1 km (N)	2018	12 (0)	4,682	4,387	0	144	3,463	14,133	22,178	5,310
P_{dens} 100m (N)	2018	262 (0.1)	97.4	87.0	0	8	70	296	1,516	109
Air pollution										
ELAPSE model										
$PM_{2.5}$ (μg/m^3)	2010	0 (0)	17.3	2.0	9.0	14.1	17.2	20.6	23.9	2.9
$PM_{2.5}$abs (10^{-5}/m)	2010	0 (0)	1.7	0.4	0.7	1.0	1.6	2.3	4.1	0.5
NO_2 (μg/m^3)	2010	0 (0)	27.2	8.2	4.7	14.3	26.9	41.4	78.1	10.6
O_3 (μg/m^3)	2010	0 (0)	84.0	5.4	46.2	74.4	84.7	91.4	102.6	6.4
UBA model										
PM_{10} (μg/m^3)	2014	0 (0)	18.7	3.7	7.6	11.2	18.8	25.3	27.0	3.8
	2019	0 (0)	14.5	2.3	6.9	10.7	14.4	18.4	21.4	2.8
$PM_{2.5}$ (μg/m^3)	2014	0 (0)	14.1	2.9	6.5	9.4	14.2	20.0	20.5	2.6
	2019	0 (0)	10.4	1.6	6.0	8.2	10.2	13.8	14.6	2.0
NO_2 (μg/m^3)	2014	0 (0)	17.4	6.8	4.3	5.5	17.8	29.3	35.7	9.8
	2019	0 (0)	15.8	6.2	3.7	5.5	15.6	26.8	33.6	8.8
O_3 (μg/m^3)	2014	0 (0)	81.5	4.9	65.5	72.3	82.3	88.8	96.5	6.1
	2019	0 (0)	87.4	3.5	73.7	80.7	87.9	92.1	95.1	5.3
Noise										
Lden 10m (dB(A))	2017	0 (0)	44.4	7.9	40.0	40.0	40.0	62.8	75.0	5.6
Lden 100m (dB(A))	2017	0 (0)	44.6	6.1	40.0	40.0	40.7	57.1	73.0	8.3
Meteorology										
Air temperature										
T_{mean} (°C)	2014	64 (0)	11.2	0.7	8.0	9.7	11.4	12.0	12.4	0.9
	2019	64 (0)	11.3	0.8	7.8	9.6	11.4	12.3	12.7	1.0
T_{min} (°C)	2014	64 (0)	6.8	0.7	3.7	5.4	7.0	7.7	8.3	1.0
	2019	64 (0)	6.5	0.7	2.9	4.9	6.7	7.4	7.7	1.0
T_{max} (°C)	2014	64 (0)	15.8	0.7	12.4	14.6	15.8	16.7	17.6	0.9
	2019	64 (0)	15.9	0.6	12.6	14.8	15.9	16.8	17.4	1.0
T_{range} (°C)	2014	64 (0)	9.0	0.5	6.3	8.2	8.9	9.7	10.6	0.6
	2019	64 (0)	9.4	0.6	7.1	8.5	9.4	10.4	11.8	0.8
Relative humidity										
RH Mean (%)	2014	129 (0.1)	79.3	1.8	75.6	76.2	79.3	82.1	85.1	3.0
	2019	129 (0.1)	74.9	2.4	70.2	71.4	74.9	79.0	81.8	3.7
RH SD (%)	2014	129 (0.1)	10.1	1.3	7.0	8.3	10.0	12.1	13.3	2.4
	2019	129 (0.1)	12.0	1.2	7.2	9.3	12.2	13.7	15.3	1.4
Greenspace										
MODIS										
NDVI	2014	6,641 (3.2)	0.56	0.10	0.08	0.38	0.57	0.70	0.83	0.15
	2019	6,641 (3.2)	0.54	0.10	0.08	0.37	0.55	0.68	0.84	0.14
German Aerospace Center										
NDVI 300m	2016	422 (0.2)	0.10	0.03	0.00	0.05	0.10	0.16	0.28	0.04
NDVI 1 km	2016	422 (0.2)	0.11	0.03	0.01	0.05	0.11	0.16	0.29	0.05
Land cover										
Land cover 300m										
Artificial land (%)	2015	521 (0.2)	67.9	24.8	0	18	74	98	100	37
Open soil (%)	2015	521 (0.2)	0.07	0.63	0	0	0	0	33	0
Vegetation (%)	2015	521 (0.2)	31.0	24.6	0	2	25	80	100	37
Water (%)	2015	521 (0.2)	1.0	3.8	0	0	0	6	76	0
Land cover 1 km										
Artificial land (%)	2015	521 (0.2)	53.5	26.2	0	6	56	91	99	43
Open soil (%)	2015	521 (0.2)	0.15	0.58	0	0	0	1	21	0
Vegetation (%)	2015	521 (0.2)	44.0	26.3	1	8	41	92	100	42
Water (%)	2015	521 (0.2)	2.2	5.0	0	0	0	11	66	2

N: Total number; SD: Standard deviation; IQR: interquartile range; P_{dens}: population density; $PM_{2.5}$: particulate matter ≤2.5 μm; $PM_{2.5}$abs: $PM_{2.5}$ absorbance; NO_2: nitrogen dioxide; O_3: ozone; PM_{10}: particulate matter ≤10 μm; Lden: Ambient road traffic noise day-evening-night levels; T: temperature; T_{range}: Diurnal temperature range; RH: Relative humidity; NDVI: Normalised Difference Vegetation Index; MODIS: NASA Terra Moderate Resolution Imaging Spectroradiometer.

living in urban areas of which about one third were exposed to levels of 55 dB(A) and higher (Supplemental Figs. S9 and S10). Noise levels were available for 8 % of the participants living in suburban areas and for 3 % living in rural areas. Comparing the study regions, levels were highest in the city centres (Hamburg, Bremen, Hannover, Münster, Essen, Düsseldorf, Mannheim) with altogether highest levels in Düsseldorf (Supplemental Fig. S11). After setting all missing values to a lower limit of detection of 40 dB(A), the weighted mean noise levels in buffers of 10 and 100 m showed a mean of 44.4 and 44.6 dB(A), respectively (Table 2).

3.5. Meteorology

Annual mean, minimum and maximum air temperature for 2014 ranged between 8.0 and 12.4, 3.7–8.3 and 12.4–17.6 °C and T_{range} between 6.3 and 10.6 °C (Table 2). While minimum temperature decreased, the other indicators slightly increased from 2014 to 2019, especially T_{range} from a mean of 9.0–9.4 °C (Table 2 and Supplemental Fig. S12). Similar to noise, highest levels were observed for urban areas and lowest for rural areas except for T_{range} which showed an opposite trend (Supplemental Fig. S13). Moreover, the violin plots and boxplots across study regions indicated heterogeneity in the levels and ranges but also with regard to the changes from 2014 to 2019, e.g., mean air temperature increased considerably for Berlin and Hannover but was rather stable or slightly decreased for other regions (Supplemental Fig. S14). Annual mean relative humidity decreased from 79.3 % in 2014 to 74.9 % in 2019, whereas the mean standard deviation increased from 10.1 to 12.0 % (Table 2 and Supplemental Fig. S15). The range of mean relative humidity was comparably larger in urban areas than in suburban or rural regions with heterogeneous distributions across the study centres (Supplemental Figs. S16 and S17).

3.6. Built environment

Long-term NDVI from the German Aerospace Center was similar for both surroundings (300 m and 1 km) with comparably small levels ranging from 0.01 to 0.29 for the latter (Table 2 and Supplemental Fig. S18). The vegetation period average from MODIS monthly values showed considerably larger levels and contrasts, e.g., 0.10–0.83 for 2014 (Table 2). The respective MODIS maps indicated some variation over the years with e.g., lower levels for 2018, but no clear time trend (Supplemental Fig. S19). As expected, a higher degree of vegetation was observed for rural regions compared to urban areas and levels decreased from 2014 to 2019 with a stronger decrease in rural regions (Supplemental Figs. S20 and S21). Land cover showed highest proportions for artificial land with a mean of 67.9 % within 300 m and 53.5 % within 1 km and vegetation (31.0 % within 300 m and 44.0 % within 1 km, see Table 2 and Supplemental Fig. S22).

3.7. Multi-exposure environment

Spearman correlation was moderate to high within the different exposure groups, e.g., ranging from 0.5 to 0.9 for the air pollutants (except O_3 which showed an inverse association), 0.8 for the noise indicators, NDVI (0.9) and population density (0.6–0.8), respectively (Fig. 4). Regarding the built environment, artificial land and vegetation within 300 m showed an extremely high inverse correlation (−1.0) but no correlation with open soil or water at all. Also, vegetation and NDVI were highly correlated (0.7–0.9) and thus, both were inversely correlated with population density (−0.7 to −0.6). The meteorological indicators showed high correlation between the minimum, mean and maximum temperature (0.8–0.9) and high inverse correlation between mean relative humidity and its standard deviation or maximum temperature (−0.8). Correlations between the groups were mostly low to moderate, but high correlations were observed for population density with minimum and mean temperature, ELAPSE NO_2 and $PM_{2.5}$abs (all 0.8).

4. Discussion

This paper describes the comprehensive characterisation of the multi-exposure environment of Germany's largest prospective adult cohort NAKO. We present exposure maps for long-term air pollution, ambient road traffic noise, meteorology (air temperature, relative humidity), and characteristics of the built environment (urbanisation, greenspace, land cover) based on their high relevance for health. After harmonisation and processing of the maps, we extracted relevant indicators at the participants' residential addresses to assess individual exposures. We observed a large variation in all of the assigned environmental exposures which is based on the heterogeneity of the 16 study regions including highly urbanised areas, medium-sized cities but also rural regions.

With regard to air pollution, the $PM_{2.5}$ and NO_2 maps of both sources (ELAPSE and UBA) generally showed similar exposure patterns and spatial contrasts. Although the assigned concentrations displayed a greater variability for the higher spatially resolved ELAPSE data with higher 2010 averages compared to the lower spatially resolved UBA data for 2014 and 2019, the correlation was high (0.6 and 0.8 for UBA 2019 $PM_{2.5}$ and NO_2 with ELAPSE). For O_3, the spatial contrasts varied over the years for the UBA predictions and showed only a low correlation with ELAPSE (0.3 with UBA 2019). Similar to $PM_{2.5}$ and NO_2, the assigned ELAPSE O_3 concentrations displayed greater variability than

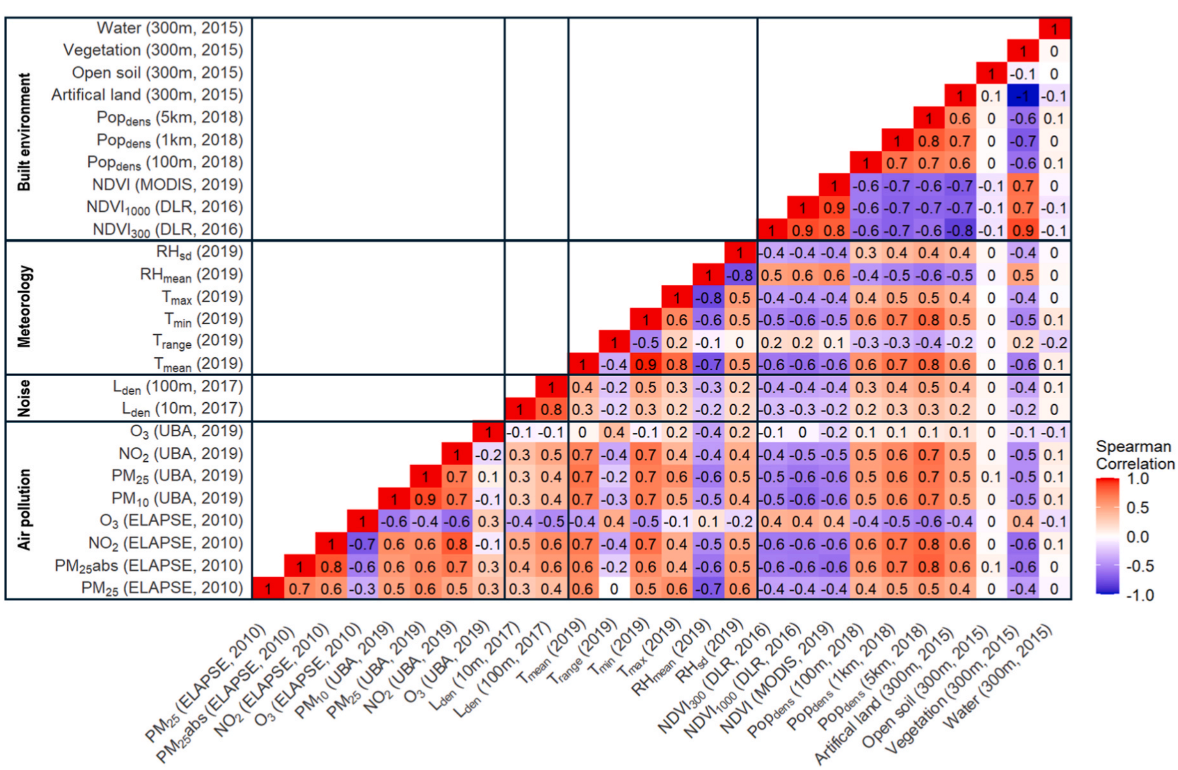

Fig. 4. Spearman correlation coefficients of the environmental exposures at residential baseline addresses (most recent available year).

the UBA O_3 concentrations. However, while O_3 increased from the start of the baseline examination in 2014 to the end in 2019, we observed a decrease in $PM_{2.5}$ and NO_2 which aligns with European-wide models (Shen et al., 2022) and measurements (European Environment Agency (EEA)b). In 2019, all participants were exposed to concentrations below the current annual EU air quality standards of 25 and 40 μg/m^3 for $PM_{2.5}$ and NO_2, but most of them were above the annual WHO guideline levels of 5 and 10 μg/m^3. The European Union (EU) has recently revised its Ambient Air Quality Directive (AAQD) which entered into force in December 2024 (Directive, 2024). The revised AAQD aims to align more closely with the WHO recommendations and foresees 10 and 20 μg/m^3 for $PM_{2.5}$ and NO_2 by 2030. In addition to regulated air pollutants, the WHO suggested to assess exposure to black carbon and ultrafine particles (UFP) due to their potential health relevance, which has been taken up by the EU in its revised AAQD by including mandatory UFP monitoring (World Health Organization WHO, 2021; Directive, 2024). Evidence is still limited since measurements and models are lacking. We assigned $PM_{2.5}$abs as indicator for black carbon and aim to add UFP as soon as data is available for our NAKO study regions.

Air pollution is often correlated with road traffic noise due to shared sources, but we observed only a low to moderate correlation between our air pollution and noise indicators. We used harmonised strategic noise maps delivered under the END (Directive, 2002; European Commision (EC), 2002) since a Germany-wide noise model was not available. Of all NAKO participants, 22 % were exposed to road traffic noise levels above 55 dB Lden which are considered harmful for health (European Environment Agency (EEA)c). However, recent studies indicate that even noise levels below 55 dB Lden, which are currently not required in the END mapping, can already contribute to adverse health effects (Veber et al., 2022; Hegewald et al., 2021). Since the modelling and documentation of levels below 55 dB(A) is not required, the NAKO noise database contains this information only for a subset of the study population. Moreover, we could not assign noise values to 31 % of our participants since they lived in regions outside the mandatory END mapping. The END noise maps also showed discrepancies regarding the underlying noise mapping methods, data formats, borders, and reporting (Staab et al., 2024; Khomenko et al., 2022). Thus, we agree with Khomenko and colleagues (Khomenko et al., 2022) that continuous noise data mapping with wider noise exposure ranges would improve the data quality and accuracy to assess population exposure to road traffic noise in current as well as future analyses. For subsequent epidemiological analyses using this data, we therefore presume an underestimation of the actual association with health.

Air temperature levels mostly increased during our baseline examination with highest levels for urban areas confirming the general European and global trends due to climate change (Copernicus). We assigned several indicators (minimum, mean, maximum, T_{range}) as next to increases in temperature and temperature extremes, also the increased intraday und interday variability can be harmful for health (Masselot et al., 2023; Zhang et al., 2023; Khraishah et al., 2022; Guo et al., 2016; Liu et al., 2023; Wu et al., 2022). In addition, relative humidity is usually taken into account as potential confounder or effect modifier but has also been reported as an independent risk factor for health (Mei et al., 2023; Guarnieri et al., 2023; Lepeule et al., 2018). Furthermore, factors of the built environment play an important role when investigating the effects of temperature, e.g., the cooling effects of greenspace and mitigation of urban heat islands (Heaviside et al., 2017; Qin et al., 2024). Greenspace is also inversely correlated with air pollution and noise. Moreover, interactive effects have been reported for heat and air pollution (Rai et al., 2023; Stafoggia et al., 2023). The role of population density or urbanicity can be considered either as an effect modifier or a risk factor (Niedermayer et al., 2024; Poulsen et al., 2023; Ohanyan et al., 2022), depending on the specific outcome of interest. This is particularly relevant for NAKO, which included study regions encompassing urban, suburban, and rural areas. Thus, future analyses should investigate not only single exposures but the joint and interactive effects from an exposome perspective to improve our understanding of the complex interplay, among each other but also with individual characteristics of the NAKO participants.

A major strength of our study is the large number or participants living in rural to urban regions reflecting a large variation in their multi-exposure environment. We enriched the wealth of NAKO data by adding high-quality environmental indicators which enables future multi-exposure analyses. The environmental exposures characterised in this paper showed high to moderate overall correlation. It is important to point out that the study regions display different correlation patterns and therefore, the overall power to disentangle the specific effects as well as quantify the interactions between environmental exposures is exceeding substantially the power of smaller, single region studies. We will continuously extend the portfolio by adding further indicators of climate change, for example number of heat and cold days, soil moisture, novel exposures like light pollution, walkability and biodiversity. In addition, we will enhance already characterised environmental exposures by improved exposures maps, for example assigning higher temporally and spatially resolved air pollution exposures from the EXPANSE project (Shen et al., 2022). The longitudinal analysis of environmental effects on health is enabled by two key factors: annual exposure to environmental factors over long time periods and repeated examinations in NAKO. In addition, daily exposures at participants' residences are available for a number of environmental factors, including air pollution and ambient temperature. These, combined with physical examinations such as blood pressure, cognitive and lung function tests, also allow the investigation of short-term effects on a range of health outcomes. Furthermore, we will also consider regional and neighbourhood indicators such as unemployment rates, area deprivation, and education or income levels, in addition to individual socioeconomic factors. Similar to urbanicity, these factors can be considered either as modifier for environmental exposures or as an independent risk factor for various health outcomes (Dreger et al., 2019; Cui et al., 2024; Lin et al., 2023). Finally, we tried to minimise the uncertain geographic context problem by i) assessing the individual exposures at the residential locations which we proxy as a key place of exposure, ii) using the highest spatial resolution that was comparable for all data points across Germany, and iii) calculating different buffer sizes around the residencies to assess different spatial neighbourhoods with buffer sizes based on the literature and prior knowledge.

Nevertheless, a major challenge is the difference in the spatial and temporal coverage and resolution of available exposure data which might introduce exposure measurement error in future epidemiological analyses. Rather than considering measurement data from routine monitoring sites, our focus was on the assignment of highly resolved spatial or spatio-temporal data available for entire Germany to assess participants' individual exposure at their residences. Especially for noise, the coverage is limited which lead to a high number of missings or of participants in low exposure levels. Also, the categorical nature of the data and restricted comparability across the modelled regions will be a challenge for subsequent environmental health analyses. Moreover, exposure to railway or aircraft noise has not been assigned in this first step due to linear and selective exposure but might be included in future. Moreover, the use of exposure variables with different time periods might influence the results of the epidemiological analyses. However, long-term studies are mainly investigating spatial contrasts which have been reported to remain stable over time (Brunekreef et al.; de Hoogh et al., 2018; Cesaroni et al., 2012; Vienneau et al., 2017). For air pollution, we therefore decided to not only assign the UBA data which cover the NAKO baseline examination period but also the older 2010 annual averages from ELAPSE due to the higher spatial resolution. A general challenge is the exposure assessment by linking environmental data to the residential addresses without knowing the exact amount of time that people spend at home as currently, time-activity patterns are not available for the NAKO participants. However, studies comparing differences between residential and time-activity integrated exposures showed large correlations between exposure levels (>0.8) and almost identical health effect estimates (Hoek et al., 2024). As these comparative studies were mainly conducted in North America and Europe, we are confident that this also applies to our cohort and that the bias related to the assessment of long-term exposure at the residential address in subsequent epidemiological analyses is likely small. Last, we did not consider synergistic or interactive effects to identify co-occurring exposure profiles and disentangle the main drivers. Sophisticated methods are required to further elucidate the exposome perspective, which are beyond the scope of this paper but should be investigated in the future.

5. Conclusion

For the first time in Germany, a comprehensive population-based dataset with high-quality environmental indicators is available. This opens new potential for innovative research and deriving policy-relevant information. Questions such as whether social disparities in health are interlinked with environmental exposures can now be analysed, covering the population in whole Germany in a comparative approach. Expanding the database by adding innovative indicators such as light pollution, walkability, or biodiversity as well as socioeconomic factors such as unemployment rate or area deprivation will further increase its impact on science and public health.

CRediT authorship contribution statement

Kathrin Wolf: Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Marco Dallavalle:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Fiona Niedermayer:** Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Gabriele Bolte:** Writing – original draft, Conceptualization. **Tobia Lakes:** Writing – original draft, Conceptualization. **Tamara Schikowski:** Writing – original draft, Conceptualization. **Karin Halina Greiser:** Writing – review & editing. **Lars Schwettmann:** Writing – review & editing. **Ronny Westerman:** Writing – review & editing. **Nikolaos Nikolaou:** Writing – review & editing, Resources. **Jeroen Staab:** Writing – review & editing, Resources. **Robert Wolff:** Writing – review & editing, Resources. **Gunthard Stübs:** Writing – review & editing, Resources. **Stefan Rach:** Writing – review & editing, Resources. **Alexandra Schneider:** Writing – review & editing, Supervision. **Annette Peters:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Barbara Hoffmann:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Ethics approval and consent to participate

The German National Cohort (NAKO) study is performed with the approval of the relevant ethics committees, and is in accordance with national law and with the Declaration of Helsinki of 1975 (in the current, revised version). Written informed consent was obtained from all participants.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marco Dallavalle reports financial support was provided by the Federal Ministry of Education and Research. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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List of abbreviations

AAQD	Ambient Air Quality Directive
EDU	Environmental data unit
EIONET	European Environment Information and Observation Network
END	Environmental Noise Directive
EU	European Union
INSPIRE	Infrastructure for Spatial Information in the European Community
Lden	Ambient road traffic noise day-evening-night level
LAU	Local administrative units
LST	Land surface temperature
LUR	Land use regression
NAKO	German National Cohort
MODIS	NASA Terra Moderate Resolution Imaging Spectroradiometer
NDVI	Normalised difference vegetation index
NO2	Nitrogen dioxide
O3	Ozone
PM2.5	Fine particles, particles smaller than 2.5 μm
PM2.5 abs	Absorbance of PM2.5
Trange	Diurnal temperature range
UBA	Federal Environment Agency
UFP	Ultrafine particles

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2025.121259.

Data availability

The data that has been used is confidential.

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