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ABSTRACT

BACKGROUND

Cumulative environmental exposures and social deprivation increase health vulnerability and limit the capacity of populations to adapt to climate change.

OBJECTIVE

Our study aimed at providing a fine-scale characterization of exposure to heat, air pollution, and lack of vegetation in continental France between 2000 and 2018, describing spatiotemporal trends and environmental hotspots (i.e., areas that cumulate the highest levels of overexposure), and exploring any associations with social deprivation.

METHODS

The European (EDI) and French (FDep) social deprivation indices, the normalized difference vegetation index, daily ambient temperatures, particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide, and ozone (O_3) concentrations were estimated for 48,185 French census districts. Reference values were chosen to characterize (over-)exposure. Hotspots were defined as the areas cumulating the highest overexposure to temperature, air pollution, and lack of vegetation. Associations between heat overexposure or hotspots and social deprivation were assessed using logistic regressions.

RESULTS

Overexposure to heat was higher in 2015-2018 compared with 2000-2014. Exposure to all air pollutants except for O_3 decreased during the study period. In 2018, more than 79% of the urban census districts exceeded the 2021 WHO air quality guidelines. The evolution of vegetation density between 2000 and 2018 was heterogeneous across continental France. In urban areas, the most deprived census districts were at a higher risk of being hotspots (odds ratio (OR): 10.86, 95% CI: 9.87-11.98 using EDI and OR: 1.07, 95% CI: 1.04-1.11 using FDep).

SIGNIFICANCE

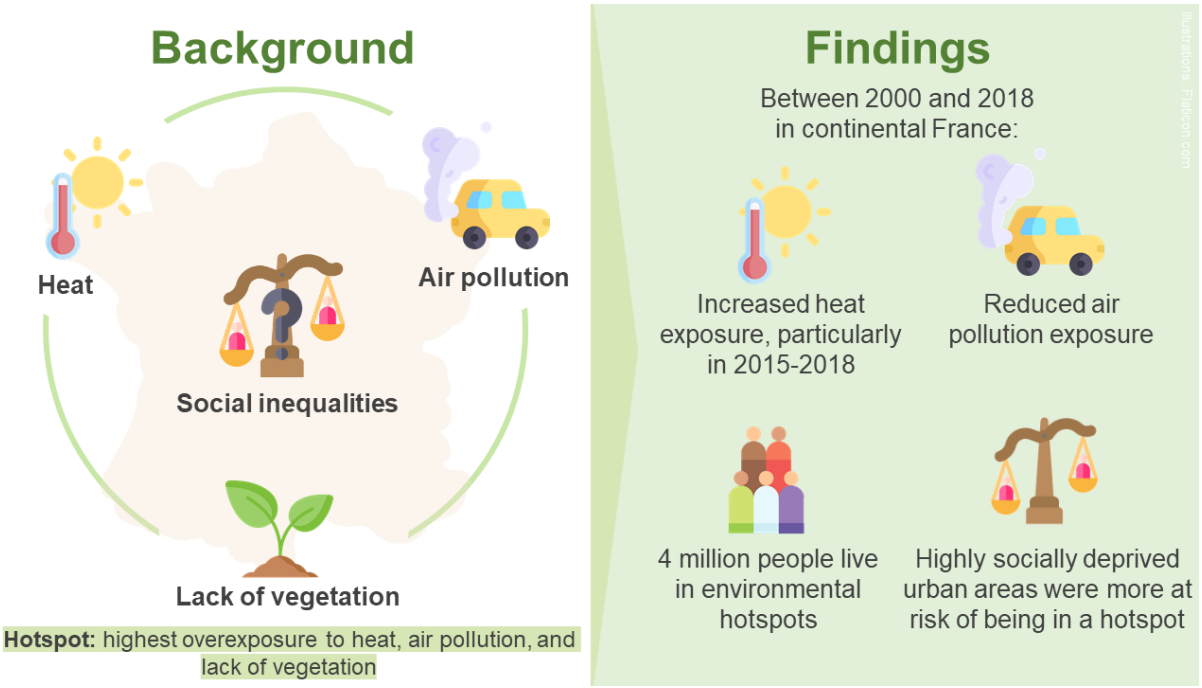
This nationwide fine-scale study provides a framework to identify environmental hotspots and reveals social inequalities in the cumulative exposure to heat, air pollutants, and lack of vegetation, in France. This approach lends support to the inclusion of environmental and social inequities in adaptation strategies to climate change.

KEYWORDS: temperature, particulate matter, green spaces, social deprivation, hotspots, environmental justice

IMPACT STATEMENT

We studied cumulative environmental exposures and social deprivation in French census districts. The 2015-2018 period showed the highest overexposure to heat between 2000 and 2018. In 2018, the air quality did not meet the 2021 WHO guidelines in most census districts and 8.6 million people lived in environmental hotspots. Highly socially deprived urban areas had a higher risk of being in a hotspot. This study proposes for the first time, a methodology to identify hotspots of exposure to heat, air pollution, and lack of vegetation and their associations with social deprivation at a national level.

GRAPHICAL ABSTRACT



INTRODUCTION

In the context of rapid climate change, heat exposure associated with the cumulative exposure to multiple environmental factors and social deprivation can increase health vulnerabilities and limit the capacity of exposed populations to adapt to climate change. This not only raises serious public health concerns but is also a source of injustice, as unequal exposure to environmental risks and unequal access to environmental goods such as parks and forests result in environmental inequities.

In Europe, areas with cumulative exposure to multiple environmental stressors tend to be more deprived (1, 2). Depending on their location, the deprived or poorer areas may be more exposed to heat (3), have lower green space availability (4, 5), and/or be more exposed air pollution (4, 6, 7).

Exposure to heat and air pollution has multiple synergistic health effects such as cardiovascular or respiratory morbidity and negative reproductive outcomes (8-11). Vegetation plays a protective role against heat (12, 13) and air pollution (14) and has numerous health benefits on mental health, cognitive function, cardiovascular morbidity, and pregnancy outcomes among others (15). In addition, socioeconomic characteristics influence the population's ability to avoid or adapt to these environmental health hazards (2).

In accordance with a holistic planetary health approach, reducing cumulative exposure to environmental risks and social deprivation should be at the heart of both public health policies and climate policies. A preliminary step in this direction is to produce comprehensive data to describe, analyze, and compare environmental exposures in time and space. However, to our knowledge, no study to date has investigated cumulative exposure to heat, air pollution, lack of vegetation, and social deprivation at a fine geographical scale and at the national level. Describing cumulative exposure at a national level allows the characterization of poorly studied territories and the targeting of heat adaptation interventions to the areas and populations most at risk.

Existing studies mostly focus on air pollution and, to a lesser extent, on vegetation, and are limited to city-level or regional analyses (16). However, air pollution, vegetation, and heat are interdependent. Vegetation contributes to air and surface cooling and thermal comfort through solar radiation absorption, evapotranspiration, evaporation, albedo modification, and radiative shading (17). It also reduces ambient air pollution by increasing the deposition of particulate matter (PM) and absorbing gaseous pollutants (14, 18) as well as by promoting non-motorized transport (18). Vegetation can also act as a physical barrier against pollutants, thus reducing their dispersion. However, this barrier effect may simultaneously increase pollutant concentrations on roads and reduce exposure to air pollution on the other side of this barrier (18). Vegetation also emits biogenic volatile organic compounds (bVOC), which can react with other chemical species that form secondary particles. For example, isoprene emissions associated with NO_x contribute to ozone (O_3) formation. Monoterpenes and sesquiterpenes can increase $PM_{2.5}$ and PM_{10} concentrations (14). Heat increases air pollution through ozone formation

due to UV radiation in the presence of nitrogen dioxide (NO_2) (19). Air pollutants such as O_3 have a negative effect on vegetation growth by affecting the metabolic function of leaves (20). More broadly, the presence of vegetation and favorable meteorological conditions have a positive impact on human behavior and thus indirectly influence air pollution. Describing cumulative exposure to heat, air pollution, and lack of vegetation could thus help support adaptation policies.

Our study aimed to characterize fine-scale exposure to heat, air pollution, and lack of vegetation across continental France between 2000 and 2018, to describe spatiotemporal trends and environmental hotspots (i.e., areas that cumulate the highest levels of overexposure), and to explore any associations with social deprivation.

MATERIALS AND METHODS

Study area and period

Drawing on the 2021 geography reference files, we analyzed the 48,185 IRIS of the 34,477 municipalities located in the 94 departments of continental France for the period 2000-2018. An IRIS is a sub-municipal geographical unit equivalent to a census district (21). Large municipalities (> 5,000 inhabitants) are divided into several IRIS, while smaller municipalities constitute their own IRIS. IRIS is the smallest geographical unit for which French census data are available.

Data

Urbanization

The 2021 urbanization level of each municipality and IRIS were obtained from the National Institute of Statistics and Economic Studies (INSEE). INSEE distinguishes between urban and rural municipalities depending on their population density. Densely populated municipalities and municipalities of intermediate density were defined as urban municipalities. Low-density and sparsely populated municipalities were considered rural municipalities (22).

Population

Population data (i.e., number of inhabitants) were obtained from INSEE at the IRIS level for the period 2014-2018 and at the municipality level for 2006-2018 (23). The population at the IRIS level for 2006-2013 was estimated using the evolution percentage of the population at the municipality level. The evolution percentage E for the year i and municipality j was thus:

$$E_{i,j} = \frac{population_{\,i,j}}{population_{\,i+1,j}}$$

Where $population$ was the number of inhabitants. Then, the estimated population $populationest$ for each IRIS k was calculated as follows:

$$populationest_{i,j,k} = population_{i+1,j} \times E_{i,j}$$

Due to the lack of harmonized data prior to 2006, we assumed that the population of each IRIS was constant between 2000 and 2006.

Climate types

We used the classification of the French meteorological information system, Météo-France, which categorizes French municipalities into eight different climates (Supplementary Figure 1): mountain climate, semi-continental climate and climate of mountainous margins, modified oceanic climate, transitional oceanic climate, oceanic climate, moderate Mediterranean climate, southwest basin climate, and Mediterranean climate (24).

Temperature

Daily minimum, mean, and maximum temperatures from 2000 to 2018 were obtained from a multi-resolution model with a 200 m² resolution for large urban areas (> 50,000 inhabitants) and 1 km² across the rest of continental France (25). These estimates were generated using spatiotemporal models based on Météo-France weather station data, satellite land surface temperature data, and additional spatial and temporal predictors such as the normalized difference vegetation index (NDVI), elevation, and land cover. Hough et al. provides more in-depth modeling methodologies and performance results (25). Daily exposure to minimum, mean, and maximum temperatures for each IRIS was estimated by calculating the area-weighted average gridded temperature data.

Vegetation

To approximate the level of vegetation, we used the NDVI, a greenness indicator ranging from -1 to +1, with higher values indicating denser vegetation. The NDVI was derived from Landsat satellite images with a 30 m spatial resolution (26). Mean summer (i.e., from June 1 to August 31 each year) NDVI was computed for each year between 2000 and 2018.

For each IRIS, the annual mean summer NDVI was estimated by calculating the area-weighted average of the gridded NDVI data.

Air pollution concentrations

Daily mean $PM_{2.5}$ and PM_{10} concentrations from 2000 to 2018 were obtained at a 1 km² resolution across continental France from a multi-stage ensemble model combining air quality monitoring data, satellite-derived aerosol optical depth, and other spatiotemporal predictors such as meteorological parameters, NDVI, and elevation (27). The increases observed in 2008-2009 for $PM_{2.5}$ and in 2007 for PM_{10} were

due to a change in the measurement techniques used by the national air quality monitoring stations to include semi-volatile PM (27, 28). We used daily mean NO_2 and daily maximum O_3 concentrations estimated by the French Institute for Industrial Environment and Risks (INERIS) based on models combining background measurements of air quality monitoring stations and modeling of the chemistry transport model with a spatial resolution of around 4 km for the period 2000-2017 and around 2 km for 2018 (29).

For each IRIS, daily exposure to $PM_{2.5}$, PM_{10}, NO_2, and O_3 was estimated by calculating the area-weighted average of the gridded concentration data.

Social deprivation

We used the 2015 version of two deprivation indices: the European Deprivation Index (EDI) (30) and the French Deprivation Index (FDep) (31) at the IRIS level. Both indices are composite measures based on a combination of census data to characterize the socioeconomic environment of the IRIS.

The EDI is a European index constructed using Eurostat data and capable of measuring relative deprivation in a transcultural way across all European countries. Its French version is a weighted combination of ten census variables grouped into two dimensions: a material dimension (non-homeowners, households without a car, households with more than two occupants, overcrowded dwellings with more than one person per room) and a social dimension (unemployment, foreigners, unskilled workers, low education level, single-parent households, unmarried status) (32). The FDep is computed using principal component analysis from four census variables: median household income, proportion of secondary school graduates (15 years and over), proportion of laborers in the active population, and proportion of unemployment in the active population.

The first quintile of FDep and EDI represents the least deprived IRIS, while the fifth quintile the most deprived.

We considered both indicators, because a clear concordance between them has not yet been demonstrated (33, 34), and there is currently no recommendation favoring one of them (32).

Reference values to describe relative exposure to environmental factors

Relative exposure to heat, air pollution, and lack of vegetation was assessed by defining the reference values to harmonize the description of exposures, thus facilitating the interpretation of temperature and NDVI exposure across climate types. These indicators are summarized in Supplementary Table 1.

Heat

A climatological approach based on 10-day means was used to develop a reference for each IRIS. 10-day temperature means smoothed the data while accounting for climatic variability over time. The

reference 10-day mean, minimum, and maximum temperatures d_m were computed over the period 2000-2018 for each department and each type of climate as follows:

$$d_m = \frac{\sum_{n=2000}^{2018} \frac{\sum_{l=1}^{10} T_{l,m,n}}{10}}{19}$$

Where T was the daily temperature (i.e., Tmean, Tmin, or Tmax) for the l^{th} day (from 1 to 365), period of 10 days m (from 1 to 37), and year n (from 2000 to 2018). Then, the daily difference between daily temperatures and the corresponding 10-day reference values $\Delta T_{l,m,n}$ (i.e., relative temperature indicators ΔTmean, ΔTmin, or ΔTmax) for each IRIS was thus:

$$\Delta T_{l,m,n} = T_{l,m,n} - d_m$$

This approach allowed us to identify the IRIS overexposed to heat compared to other IRIS with similar geographical and climatological conditions. This also provides a proxy to identify the urban heat island.

ΔTmean, ΔTmin, and ΔTmax were averaged by season: in this dataset, summer from June 21 to September 22, autumn from September 23 to December 21, winter from December 22 to March 19, and spring from March 20 to June 20.

Lack of vegetation

For each type of climate, reference values were defined as the median values of the mean summer NDVI in rural areas, as rural areas were assumed to be closer to the most vegetated areas than urban areas. Lack of vegetation was then assessed each year for each IRIS by calculating the difference between the mean summer NDVI and the reference value (ΔNDVI).

Air pollution

To identify the IRIS overexposed to air pollution, the WHO air quality guidelines developed to protect public health were used as reference values (35).

The annual and summer mean differences between daily mean $PM_{2.5}$, PM_{10}, and NO_2 concentrations and annual WHO air quality guideline values (5 µg/m^3, 15 µg/m^3, and 10 µg/m^3, respectively) were calculated ($\Delta PM_{2.5}$, ΔPM_{10}, ΔNO_2) for each IRIS. For O_3, the summer mean difference between daily maximum concentrations and WHO air quality guideline values for the peak season (60 µg/m^3) was calculated (ΔO_3) for each IRIS.

Cumulative exposure indicator and identification of environmental hotspots

A cumulative exposure indicator with four classes was created for each IRIS and each year (Supplementary Table 1) based on the distribution quartiles of the environmental factors according to the period (2000-2004, 2005-2009, 2010-2014, 2015-2018) and urbanization level (urban/rural).

Hotspots (class 4) were defined as IRIS with the highest overexposure to all factors: (i) summer ΔTmean in the last quartile, (ii) at least one of the four air pollution indicators (annual $\Delta PM_{2.5}$, annual ΔPM_{10}, annual ΔNO_2, or summer ΔO_3) in the last quartile, and (iii) summer ΔNDVI in the first quartile. IRIS of class 1 had the lowest exposure quartiles for all factors. IRIS of class 2 and class 3 were in the upper quartiles for one and two factors, respectively.

Statistical analysis

Descriptive analysis and temporal evolution of indicators

The number and percentage of IRIS by deprivation index quintiles were described according to urbanization level. The evolution of summer ΔTmean, summer ΔTmin, summer ΔTmax, summer ΔNDVI, annual ΔNO_2, summer ΔO_3, annual $\Delta PM_{2.5}$, and annual ΔPM_{10} concentrations was described between 2000 and 2018. Analyses were stratified by urbanization level (urban/rural) and by 4- to 5-year periods (2000-2004, 2005-2009, 2010-2014, 2015-2018). Heat indicators (ΔTmean, ΔTmin, ΔTmax) were described by season and climate type.

Spearman correlation coefficients for the exposure indicators (summer ΔTmean, summer ΔTmin, summer ΔTmax, annual and summer $\Delta PM_{2.5}$, annual and summer ΔPM_{10}, annual and summer ΔNO_2, summer ΔO_3, and summer ΔNDVI) and between EDI and FDep were computed for the entire period 2000-2018 and by urbanization level.

Exposure indicators (summer ΔTmean, summer ΔNDVI, annual $\Delta PM_{2.5}$, annual ΔPM_{10}, annual ΔNO_2, and summer ΔO_3) were described according to the deprivation index quintiles and the cumulative exposure indicator class, with a focus on hotspots.

Associations between environmental exposure and social deprivation

Associations between environmental exposure indicators and social deprivation were studied by (i) regressing hotspots (yes/no) (main analysis) and then (ii) regressing the cumulative exposure indicator (four classes) against each social deprivation index (EDI and FDep) by quintiles using (i) binary logistic regressions and (ii) non-ordinal polytomous logistic regressions.

Given that heat exposure arouses special interest in climate adaptation policies and that its reduction can only be achieved through indirect actions such as planting vegetation or reducing air pollution, we used non-ordinal polytomous logistic regressions to investigate the association between the categorized summer ΔTmean and the categorized indicators summer ΔNDVI, $\Delta PM_{2.5}$, ΔNO_2, and ΔO_3 adjusted for deprivation indices (EDI and FDep) and year (Supplementary Table 1). We included an interaction term between social deprivation indices and environmental exposure indicators.

All analyses were stratified by urbanization level.

RESULTS

Descriptive analysis and temporal evolution of indicators

Overall, 64% of the 48,185 IRIS were classified as rural, and the main climate type was the modified oceanic climate (Supplementary Figure 1). Highly socially deprived IRIS (quintile 5) were more likely to be in urban areas than in rural areas, especially using the EDI (40.3% of urban IRIS vs. 7.5% of rural IRIS) (Table 1).

Table 1. Distribution of IRIS by quintiles and urbanization level

	EDI		FDep	
	Urban IRIS n (%)	**Rural IRIS n (%)**	**Urban n (%)**	**Rural IRIS n (%)**
Quintile 1	2,118 (12.1 %)	7,346 (24.0 %)	5,882 (33.5 %)	3,743 (12.2 %)
Quintile 2	2,011 (11.5 %)	7,436 (24.3 %)	3,069 (17.5 %)	6,503 (21.2 %)
Quintile 3	2,223 (12.7 %)	7,169 (23.3 %)	2,383 (13.6 %)	7,203 (23.5 %)
Quintile 4	2,988 (17.0 %)	6,383 (20.8 %)	2,102 (12.0 %)	7,500 (24.5 %)
Quintile 5	7,067 (40.3 %)	2,296 (7.5 %)	3,954 (23.0 %)	5,687 (18.6 %)
Missing	1,135 (6.5 %)	13 (<0.01 %)	152 (0.01%)	7 (<0.01 %)
Total	17,542	30,643	17,542	30,643

Concerning the exposure indicators, the summers of 2003, 2006, 2016, and 2018 had the highest mean ΔTmean in both urban and rural areas and across all climate types (Figures 1A and 2; Supplementary Figure 2). More generally, for all seasons and across all periods, mean ΔTmean, ΔTmin, and ΔTmax were higher in urban IRIS than in rural IRIS (Supplementary Table 2). The 2015-2018 period showed the highest summer ΔTmean, ΔTmin, and ΔTmax for both urban and rural areas.

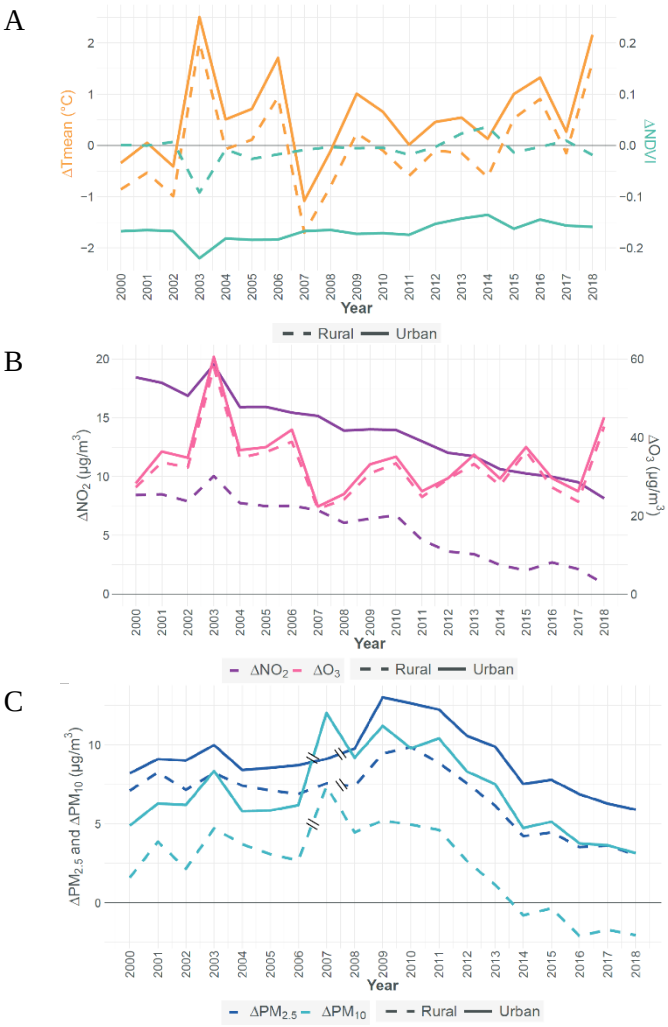


Figure 1. Evolution of (A) mean summer ΔTmean and ΔNDVI, (B) mean annual ΔNO_2 and ΔO_3 evolution and (C) mean annual $\Delta PM_{2.5}$ and ΔPM_{10} between 2000 and 2018 in urban and rural IRIS in continental France. // corresponds to the inclusion of semi-volatile particulate matter.

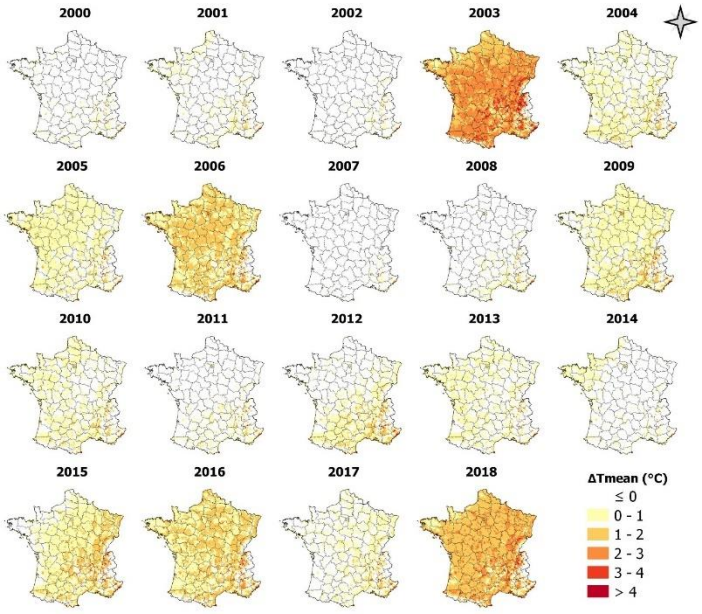


Figure 2. Mean summer ΔTmean between 2000 and 2018 in continental France

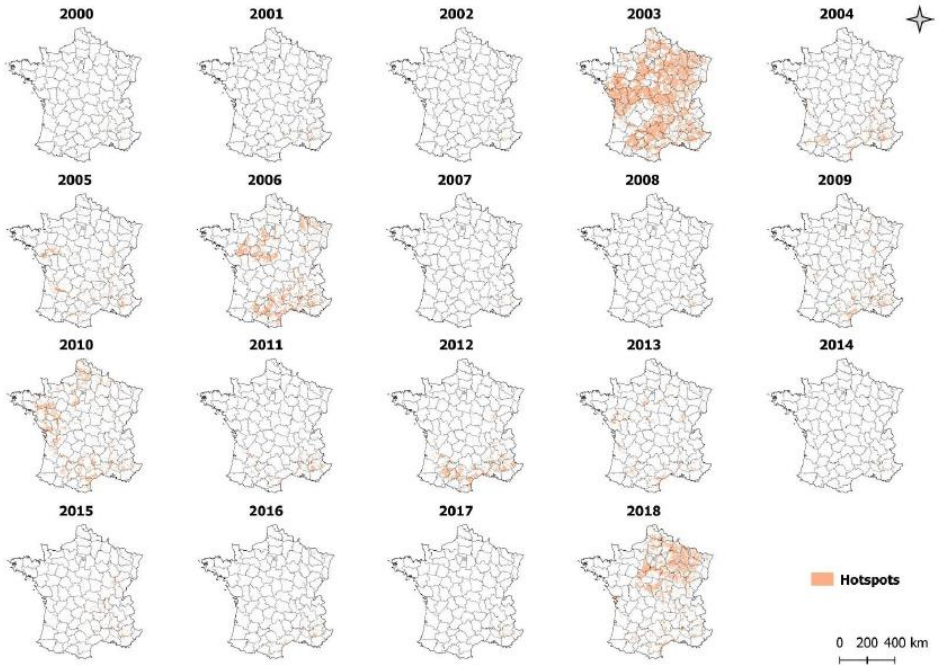
Summer mean ΔNDVI was characterized by a decrease in 2003 and a marked spatial heterogeneity between 2000 and 2018 (Figure 1A; Supplementary Figure 3). During this period, ΔNO_2 dropped by 55.9% in urban IRIS (from 18.5 µg/m^3 in 2000 to 8.1 µg/m^3 in 2018) and by 89.8% in rural IRIS (from 8.4 µg/m^3 in 2000 to 0.86 µg/m^3 in 2018) (Figure 1B). For ΔO_3, two sharp increases were observed in 2003 and 2018 (Figure 1B). In 2018, almost all IRIS (93.7%) in urban areas exceeded the WHO air quality guideline levels (> 10 µg/m^3) for NO_2 compared with 59.3% in rural areas. For O_3, all IRIS were above these guidelines in 2018 (> 60 µg/m^3). On average, ΔNO_2 and ΔO_3 were higher in urban areas than in rural areas (Supplementary Figure 4).

Since 2009, $\Delta PM_{2.5}$ and ΔPM_{10} have steadily decreased in urban and rural areas (Figure 1C). Mean $\Delta PM_{2.5}$ dropped by 54.6% (from 13.0 µg/m^3 in 2009 to 5.9 µg/m^3 in 2018) in urban IRIS and by 67.9% (from 9.4 µg/m^3 in 2009 to 3.0 µg/m^3 in 2018) in rural IRIS. Despite these reductions, 99.9% and 78.7% of urban IRIS and 97.6% and 20.0% of rural IRIS exceeded the WHO air quality guidelines for $PM_{2.5}$ and PM_{10}, respectively, in 2018 (> 5 µg/m^3 and > 15 µg/m^3). On average, $\Delta PM_{2.5}$ and ΔPM_{10} concentrations were higher in urban areas than in rural areas (Supplementary Figure 5).

In both urban and rural areas, the different summer ΔT indicators were positively correlated with summer ΔO_3 and negatively (or close to 0) correlated with ΔPM and ΔNO_2 (Supplementary Figure 6). Summer ΔNDVI was negatively correlated with all pollutant and temperature indicators. In urban IRIS, EDI and FDep showed different correlation patterns with the environmental exposure indicators. According to EDI, the most deprived IRIS in urban areas were more exposed to heat (summer ΔTmean), air pollution (annual $\Delta PM_{2.5}$, ΔPM_{10}, and ΔNO_2), and lack of vegetation (summer ΔNDVI). For example, mean ΔTmean and annual $\Delta PM_{2.5}$ were respectively +0.68 °C and +9.6 µg/m^3 in highly

socially deprived IRIS (quintile 5) versus +0.35 °C and +8.35 µg/m^3 in the least deprived IRIS (quintile 1). Summer ΔO_3 remained stable across EDI quintiles. This pattern was not observed in rural areas. With FDep, a U-shaped relationship was observed in urban areas in which the least and most deprived IRIS were more exposed to air pollution (annual $\Delta PM_{2.5}$, ΔPM_{10}, and ΔNO_2) and lack of vegetation (summer ΔNDVI). In rural areas, a higher FDep was associated with a lower exposure to all air pollutants (Supplementary Figures 7 and 8).

In terms of cumulative exposure, most IRIS (70.0%) were class 2 (i.e., in the strongest quartiles for one factor) (Supplementary Table 3). On average, 6.8% of rural IRIS were classified as hotspots (i.e., IRIS in the strongest quartiles for all factors) (1,554,243 inhabitants) versus 7.2% of urban IRIS (3,052,728 inhabitants) (Figure 3). While the percentage of hotspots was rather stable in urban areas (6.0% to 8.0%), it was the highest in 2000-2004 (11.3%) in rural areas (mainly due to 2003, which recorded the highest number of hotspots for the entire period 2000-2018) and then increased again in 2015-2018 (6.5%) compared with 2005-2014 (4.7%).



	Urban areas		Rural areas	
	Annual average population	Percentage of IRIS hotspots % (n)	Annual average population	Percentage of IRIS hotspots % (n)
2000-2004	3,126,526	7.7% (6,719)	2,316,339	11.3% (17,362)
2005-2009	3,276,641	7.8% (6,866)	1,201,072	4.7% (7,232)
2010-2014	3,114,488	7.3% (6,379)	1,407,592	4.7% (7,249)
2015-2018	2,603,387	6.1% (4,297)	1,226,401	6.4% (7,905)

Figure 3. Spatial distribution of IRIS hotspots by year, annual average population living in an IRIS hotspot, and percentage of IRIS hotspots by period and urbanization level between 2000 and 2018 in continental France

Exposures were higher in urban hotspots than in rural hotspots (Supplementary Figure 9). For example, IRIS hotspots were exposed to mean summer ΔTmean of +1.9 °C in urban areas and +1.7 °C in rural areas compared with non-hotspots. For annual $\Delta PM_{2.5}$, summer ΔO_3, and summer ΔNDVI in urban and rural hotspots, these differences were respectively +2.7 µg/m^3 versus +0.92 µg/m^3, +15.60 µg/m^3 versus +17.91 µg/m^3, and -0.20 versus -0.15. The mean percentages of IRIS overexposed to each environmental exposure indicator according to the cumulative exposure indicator class and urbanization level are presented in Supplementary Table 4.

Associations between environmental exposure and social deprivation

In urban areas, increased deprivation was strongly associated with the risk of being in a hotspot ($p < 0.001$) based on EDI (Figure 4). With FDep, this association was only observed for highly socially deprived IRIS (quintile 5) ($p < 0.001$) with a U-shaped relationship between social deprivation and the risk of living in a hotspot. In rural areas, higher social deprivation was negatively associated with the risk of being in a hotspot for both EDI and FDep.

Deprivation indices	Number of hotspots	Number of non-hotspots	OR [95% CI]
Urban areas			
EDI			
Quintile 1	428	39,814	Ref.
Quintile 2	1,281	36,928	3.23 [2.89 ; 3.61]
Quintile 3	2,149	40,088	4.99 [4.50 ; 5.54]
Quintile 4	4,307	52,465	7.64 [6.92 ; 8.45]
Quintile 5	14,037	120,236	10.86 [9.87 ; 11.98]
FDep			
Quintile 1	8,396	103,362	Ref.
Quintile 2	3,882	54,429	0.88 [0.84 ; 0.91]
Quintile 3	2,979	42,298	0.87 [0.83 ; 0.91]
Quintile 4	2,645	37,293	0.87 [0.83 ; 0.91]
Quintile 5	6,018	69,108	1.07 [1.04 ; 1.11]
Rural areas			
EDI			
Quintile 1	10,207	129,367	Ref.
Quintile 2	9,298	131,986	0.89 [0.87 ; 0.92]
Quintile 3	8,925	127,286	0.89 [0.86 ; 0.92]
Quintile 4	8,079	113,198	0.90 [0.88 ; 0.93]
Quintile 5	3,221	40,403	1.01 [0.97 ; 1.05]
FDep			
Quintile 1	5,654	65,463	Ref.
Quintile 2	9,436	114,121	0.96 [0.93 ; 0.99]
Quintile 3	9,443	127,414	0.86 [0.83 ; 0.89]
Quintile 4	8,877	133,623	0.77 [0.74 ; 0.80]
Quintile 5	6,338	101,715	0.72 [0.70 ; 0.75]

OR = Odd Ratio; CI = Confidence Interval

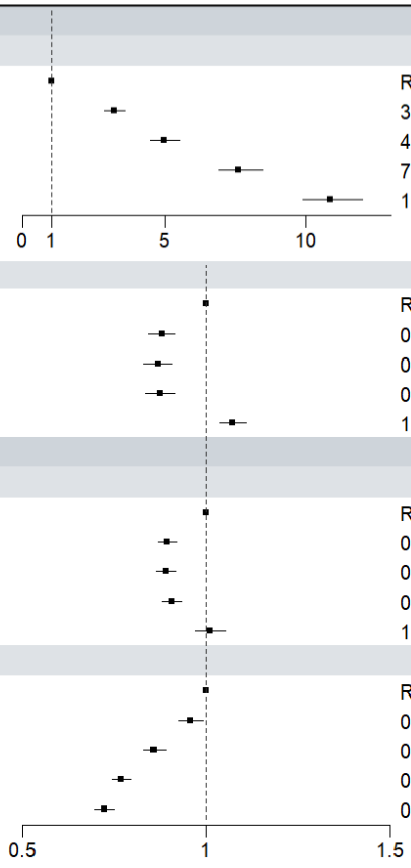


Figure 4. Associations between hotspots and non-hotspots and deprivation indices (EDI and FDep) between 2000 and 2018 in urban and rural areas in continental France. OR (95% CI) estimated by binary logistic regressions.

Using EDI and in urban areas, the risk of cumulating several exposures increased with social deprivation, regardless of the cumulative exposure class (Supplementary Figure 10). In rural areas, a U-shaped relationship was observed. Using FDep, a U-shaped relationship was observed in urban areas, whereas a decreasing risk with social deprivation was found in rural areas.

In summer, IRIS were more likely to have a medium or high exposure to heat if they also had a medium or high exposure to a lack of vegetation or to O_3 in both urban and rural areas (models 1 and 2, Table 2). In rural areas, they were more likely to have a medium or high exposure to heat if they also had a medium or high exposure to $PM_{2.5}$ (models 1 and 2). In urban areas, IRIS were less likely to have a medium or high exposure to heat if they had a high exposure to NO_2 or medium exposure to $PM_{2.5}$. In both urban and rural areas, highly socially deprived IRIS (quintile 5) were at a lower risk of being exposed to high heat.

Table 2. Associations between (over-)exposure to heat (ΔTmean) and deprivation indices (EDI and FDep), lack of vegetation, and air pollutants during summer between 2000 and 2018 in urban and rural areas of continental France (OR [95% CI][a])

	Urban areas		**Rural areas**	
	Medium overexposure to heat	High overexposure to heat	Medium exposure to heat	High exposure to heat
Model 1				
EDI				
Quintile 1	Ref.	Ref.	Ref.	Ref.
Quintile 2	1.82 [1.43; 2.31]	2.77 [1.91; 4.01]	1.53 [1.28; 1.82]	2.66 [2.05; 3.46]
Quintile 3	1.33 [1.05; 1.70]	0.67 [0.46; 0.98]	1.70 [1.43; 2.02]	1.16 [0.89; 1.50]
Quintile 4	0.90 [0.71; 1.14]	0.27 [0.19; 0.40]	0.68 [0.56; 0.83]	0.27 [0.20; 0.36]
Quintile 5	1.88 [1.51; 2.33]	0.91 [0.64; 1.29]	1.04 [0.71; 1.52]	0.31 [0.18; 0.52]
ΔNDVI exposure (lack of vegetation)				
Low	Ref.	Ref.	Ref.	Ref.
Medium	2.31 [2.17; 2.46]	3.69 [3.39; 4.02]	1.21 [1.16; 1.26]	1.53 [1.44; 1.62]
High	10.8 [9.63; 12.0]	52.8 [46.2; 60.4]	1.15 [1.11; 1.20]	1.58 [1.49; 1.68]
Δ$PM_{2.5}$ exposure				
Low	Ref.	Ref.	Ref.	Ref.
Medium	0.62 [0.55; 0.70]	0.49 [0.42; 0.57]	3.35 [3.07; 3.65]	10.0 [8.86; 11.4]
High	0.61 [0.53; 0.70]	0.51 [0.43; 0.60]	6.38 [5.81; 7.01]	18.7 [16.3; 21.6]
ΔNO_2 exposure				
Low	Ref.	Ref.	Ref.	Ref.

Medium	0.69 [0.63; 0.76]	0.45 [0.40; 0.51]	0.84 [0.80; 0.89]	0.75 [0.70; 0.80]
High	0.53 [0.47; 0.59]	0.27 [0.24; 0.32]	0.71 [0.68; 0.74]	0.81 [0.75; 0.87]
ΔO_3 exposure				
Low	Ref.	Ref.	Ref.	Ref.
Medium	2.79 [2.37; 3.29]	10.4 [7.83; 13.9]	2.89 [2.57; 3.26]	9.02 [7.57; 10.7]
High	6.06 [5.12; 7.17]	60.3 [45.2; 80.6]	3.07 [2.72; 3.46]	2.10 [1.76; 2.50]
Model 2				
FDep				
Quintile 1	Ref.	Ref.	Ref.	Ref.
Quintile 2	0.96 [0.80; 1.15]	1.88 [1.43; 2.47]	0.93 [0.73; 1.17]	0.42 [0.29; 0.59]
Quintile 3	0.80 [0.65; 0.98]	0.59 [0.42; 0.84]	0.69 [0.55; 0.86]	0.19 [0.14; 0.27]
Quintile 4	0.42 [0.33; 0.52]	1.22 [0.88; 1.69]	0.73 [0.59; 0.91]	0.15 [0.11; 0.21]
Quintile 5	0.60 [0.50; 0.73]	0.11 [0.08; 0.15]	0.73 [0.57; 0.92]	0.20 [0.14; 0.29]
ΔNDVI exposure (lack of vegetation)				
Low	Ref.	Ref.	Ref.	Ref.
Medium	2.59 [2.46; 2.73]	5.83 [5.43; 6.26]	1.34 [1.27; 1.42]	1.54 [1.42; 1.68]
High	4.95 [4.67; 5.24]	27.6 [25.6; 29.9]	0.99 [0.93; 1.05]	1.56 [1.43; 1.70]
$\Delta PM_{2.5}$ exposure				
Low	Ref.	Ref.	Ref.	Ref.
Medium	0.58 [0.53; 0.64]	0.73 [0.64; 0.83]	4.67 [4.12; 5.30]	8.95 [7.42; 10.8]
High	1.01 [0.91; 1.12]	1.18 [1.03; 1.35]	7.84 [6.86; 8.96]	6.10 [5.16; 7.22]
ΔNO_2 exposure				
Low	Ref.	Ref.	Ref.	Ref.
Medium	1.03 [0.95; 1.12]	1.33 [1.20; 1.48]	0.78 [0.73; 0.82]	1.39 [1.27; 1.52]
High	0.59 [0.54; 0.64]	0.38 [0.34; 0.43]	0.89 [0.83; 0.95]	2.40 [2.16; 2.67]
ΔO_3 exposure				
Low	Ref.	Ref.	Ref.	Ref.
Medium	1.64 [1.49; 1.81]	2.78 [2.34; 3.30]	1.03 [0.87; 1.22]	0.56 [0.43; 0.72]
High	3.08 [2.78; 3.40]	25.0 [21.0; 29.8]	1.08 [0.92; 1.28]	1.79 [1.39; 2.31]

[a] OR (95% CI) estimated by non-ordinal polytomous logistic models.

DISCUSSION

Our findings showed that overexposure to heat was higher for the period 2015-2018 compared with the other periods, which is consistent with the climatic trends observed in France (36, 37). The year 2003 showed a sharp increase in summer ΔTmean and air pollutants and a decrease in summer ΔNDVI. This

year was marked by a severe heatwave in Europe and France, which led to 15,000 excess deaths in France alone (38). These abnormally high temperatures explain the decrease in NDVI due to the drought, the increase in O_3 concentrations (20), and more generally, the rise in all air pollutants. This increase in air pollutants was probably due to the generation of O_3 (20), the lower absorption of pollutants by drought-affected vegetation, and the soil mineral dust resuspension caused by the drought, limited dispersion, and washing of particulate matter. Until 2018, we also observed a continuous and large decrease in air pollutant concentrations for PM and NO_2 (two- to tenfold reduction on average depending on the pollutant and urbanization level), which reflects the impact of successive action plans in various sectors to improve air quality in France (39). However, most IRIS still exceeded the most recent WHO air quality guidelines in 2018 (20% to 100% of IRIS depending on the pollutant and urbanization level).

On average, more than 4 million people lived in hotspots, i.e., areas cumulating adverse overexposure to all environmental determinants. This study confirmed that between 2000-2018, urban IRIS were generally more exposed to heat during summer and to air pollution throughout the year, while they had less vegetation than rural IRIS. Differential exposure was greater in urban areas than in rural areas, showing that environmental inequities were stronger in the urban environment. In urban areas, greater deprivation was strongly associated with the risk of living in a hotspot or having more cumulative exposure but only when using the EDI and not the FDep. In rural areas, the associations were more consistent but inverted: greater deprivation measured by both the EDI and FDep was associated with a lower risk of living in a hotspot. With the cumulative exposure indicator in rural areas, a U-shaped relationship and a lower risk of cumulative exposure were observed with the EDI and FDep, respectively.

In urban areas, our results support the findings of several studies that have identified associations between heat, air pollution, or low vegetation/green space availability and social deprivation, with higher exposure levels being linked to the most deprived populations (3-7, 40). However, some studies found reverse associations, showing, for example, that less deprived populations have greater exposure or that both the least and the most deprived populations have a greater exposure to air pollution (6, 40).

The differences observed between the two deprivation indices, which have already been discussed in other studies (33, 34), can be explained by several reasons related to their construction methods. First, the EDI was built to allow comparability between European countries (30), whereas the FDep was created to characterize spatial socioeconomic heterogeneity in France (31). Second, these two indices were estimated using different statistical methods. The EDI combines ten ecological weighted socioeconomic and material variables based on census studies (30), whereas the FDep is based on four ecological variables from principal component analysis (31). Finally, the components included in the two indices also differ. For example, the EDI includes “the proportion of non-homeowners,” “the proportion of households without a car,” and “the proportion of primary residences with more than one

person per room," although these items do not reflect socioeconomic deprivation in the same way in rural and urban areas (33, 34, 41). For example, urban areas often have well-developed public transport systems, which limits the need to own a car. By contrast, rural areas often lack public transport, and thus not owning a car can reflect social deprivation, as it limits mobility. Nevertheless, the variable "proportion of households without a car" does not contribute the most to this index. Overcrowded dwellings and homeownership may also have different associations with social deprivation in rural compared with urban areas. The variables contributing the most are overcrowded households and single-parent households (42). The apparent protective effect of social deprivation (as estimated by the EDI and FDep) in rural areas can be explained by the specific spatial distribution of environmental exposures and social deprivation. For example, low-density areas located far from attractive poles of activity tend to be more vegetated and less affected by urban heat islands and air pollution, although their low housing costs may attract residents with higher social deprivation scores. At the same time, IRIS closer to urban poles or attractive areas (e.g., tourist zones) may be more exposed to deleterious environmental factors but may also attract residents with a higher socioeconomic status.

In urban areas, highly socially deprived IRIS were less likely to be highly exposed to heat using the EDI. IRIS overexposed to heat were also overexposed to a lack of vegetation in both rural and urban areas. Surprisingly, in urban areas, high exposure to NO_2 or $PM_{2.5}$ was negatively associated with medium or high exposure to heat. Medium and high exposure to O_3 was associated with medium or high exposure to heat.

Our methods have several limitations. First, we estimated the relative exposure of each IRIS population based on the area-weighted average of temperatures, air pollution, and NDVI rather than the population-weighted average. This may have under- or overestimated the exposure in some IRIS. Using the IRIS as a spatial unit may also mischaracterize some levels of exposure, because rural IRIS have larger areas and somewhat smaller populations compared with IRIS in towns and cities.

Second, the reference values for temperature were calculated over the period 2000-2018, including the 2003 heatwave, which was the most severe and deadliest heatwave episode in France's history, as well as other particularly warm years (2006, 2018). This could have increased the reference values and thus lead to an underestimation of the relative exposure to temperature. Likewise, it might have underestimated the number of hotspots for the 2000-2004 period.

Several limitations can be attributed to the use of the FDep and EDI. First, we used a constant value for each index and IRIS over the entire study period, since annual values using 2021 geography references were not available, and little change was found in the EDI values in 2009, 2013, and 2017 and the FDep values between 2011 and 2017. Second, these indicators seem less adapted to rural areas, which might introduce an approximation bias into their representativeness of rural and urban areas (32). Finally, the EDI was not computed for large, sparsely populated IRIS with forests and leisure parks.

We assumed that population density was stable over the entire study period. Given the lack of data at the IRIS level before 2014, we assumed that all IRIS in a given municipality changed population at the same annual rate as the municipality. We also assumed that the population of each IRIS was constant prior to 2006 due to the lack of harmonized census data for this period.

Finally, $\Delta PM_{2.5}$ was underestimated before 2008-2009 and ΔPM_{10} before 2007, because the semi-volatile PM fraction was not yet measured. This underestimation represents about 30% of the annual mean of PM_{10} (43, 44). No such evaluation was performed for $PM_{2.5}$. Consequently, the number of IRIS overexposed to PM might have been slightly underestimated before 2009 in our study. Our exposure indicators are proxies for population exposure and do not reflect the true daily exposure, which likely varies between individuals in each IRIS. For example, a poor resident of an IRIS living in poorly ventilated and insulated housing in a dense neighborhood and working in an outdoor job will be more exposed to heat and air pollution than a wealthier resident of the same IRIS, even though both would be assigned the same exposure level (40).

Our study has several strengths. Characterizing the socioeconomic and environmental burden of populations at a fine scale and in a comparable manner highlights the environmental justice issues and public health concerns of environmental exposures. To our knowledge, this is the first study to identify hotspots of exposure to heat, air pollution, and lack of vegetation and their associations with social deprivation. For instance, population-weighted summer temperatures and population-weighted NDVI at the national level are currently monitored by the Lancet countdown as relevant indicators of climate change impacts and adaptation policies, respectively (45). However, the Lancet countdown fails to consider co-exposure, and the indicators are not always comparable across space. For instance, a given temperature and a given NDVI have different impacts depending on the underlying climate and type of vegetation.

We used exposure data at a fine spatiotemporal scale over a long period of time and across continental France. These data were aggregated at the finest spatial administrative level available in France. We used relative exposure indicators for NDVI and temperature to ensure comparability across areas and climate types, while for air pollutants, we assessed exposure relative to the WHO guidelines that relate to the underlying health risks. This approach is useful to study the effect of heat, air pollution, and lack of vegetation on health outcomes.

This study provides the first overview of fine-scale exposure to heat stress and its co-exposures at a national level. Hotspots, which represent the areas with the strongest environmental inequities, were identified. This approach can support the inclusion of environmental inequities into adaptation strategies to climate change.

DATA AVAILABILITY STATEMENT

The datasets generated during and analyzed during the current study are available from the corresponding author on reasonable request.

REFERENCES

1. Ganzleben C, Kazmierczak A. Leaving no one behind – understanding environmental inequality in Europe. Environmental Health. 2020;19(1):57.
2. EEA. Unequal exposure and unequal impacts: social vulnerability to air pollution, noise and extreme temperatures in Europe. Copenhagen: EEA; 2018. Report No.: 22.
3. Hsu A, Sheriff G, Chakraborty T, Manya D. Disproportionate exposure to urban heat island intensity across major US cities. Nature Communications. 2021;12(1):2721.
4. Venter ZS, Figari H, Krange O, Gundersen V. Environmental justice in a very green city: Spatial inequality in exposure to urban nature, air pollution and heat in Oslo, Norway. Science of The Total Environment. 2023;858:160193.
5. Schüle SA, Hilz LK, Dreger S, Bolte G. Social Inequalities in Environmental Resources of Green and Blue Spaces: A Review of Evidence in the WHO European Region. International Journal of Environmental Research and Public Health [Internet]. 2019; 16(7).
6. Padilla CM, Kihal-Talantikite W, Vieira VM, Rossello P, Nir GL, Zmirou-Navier D, et al. Air quality and social deprivation in four French metropolitan areas—A localized spatio-temporal environmental inequality analysis. Environmental Research. 2014;134:315-24.
7. Brunt H, Barnes J, Jones SJ, Longhurst JWS, Scally G, Hayes E. Air pollution, deprivation and health: understanding relationships to add value to local air quality management policy and practice in Wales, UK. Journal of Public Health. 2017;39(3):485-97.
8. Ebi KL, Capon A, Berry P, Broderick C, de Dear R, Havenith G, et al. Hot weather and heat extremes: health risks. Lancet. 2021;398(10301):698-708.
9. EEA. Healthy environment, healthy lives: how the environment influences health and well-being in Europe. Copenhagen; 2020. Report No.: 21.
10. Son J-Y, Liu JC, Bell ML. Temperature-related mortality: a systematic review and investigation of effect modifiers. Environmental Research Letters. 2019;14(7):073004.
11. Analitis A, De' Donato F, Scortichini M, Lanki T, Basagana X, Ballester F, et al. Synergistic Effects of Ambient Temperature and Air Pollution on Health in Europe: Results from the PHASE Project. International Journal of Environmental Research and Public Health [Internet]. 2018; 15(9).
12. Pascal M, Goria S, Wagner V, Sabastia M, Guillet A, Cordeau E, et al. Greening is a promising but likely insufficient adaptation strategy to limit the health impacts of extreme heat. Environment International. 2021;151:106441.
13. Schinasi LH, Benmarhnia T, De Roos AJ. Modification of the association between high ambient temperature and health by urban microclimate indicators: A systematic review and meta-analysis. Environmental Research. 2018;161:168-80.
14. Kumar P, Druckman A, Gallagher J, Gatersleben B, Allison S, Eisenman TS, et al. The nexus between air pollution, green infrastructure and human health. Environ Int. 2019;133(Pt A):105181.

15. WHO. Urban green spaces and health. A review of evidence. Copenhagen: WHO Regional Office for Europe; 2016.
16. Lalloué B, Monnez JM, Padilla C, Kihal W, Zmirou-Navier D, Deguen S. Data analysis techniques: a tool for cumulative exposure assessment. J Expo Sci Environ Epidemiol. 2015;25(2):222-30.
17. Jay O, Capon A, Berry P, Broderick C, de Dear R, Havenith G, et al. Reducing the health effects of hot weather and heat extremes: from personal cooling strategies to green cities. Lancet. 2021;398(10301):709-24.
18. Markevych I, Schoierer J, Hartig T, Chudnovsky A, Hystad P, Dzhambov AM, et al. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ Res. 2017;158:301-17.
19. Corso M, Pascal M. Agir pour le climat et la qualité de l'air pour la santé de tous. La revue de l'infirmière. 2020;69(262):p. 24-6.
20. Monks PS, Archibald AT, Colette A, Cooper O, Coyle M, Derwent R, et al. Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer. Atmos Chem Phys. 2015;15(15):8889-973.
21. Insee. IRIS 2016 [Available from: https://www.insee.fr/fr/metadonnees/definition/c1523.
22. Insee. La grille communale de densité à 4 niveaux 2022 [Available from: https://www.insee.fr/fr/information/2114627.
23. Insee. Recensement de la population 2022 [Available from: https://www.insee.fr/fr/information/2880845.
24. Joly D, Brossard T, Cardot H, Cavailhes J, Hilal M, Wavresky P. Les types de climats en France, une construction spatiale. Cybergeo : European Journal of Geography. 2010.
25. Hough I, Just AC, Zhou B, Dorman M, Lepeule J, Kloog I. A multi-resolution air temperature model for France from MODIS and Landsat thermal data. Environ Res. 2020;183:109244.
26. Robinson NP, Allred BW, Jones MO, Moreno Á, Kimball JS, Naugle DE, et al. A Dynamic Landsat Derived Normalized Difference Vegetation Index (NDVI) Product for the Conterminous United States. Remote Sens. 2017;9:863.
27. Hough I, Sarafian R, Shtein A, Zhou B, Lepeule J, Kloog I. Gaussian Markov random fields improve ensemble predictions of daily 1 km PM2.5 and PM10 across France. Atmospheric Environment. 2021;264:118693.
28. Favez O, Cachier H, Sciare J, Le Moullec Y. Characterization and contribution to PM2.5 of semi-volatile aerosols in Paris (France). Atmospheric Environment. 2007;41(36):7969-76.
29. Real E, Couvidat F, Ung A, Malherbe L, Raux B, Gressent A, et al. Historical reconstruction of background air pollution over France for 2000–2015. Earth Syst Sci Data. 2022;14(5):2419-43.

30. Pornet C, Delpierre C, Dejardin O, Grosclaude P, Launay L, Guittet L, et al. Construction of an adaptable European transnational ecological deprivation index: the French version. J Epidemiol Community Health. 2012;66(11):982-9.
31. Rey G, Jougla E, Fouillet A, Hémon D. Ecological association between a deprivation index and mortality in France over the period 1997 – 2001: variations with spatial scale, degree of urbanicity, age, gender and cause of death. BMC Public Health. 2009.
32. Gorza M, Eilstein D. Outils élaborés dans la cadre du programme « Inégalités sociales de santé », 2013-2015. Saint-Maurice: Santé publique France; 2018.
33. Barry Y, Le Strat Y, Azria E, Gorza M, Pilkington H, Vandentorren S, et al. Ability of municipality-level deprivation indices to capture social inequalities in perinatal health in France: A nationwide study using preterm birth and small for gestational age to illustrate their relevance. BMC Public Health. 2022;22(1):919.
34. Temam S, Varraso R, Pornet C, Sanchez M, Affret A, Jacquemin B, et al. Ability of ecological deprivation indices to measure social inequalities in a French cohort. BMC Public Health. 2017;17(1):956.
35. WHO. WHO global air quality guidelines. Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. . Geneva, Switzerland: World Health Organization; 2021.
36. Sorel M, Soubeyroux J-M, Drouin A, Jourdain S, Kerdoncuff M, Cassaigne B, et al. Normales climatiques 1991-2020., 119, 73-79, 2022. . La Météorologie. 2022;119:73-9.
37. Ribes A, Boé J, Qasmi S, Dubuisson B, Douville H, Terray L. An updated assessment of past and future warming over France based on a regional observational constraint. Earth Syst Dynam. 2022;13(4):1397-415.
38. Fouillet A, Rey G, Laurent F, Pavillon G, Bellec S, Guihenneuc-Jouyaux C, et al. Excess mortality related to the August 2003 heat wave in France. Int Arch Occup Environ Health. 2006;80(1):16-24.
39. comptes Cd. Les politiques de lutte contre la pollution de l'air. Cour des comptes; 2020.
40. Deguen S, Zmirou-Navier D. Social inequalities resulting from health risks related to ambient air quality-A European review. European Journal of Public Health. 2010;20(1):27-35.
41. Gilthorpe MS, Wilson RC. Rural/urban differences in the association between deprivation and healthcare utilisation. Soc Sci Med. 2003;57(11):2055-63.
42. Merville O, Launay L, Dejardin O, Rollet Q, Bryère J, Guillaume É, et al. Can an Ecological Index of Deprivation Be Used at the Country Level? The Case of the French Version of the European Deprivation Index (F-EDI). Int J Environ Res Public Health. 2022;19(4).
43. Malherbe L, Beauchamp M, Bourin A, Sauvage S. Analyse de tendances nationales en matière de qualité de l'air. 2017.

44. Bessagnet B, Malherbe L, Aymoz G. Bilan de la première année de mesure des PM10 ajustées en France et évaluation des outils de modélisation. 2008.
45. Countdown TL. Lancet Countdown: Tracking Progress on Health and Climate change [Available from: https://www.lancetcountdown.org/data-platform/adaptation-planning-and-resilience-for-health.

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AUTHOR CONTRIBUTION STATEMENT

LA, MP and JL designed and conceived this study with support from GF. LA conducted the analysis and prepared the original draft of the manuscript with support from MP and JL. IH and ES contributed to data curation. IH, ES, JL and IK acquired the data. LA, IH, ES, GF, GL, LL, MP and JL interpreted the results. IH, ES, GF, IK, GL, LL, MP and JL reviewed the manuscript and provided substantial feedback. All authors read and approved the final manuscript.

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COMPETING INTERESTS

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.