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Determination of the human impact on the drop in NO\textsubscript{2} air pollution due to total COVID-19 lockdown using Human-Influenced Air Pollution Decrease Index (HIAPDI)\textsuperscript{☆}

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ARTICLE INFO

**Keywords:**
Anthropogenic influence
Air pollution
NO\textsubscript{2} decrease
Confinement
HIAPDI

ABSTRACT

This study investigates the relationship between territorial human influence and decreases in NO\textsubscript{2} air pollution during a total COVID-19 lockdown in Metropolitan France. NO\textsubscript{2} data from the confinement period and the Human Influence Index (HII) were implemented to address the problem. The relative change in tropospheric NO\textsubscript{2} was calculated using Sentinel-5P (TROPOMI) satellite data. Hotspot-Coldspot analysis was performed to examine the change in NO\textsubscript{2}. Moreover, the novel Human-Influenced Air Pollution Decrease Index (HIAPDI) was developed. Weather bias was investigated by implementing homogeneity analysis with \(\chi^2\) test. The correlations between variables were tested with the statistical T-test. Likewise, remote observations were validated with data from in-situ monitoring stations. The study showed a strong correlation between the NO\textsubscript{2} decrease during April 2020 under confinement measures and HII. The greater the anthropogenic influence, the greater the reduction of NO\textsubscript{2} in the regions (\(R^2 = 0.62\)). The new HIAPDI evidenced the degree of anthropogenic impact on NO\textsubscript{2} change. HIAPDI was found to be a reliable measure to determine the correlation between human influence and change in air pollution (\(R^2 = 0.93\)). It is concluded that the anthropogenic influence is a determining factor in the phenomenon of near-surface NO\textsubscript{2} reduction. The implementation of HIAPDI is recommended in the analysis of other polluting gases.

Author contribution statement

K. DánIEL Kovács: Conceptualization, Methodology, Software. K. DánIEL Kovács: Data curation, Writing- Original draft preparation. K. DánIEL Kovács: Visualization, Investigation. K. DánIEL Kovács: Software, Validation. K. DánIEL Kovács: Writing- Reviewing and Editing. K. DánIEL Kovács: Graphical abstract.

1. Introduction and literature review

Is there a connection between the degree of human influence on land use and the decline in NO\textsubscript{2} air pollution in the context of anti-COVID-19 measures?

The appearance of the SARS-CoV-2 coronavirus (COVID-19) pandemic caused great damage in the loss of human lives and the economy worldwide (Jackson et al., 2021; Zawbaa et al., 2022). At the beginning of 2020, few confirmed positive cases of contagion appeared in Europe (Stoecklin et al., 2020; WHO, 2020c). However, as the new disease spread across the continent, on March 13, 2020, the World Health Organization (WHO) declared Europe the second epicenter of the coronavirus after China (Cucinotta & Vanelli, 2020; WHO, 2020b). Research already pointed to the correlation between air pollution and infections (Ali & Islam, 2020; Paiial & Agrawal, 2021).

Starting from March 2020, several European countries ordered total or partial lockdowns and mobility restrictions (WHO, 2020a). These anti-COVID-19 measures caused a strong reduction in human activities, which resulted in a general improvement in air quality (Cameletti, 2020; Kumari & Toshniwal, 2020; Rugani & Caro, 2020; Saha et al., 2022; Sokhi et al., 2021; Zambrano-Monserratte et al., 2020). In France, the largest lockdown of the three during 2020–2021 was in effect between March 17, 2020 and May 11, 2020 (Gouvernement Français, n.d.; Salje et al., 2020). During the emergency state, mobility was reduced by 79% (Galeazzi et al., 2020). As a result of this impact, an immediate decline in air pollution was observed in France and the whole of Europe (Ikhlasel et al., 2021; Magazzino et al., 2020; Piazzola et al., 2020, Sbai et al., 2021). Other authors pointed to the connection between economic

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\* This paper has been recommended for acceptance by Pavlos Kassomenos.

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https://doi.org/10.1016/j.envpol.2022.119441

Received 7 March 2022; Received in revised form 22 April 2022; Accepted 6 May 2022

Available online 10 May 2022

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development and loss of air pollution (Kovács, 2022; Kovács & Haidu, 2021; Magazzino et al., 2021; Mele & Magazzino, 2021). Despite this, the correlation between human influence on land use and decreased near-surface air pollution due to lockdown have yet to be robustly investigated.

Several studies have shown, using satellite measurements, that the decrease in the atmospheric concentration of particulate matter (PM) and nitrogen dioxide (NO$_2$) depends on the change in anthropogenic activities (Hashim et al., 2021; Potts et al., 2021; Prunet et al., 2020; Skiriene & Stasikienè, 2021; Yan, Zang, Jiang, et al., 2021a, 2021b; Yan, Zang, Zhao, et al., 2021a, 2021b; Zheng et al., 2018). The improvement in urban air quality was demonstrated using both satellite and ground station monitoring data (Bar et al., 2021; Biswal et al., 2021; Chan et al., 2021). To date, however, it has not been examined whether territorial human influence expressed through land use may contribute to reductions in NO$_2$ near-surface air pollution.

Air pollution mitigation in large French metropolitan areas has been of great interest in the past (Coudon et al., 2021). Research focused on France also highlighted the relevance of the recent COVID-19 lockdown on air quality and health (Adeléa et al., 2021; INERIS, 2020; Pazmiño et al., 2021). Some authors demonstrated the role of heavy road traffic on air quality in Paris in the context of anti-COVID-19 measures (Oabech et al., 2022). Other researchers pointed to the impact of different government lockdown policies on the decline in air pollution (Schneider et al., 2022). Discussion was also generated about the biases of meteorological conditions influencing changes in air pollution during lockdowns (Kovács & Haidu, 2021; Menut et al., 2020). Recent research generally sought to evidence the magnitude of the NO$_2$ decrease phenomenon and other gases. However, apart from quantifying the decrease in NO$_2$ and excluding meteorological biases, this paper analyzes the degree of territorial human influence on the decline in tropospheric NO$_2$ pollution under anti-COVID-19 measures.

The purpose of this study is to determine the anthropogenic contribution to the reduction of near-surface NO$_2$ air pollution in Metropolitan France during the first part of the first total lockdown (April 2020). The relative change in tropospheric NO$_2$ concentration was calculated using Sentinel-5P high spatial resolution satellite data.

The novelty that this study brings to the literature is to determine, using a novel spatial index, the decrease in air pollution influenced by man. The research hypothesis was raised that the greater the human influence in a certain territory, the greater the decrease in NO$_2$ air pollution during the first month of total confinement. The possible uncertainties of this hypothesis are the other temporal factors that may interfere in the process. Mainly the variation in meteorological conditions that influences the concentration and density of air pollution, or other factors – from the macro-regional perspective of the study – of minor importance such as hourly traffic flow, weekdays, holidays, weekends, location of major cities, etc. However, these minor factors are less significant than the weather bias because the latter can cause abrupt shifts, mixing, and chemical changes over large air masses, especially in an area exposed to high oceanic influence such as vast parts of France. The uncertainty of the meteorological bias was addressed in the study by implementing statistical test analyses for ten meteorological parameters that could influence the process of the baseline hypothesis. The bias analysis included the planetary boundary layer height (PBLH) as an indirect meteorological variable.

2. Materials

Using depth optics technology, the TROPOspheric Monitoring Instrument (TROPOMI) sensor installed onboard the Sentinel-5P satellite measures NO$_2$ density in three vertical columns: total, tropospheric, and stratospheric. In this study, the NO$_2$ tropospheric column density corresponding to the lower part of the atmosphere was analyzed. This is the layer most affected by the processes and phenomena that occur on the Earth’s surface. To obtain the NO$_2$ data, the Google Earth Engine (GEE) platform was used through lines of code (Kovács, 2021d). The ‘Offline’ (OFFL) data collection was accessed via ee. ImageCollection (’COPERNICUS/SSP/OFFL/L3_NO2’). Within the collection, the band ‘tropospheric_NO2_column_number_density’ was selected. TROPOMI NO$_2$ data are accessible since June 28, 2018.

The data relating to the human influence on land use were obtained from a global raster that contains the estimated human impact on the land surface measured over ten years (1995–2004) (WCS & CIESIN, 2005). The Global Human Influence Index Dataset is based on nine global indicators: human population pressure (population density), land use and infrastructure (built-up areas, nightlights, land use/land cover), and accessibility (coasts, roads, railways, navigable rivers). Human Influence Index (HII) is a measure of the anthropogenic influence on terrestrial ecosystems (Sanderson et al., 2002). HII was calculated using the best available datasets regarding human settlements (population density, built-up areas), regional accessibility (roads, railways, navigable rivers, coastline), landscape impact (land use/land cover), and electric power infrastructure (nightlights). The HII value ranges from 0 (no human influence) to 64 (the greatest possible anthropogenic influence).

For the bias analysis of ten meteorological parameters, daily satellite data were used from ERA5 ECMWF Reanalysis (Copernicus program) (Hersbach et al., 2018), GLDAS-2.1 (NOAA/NASA) (Earth Engine Data Catalog, n.d.-a; Rodell et al., 2004), and NCEP/NCAR Reanalysis (NOAA/NASA) (Earth Engine Data Catalog, n.d.-b; Physical Sciences Laboratory, 1994). Daily meteorological data were accessed and downloaded using the GEE platform (Kovács, 2021a, 2021b, 2021c). Monthly PBLH data were accessed and downloaded from the MERRA-2 Model through the NASA Giovanni platform (Global Modeling and Assimilation Office (GMAO), 2015b). Likewise, monthly aerosol satellite data were obtained from MERRA-2 Model (Global Modeling and Assimilation Office (GMAO), 2015a).

Validation of the Sentinel-5P satellite results was performed with data collected from on-site monitoring stations and with a Copernicus Atmospheric Monitoring Service (CAMS) chemical transport model (CTM) sourced from the European Environment Agency (European Environment Agency (EEA), 2020).

3. Methods

3.1. Obtaining the NO$_2$ data and calculating the relative NO$_2$ change

Tropospheric NO$_2$ data for the territory of Metropolitan France were obtained using lines of code in GEE accessing the Sentinel-5P satellite COPERNICUS/SSP/OFFL/L3_NO2 database. The ‘Offline’ (OFFL) product was accessed to ensure data quality. However, recent research concluded that there are minor differences in accuracy between OFFL and ‘Near-Real Time’ (NRTI) data products (Verhoest et al., 2021).

Two raster images were generated representing the tropospheric NO$_2$ concentration over the territory of Metropolitan France: an image of average NO$_2$ density during April 2019 under no confinement measures (reference period), and another image of average NO$_2$ density during April 2020 under total confinement. In the first state, the products that contain the NO$_2$ density data are in Level 2 (L2). These products have to be converted to Level 3 (L3) before they can be used as gridded data. In the first step, the conversion to L3 was performed by implementing the harmonize tool and the $\text{harmonize.spatial}$ operation. In the second step, the data were filtered to remove those pixels that had quality values < 75%...
of the NO\textsubscript{2} tropospheric density band. In the last step, tropospheric NO\textsubscript{2} density rasters were exported for subsequent analysis.

The NO\textsubscript{2} relative change (%) between the period without confinement and the period under restriction measures was calculated as follows; Eq. (1):

$$C_{\text{NO}_2} = \left( \frac{X_b}{X_a} - 1 \right) \times 100$$

(1)

where $C_{\text{NO}_2}$ is the relative change (%), $X_a$ is the raster image representing the NO\textsubscript{2} density during confinement, and $X_b$ is the raster image representing the NO\textsubscript{2} density in an equivalent calendar period but without confinement measures.

3.2. Hotspot-coldspot analysis of NO\textsubscript{2} relative change

Hotspot-Coldspot analysis is a measure of the clustering degree of the values in a dataset attributed to spatial features (Getis & Ord, 1992; Ord & Getis, 1995). This query on the relative change in NO\textsubscript{2} between the two periods offers the advantage that the result shows two opposite spatial trends. On the one hand, the areas in which the greatest decrease in NO\textsubscript{2} concentration is statistically significant to form Coldspots (cluster of low values, i.e. greater relative decrease) and, on the other hand, the areas where the smallest reduction or increase in NO\textsubscript{2} is statistically significant to form Hotspots (cluster of high values, i.e. lower relative decrease/increment).

The Hotspot-Coldspot analysis was performed by implementing the Local Getis-Ord GI\textsuperscript{*} statistic. The query on the values attributed to the spatial features returns two results (z-scores and p-values) that together, through a logical relationship between them, give the Getis-Ord GI\textsuperscript{*} result (Table 1). The z-score in each spatial feature indicates the intensity of the clustering phenomenon. The p-value indicates the probability of the spatial pattern. A large negative z-score would express that the negative relative changes of NO\textsubscript{2} (i.e. greater decrease) are forming a coldspot. In contrast, a large positive z-score would indicate that minor negative or even positive relative changes (i.e. minor decrease or increase in NO\textsubscript{2}) are forming a hotspot. The very small p-value ($p < 0.05$) indicates that the observed spatial pattern is unlikely to be the result of a random process.

The Local Getis-Ord GI\textsuperscript{*} statistic was calculated with the following equation (ArcGIS, n.d.); Eq. (2):

$$G' = \frac{\sum_{i=1}^{n} w_{ij} X_i - \left( \frac{\sum_{i=1}^{n} X_i}{n} \right)^2}{\sqrt{\frac{\sum_{i=1}^{n} w_{ij}^2}{n} - \left( \frac{\sum_{i=1}^{n} w_{ij}}{n} \right)^2}}$$

where $X_i$ is the attribute value of the spatial feature, $w_{ij}$ is a weight between the spatial features, $n$ is the total number of spatial features involved in the analysis, $\bar{X}$ is the sample mean, and $S$ is the sample variance.

The tool used for the Hotspot-Coldspot analysis was the ‘Hotspot Analysis’ plug-in of the QGIS software (Guerrì et al., 2021; Oxoli et al., 2018). The vector units introduced in the analysis were the cells of a 10 km grid. The analysis was conducted in three stages: (1) creation of the 10 km grid for the territory of Metropolitan France, (2) obtaining the average zonal statistic of the relative NO\textsubscript{2} change raster ($C_{\text{NO}_2}$) for the grid cells, and (3) execution of the ‘Hotspot Analysis’ tool with Local Getis-Ord GI\textsuperscript{*}. All these steps were realized using QGIS software.

3.3. Calculation of the Human-Influenced Air Pollution Decrease Index (HIAPDI)

So far, the most common index in the literature for estimating air pollution was the well-known Air Quality Index (AQI). One of the key issues of AQI is that it does not address the magnitude of anthropogenic influence, only the concentrations of pollutants in the air. Kovacs & Haidu (2021) created a standardized decontamination index for urban areas known as Atmospheric Clearance Index (ACI), however, although it is broader than AQI, it also only addresses the concentrations of various air pollutants. The HIAPDI, nevertheless, is a function of the degree of anthropogenic influence in a given territory.

HIAPDI was calculated based on two parameters: Human Influence Index (HII) and Air Pollution Decrease Score (APDS). Nine socioeconomic indicators are considered when calculating the HII (WCS & CIE-SIN, 2005). HII was developed by summing the human influence scores attributed to the nine socioeconomic datasets (Sanderson et al., 2002). APDS, as a new proxy indicator, was created by reclassifying the confidence levels of Local Getis-Ord GI\textsuperscript{*} hotspots and coldspots. APDS was developed in two steps: (1) selection by logical expression of the hotspot-coldspot confidence levels and assignment of numerical scores (0-6) for them (Table 1), and (2) rasterizing the scores by creating a new raster layer with the QGIS ‘Rasterize (vector to raster)’ tool. After obtaining the average zonal statistics of HII and APDS for a certain level of administrative-territorial units, the HIAPDI was calculated with the following equation; Eq. (3):

$$\text{HIAPDI} = \sqrt{\text{HII} \times \text{APDS}}$$

(3)

where HIAPDI denotes the Human-Influenced Air Pollution Decrease Index, HII is the Human Influence Index, and APDS is the Air Pollution Decrease Score determined by the result of the Hotspot-Coldspot analysis.

HII and APDS are both gridded (raster) datasets related to geographical space representing two real-world phenomena. A raster is a matrix of cells (pixels) that is organized into rows and columns, each cell containing spatially related geographic information. The matrix is represented by the Cartesian coordinate system, i.e. the rows follow the x-axis and the columns follow the y-axis. For this reason, HIAPDI is calculated as the geometric mean of HII and APDS because HIAPDI is a spatial indicator and, the geometric mean, in this case, is interpreted as the reflection of the given space (which in this study is the geographic space of Metropolitan France). Secondly, the geometric mean between

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Table 1

| Z-score and p-value Relation | Confidence Levels | APDS |
|------------------------------|------------------|------|
| “Z-score” < -1.65 AND “p-value” < 1.65 | Not significant | 0 |
| AND “p-value” > 0.1 | | |
| “Z-score” > 2.58 AND “p-value” < 0.01 | Hotspot 99% | 1 |
| “Z-score” > 1.96 AND “Z-score” > 2.58 AND “p-value” ≤ 0.05 AND “p-value” > 0.01 | Hotspot 95% | 2 |
| “Z-score” ≥ 1.65 AND “Z-score” < 1.96 AND “p-value” ≤ 0.1 AND “p-value” > 0.05 | Hotspot 90% | 3 |
| “Z-score” < -1.65 AND “Z-score” > -1.96 AND “p-value” ≤ 0.1 AND “p-value” > 0.05 | Coldspot 90% | 4 |
| “Z-score” ≤ -1.96 AND “Z-score” > -2.58 AND “p-value” ≤ 0.05 AND “p-value” > 0.01 | Coldspot 95% | 5 |
| “Z-score” ≤ -2.58 AND “p-value” ≤ 0.01 | Coldspot 99% | 6 |
3.4. Homogeneity analysis with chi-square test ($\chi^2$) of meteorological parameters

Homogeneity analysis using $\chi^2$ test determines whether two measurement distributions are statistically similar (homogeneous). The null hypothesis (H0) of the test assumes the existence of homogeneity, i.e., the two contrasted distributions are equal or very similar, within a critical value. Instead, the alternative hypothesis (H1) assumes the difference (non-homogeneity), i.e., the two distributions are unequal. H0 condition is fulfilled if $\chi^2 \leq CV$ (critical value given in the $\chi^2$ distribution table). H1 is accepted in the case of $\chi^2 > CV$. This study assumed the statistical significance level of $\alpha = 0.01$. This implies that H0 is accepted if $p > 0.01$ and H0 is rejected by taking H1 if $p < 0.01$.

The study examined the distributions of ten meteorological parameters that influence the concentration of air pollution. These are surface temperature (2 m), total precipitation, dew point (2 m), sea level pressure, surface pressure, u and v components of wind (10 m), near-surface wind speed (10 m), humidity, and net surface solar radiation. The analysis of these parameters was performed daily for April.

To obtain the $\chi^2$ statistics, the frequency distributions of the meteorological parameters were calculated: (1) during the confinement of April 2020 and (2) during the same period but in 2019 when there were no restriction measures. The value of the $\chi^2$ statistic was obtained using contingency tables. The statistical value of the homogeneity test with $\chi^2$ distribution was calculated with the following equation (Tallarida & Murray, 1987); Eq. (4):

$$
\chi^2_{\text{homogeneity}} = nm \sum_{i=1}^{r} \frac{(f_i - \bar{f})^2}{\bar{f} + \rho_i}
$$

having $r - 1$ degrees of freedom (df) asymptotically and $\chi^2$ distribution if H0 is true. $\bar{f}_i$ is the first frequency value of the first data distribution in the contingency table, $\rho_i$ is the first frequency value of the second data distribution in the contingency table, $n$ is the total number of frequency observations in the first distribution (in this case it is equal to the number of days in the analysis period), and $m$ is the total number of frequency observations in the second distribution.

3.5. Correlation analysis among meteorological parameters

In similar multivariate analyses, it is relevant to consider the statistical relationship among meteorological parameters. For this study, the statistical relationship between meteorological parameters was addressed using Spearman’s correlation. The two main advantages of Spearman correlation over other statistical measures are that it does not require assuming distribution types of the variables and it can find and express nonlinear relationships.

Regarding the two observation datasets of April 2019 and 2020, the Spearman correlation between the ten meteorological parameters was calculated by implementing correlation matrices. The calculations were performed using R software. Spearman’s Rank Correlation Coefficient (SRCC) was computed based on the well-known formula (Glasser & Winter 1961; Spearman, 1904); Eq. (5):

$$
r_s = 1 - \frac{6 \sum_{i=1}^{n} D_i^2}{n(n^2 - 1)}
$$

where $r_s$ denotes SRCC, $D_i$ is the difference in ranks of the ith element between the two ranks of each observation, and $n$ is the total number of even data points. The output of SRCC also called Spearman’s rho ($\rho$), varies between $-1$ and $1$ where $-1$ denotes a perfect positive association of ranks while $-1$ indicates a perfect negative association of ranks. The closer SRCC is to 0, the weaker the association between the variables.

3.6. Validation of satellite measurements with on-site monitoring data

The relative change in NO$_2$ concentration between the confinement period and the reference period was validated by using data collected from 214 on-site monitoring stations throughout Metropolitan France to contrast the TROPOMI sensor’s results with the on-site ground monitoring data. Validation was based on the CAMS CTM model. Based on measurement data from stations, this model simulates the computerized reconstruction of atmospheric chemistry, thus providing air pollution forecasts for large areas. Both the model and the station data were obtained from EEA (European Environment Agency (EEA), 2020; Schulz et al., 2020).

3.7. Verification of the correlation between variables

To verify the statistical significance of the relationship between the variables, the correlation coefficient was tested using the T-test ($t_{xy}$). The result of the T-test concludes whether the correlation between two variables is significantly different from 0. Its difference from 0 indicates that the two variables are interdependent. The H0 of the test assumes that there is no difference from 0 ($\rho = 0$) while the H1 declares that between the two variables the correlation is statistically different from 0 ($\rho \neq 0$). T-test values were computed applying the following formula (Kanji, 2006); Eq. (6):

$$
t_{xy} = r_{xy} \sqrt{n - 2} \over 1 - r_{xy}^2
$$

having a Student T distribution and $n - 2$ degrees of freedom. $r_{xy}$ is the correlation coefficient between two variables, $r_{xy}^2$ is the coefficient of determination between them, and $n$ is the total number of even observations. H0 is held if the result is $t_{xy} \leq CV$. Otherwise, H0 is rejected by taking H1 if the test gives $t_{xy} > CV$. This study assumed the statistical significance level of $\alpha = 0.05$. Concerning the p-value, this implies that H0 is maintained if $p > 0.05$ and H1 is accepted if $p < 0.05$.

3.8. Testing the planetary boundary layer (PBL) parameter

Atmospheric processes are complex and include several indirect parameters that affect air pollution over a geographical area, also depending on the type of prevailing climate and relief. Recent research has focused also on PBL as an influencing factor in air contamination prevalence, pointing to the fact that PBL is not a direct meteorological variable, but is strongly related to both temperature and winds (Chen et al., 2020). Consequently, NO$_2$ air pollution and NO$_2$-meteorology interactions are strongly influenced by variations in planetary boundary layer height (PBLH).

PBLH is not a specific meteorological variable but a factor that plays an indirect role in the land-atmosphere interaction, being the lowest part of the atmosphere, and its behavior is directly influenced by its contact with the planetary surface. As a result, PBLH has an impact on temperature and near-surface winds. PBLH retrievals from various sources of satellite measurements were intercompared in recent research (Ding et al., 2021).
Since the MERRA-2 PBLH data utilized in this analysis are monthly time-averaged, two gridded datasets were downloaded for the territory of Metropolitan France: one set for April 2019 (no anti-COVID-19 measures) and one for April 2020 (total confinement). A correlation and regression analysis was conducted between the two datasets based on the statistical T-test detailed above (Eq. (6)). The extraction of the geolocated PBLH information from the gridded datasets was performed by implementing the QGIS tool 'Raster pixels to points'. Statistical analyses were performed with the obtained point data.

4. Results

4.1. Relative change of NO$_2$ and HII

During a full-month lockdown in Metropolitan France, results of TROPOMI’s high spatial resolution data revealed an extensive decline in tropospheric NO$_2$ concentrations compared to the reference period of April 2019 (Fig. 1a and b). A more salient and general decrease was observed in the northern regions (Ile-de-France, Hauts-de-France, Grand Est, Bourgogne-Franche-Comté, Centre-Val de Loire, Pays de la Loire, Bretagne, Normandie). A notable decline was also detected in the Auvergne-Rhône-Alpes region. The decrease in NO$_2$ was observed to be less strong in the southern regions (Nouvelle-Aquitaine, Occitanie, Provence-Alpes-Côte d’Azur, Corse), however, in some densely populated areas reduction was also detected.

4.2. Histogram of the dNO$_2$ raster (%): Relative change during the first total confinement concerning the reference period in Metropolitan France.

The results of the relative change of NO$_2$ evidenced that in several areas there were decreases from –35% to below –50% (Fig. 1c). The greatest decrease in contamination was detected predominantly in the north (especially in Ile-de-France, Grand Est, and Centre-Val de Loire). However, reductions from –35% to –50% and below –50% also occurred locally in the southern regions. This was especially noticeable around the localities in the valleys of the Pyrenees, Alps, and in other
regions of the Massif Central or the most populated areas of Corsica. Therefore, a larger overall decline in NO\textsubscript{2} pollution during the lockdown period was detected in the northern part of France, also in the Saone, Rhone, and Isere valley regions, and a smaller overall decline in the south-southwest, but locally there were also important reductions. On average, the greatest decrease occurred in the Ile-de-France region (–39.03%), followed by Grand Est (–33.69%) and Centre-Val de Loire (–31.71%). The smallest decrease in average values by region was observed on the island of Corsica, where in general an increase in NO\textsubscript{2} was detected concerning the reference period (4.07%), followed by Nouvelle-Aquitaine (–11.04%), and Provence-Alpes-Côte d’Azur (–12.02%). However, despite minor increases occurring in different locations, pollution loss was widespread across Metropolitan France (Fig. 2). Topography as an extra potential cause was found to be insignificant in the NO\textsubscript{2} decline process (Fig. S1).

The increase of NO\textsubscript{2} in Corsica (Corse) (4.07%) was related to the chemical complexity of the interactions between different air masses. The island of Corsica lies at the crossroads of dusty air masses from North Africa and polluted outflows from the European continent. Important research in the recent past (Ndour et al., 2009) focusing on the chemical interaction between NO\textsubscript{2} and Saharan dust revealed that the photochemistry of natural minerals, in particular dust originating from the Sahara Desert, has a significant impact on NO\textsubscript{2} chemistry. In this study, a spatio-temporal analysis of the dusty air masses originating from northern Africa (Saharan dust) was performed using aerosol MERRA-2 Model satellite data (Global Modeling and Assimilation Office (GMAO), 2015a). The results evidenced that Saharan dust intrusions regularly occur in the Mediterranean region of Corsica during March and April (between 41°N and 43°N geographical latitudes) (Figs. S2, S3, S4; Vid.1 animation video file).

Supplementary video related to this article can be found at https://doi.org/mmcdoino

The results of the Hotspot-Coldspot analysis of the relative change demonstrated with statistical evidence these two opposing trends between north-northeast and south-southwest (Fig. 1d). In the northern and eastern regions and extensive areas of the Auvergne-Rhône-Alpes region, large and highly significant change coldspots appeared. This indicated that there was the largest negative relative change (i.e. decrease) in the NO\textsubscript{2} concentration during confinement. Several coldspots of change were also detected in the central and southern part of France that corresponded to major cities and areas of great tourist interest (e.g. Limoges, Clermont-Ferrand, Nice, towns in the Pyrenees). Extensive hotspots of change were evidenced in the Nouvelle-Aquitaine, Occitania, Provence-Alpes-Côte d’Azur and Corsica regions. Other smaller hotspots appeared in the north in Bretagne, Normandie, Hauts-de-France, Bourgogne-Franche-Comté, and Auvergne-Rhône-Alpes. The case of the Corsica hotspot, where the highest percentage increase was recorded at the country level, is different because at these latitudes a greater amount of Saharan dust is usually present between March and April. These hotspots indicated the areas where there was generally the largest positive relative change in NO\textsubscript{2} during the lockdown (i.e. overall increase but also smaller decrease). It was noted that these regions are primarily mountainous (the Alps, Pyrenees, Corsica) or wide-open plains (Aquitaine Basin) where the concentration of NO\textsubscript{2} is low due to the lack of high anthropogenic pollution. Therefore, a relatively large positive change would indicate an increase, however, for that area this generally means less variation, as shown by the NO\textsubscript{2} density results in 2019 and 2020 (Fig. 1a and b).

The HII data evidenced the anthropogenic impact in Metropolitan France (Fig. 3). It became clear that it is a highly modified territory by

Fig. 3. Human Influence Index (HII) in Metropolitan France (Data source: Wildlife Conservation Society & Center for International Earth Science Information Network, from NASA Socioeconomic Data and Applications Center).
human activities. There are large continuous areas of high human impact (HII > 40), especially in the Ile-de-France, Hauts-de-France, and Grand Est regions, in the Rhône valley, on the Mediterranean coast, and around other cities. Areas with less anthropogenic impact (HII ≤ 10) only remain in certain mountainous/less populated regions (Alps, Pyrenees, Corsica, Massif Central, Landes).

Table 2
Results of the homogeneity analysis with \( \chi^2 \) test for the distributions of ten meteorological parameters during the COVID-19 confinement period (April 2020) concerning the reference period without anti-COVID-19 measures (see also Fig. A1a–j). The null hypothesis (H0) of the test holds that the two distributions are equal or very similar within the critical value (CV) (homogeneity). The alternative hypothesis (H1) assumes that the two distributions are unequal or very different (difference). H0 is maintained if \( \chi^2 \leq CV \) and \( p > 0.01 \) at a given significance level \( \alpha \). H1 is accepted if \( \chi^2 > CV \) and \( p < 0.01 \). In the column ‘\( \chi^2 \) statement’ appears the test value, which is contrasted with the CV. The value in parentheses is the degree of freedom (df).

| Meteorological parameter | \( \chi^2 \) statement | CV   | p-value (0.01) | Conclusion |
|--------------------------|-------------------------|------|----------------|------------|
| Average daily temperature (2 m) | \( \chi^2(7) = 14.40 \); \( \alpha = 0.01 \) | 18.475 | 0.045 | H0: homogeneity |
| Total precipitation       | \( \chi^2(6) = 1.47 \); \( \alpha = 0.01 \) | 16.812 | 0.961 | H0: homogeneity |
| Dew point (2 m)           | \( \chi^2(6) = 14.87 \); \( \alpha = 0.01 \) | 16.812 | 0.021 | H0: homogeneity |
| Mean sea level pressure   | \( \chi^2(6) = 5.47 \); \( \alpha = 0.01 \) | 16.812 | 0.485 | H0: homogeneity |
| Surface pressure          | \( \chi^2(6) = 2.53 \); \( \alpha = 0.01 \) | 16.812 | 0.865 | H0: homogeneity |
| u-component of wind (10 m) | \( \chi^2(10) = 2.14 \); \( \alpha = 0.01 \) | 23.209 | 0.995 | H0: homogeneity |
| v-component of wind (10 m) | \( \chi^2(10) = 6.67 \); \( \alpha = 0.01 \) | 23.209 | 0.756 | H0: homogeneity |
| Near-surface wind speed (10 m) | \( \chi^2(10) = 4.88 \); \( \alpha = 0.01 \) | 23.209 | 0.944 | H0: homogeneity |
| Specific humidity         | \( \chi^2(7) = 11.06 \); \( \alpha = 0.01 \) | 18.475 | 0.136 | H0: homogeneity |
| Surface net solar radiation | \( \chi^2(5) = 3.39 \); \( \alpha = 0.01 \) | 15.086 | 0.640 | H0: homogeneity |

During confinement in the regions of Metropolitan France, results of the regression and correlation analysis with the T-test evidenced that there was a statistically significant inverse relationship between HII and decreased NO\(_2\) concentrations (Fig. 4). The correlation coefficient between HII and dNO\(_2\) was \( R = -0.721 \). The coefficient of determination between the two variables with a quadratic function curve was \( R^2 = 0.628 \). The result of the T-test for correlation determined that: \( t(11) = -2.942 > CV = 2.201, \alpha = 0.05, p = 0.013; H1 \). These findings support that as human influence increases, the greater the reduction in NO\(_2\) pollution in the context of anti-COVID-19 measures.
4.2. Meteorological biases influencing air pollution

To determine if meteorological conditions could have influenced the changes observed in the NO$_2$ concentration during April 2020 over France, ten meteorological parameters based on daily data were investigated by implementing a homogeneity analysis of distributions with $\chi^2$ test (Table 2, Fig. A1a – j). The analysis had as reference period the same 30 days of April, but in 2019, when there were no restrictive measures. The results revealed that the detected changes could not be the effect of variation in the temporary meteorological conditions. None of the ten analyzed meteorological parameters differed significantly during the confinement period from the reference period without confinement (statistically stable homogeneity).

Regarding the indirect parameter PBLH, which is influential in some meteorological processes, the T-test result $t(11) = 3.810 > CV = 1.984$, $\alpha = 0.05$, $p = 0.000$; $H_1$ concluded that the April 2019 PBLH significantly determined the April 2020 PBLH over the territory of France ($R = 0.803$, $R^2 = 0.645$) (Fig. 5). In other words, PBLH under total confinement remained statistically significantly dependent on PBLH under no anti-COVID-19 measures. This means that the spatiotemporal behavior of the PBLH was not statistically different between the two observations. Consequently, the PBLH parameter also could not have significantly affected the downward changes in NO$_2$ pollution concentration during the total lockdown over Metropolitan France.

The SRCC results obtained from the matrix correlation analysis (SRCCM) between the ten meteorological parameters revealed the statistical association between the weather factors in the two observation periods (Fig. 6a and b, Tables S1, S2). These results evidenced that in the case of April 2019 (without confinement measures) the overall significant correlation percentage between the ten variables was 17%. On the other hand, in the case of April 2020 (under total confinement) the overall significant correlation percentage among the ten variables was slightly higher, 23.5%. Regardless, in both observations, the overall correlation percentage between meteorological parameters was considerably low and there was no potential covariance between them. Consequently, the statistical relationship between meteorological parameters does not represent a potential covariance and, therefore, could not have influenced the detected changes in near-surface NO$_2$ concentration in France.

In April 2019, two highly and another minor significant patterns were evidenced in the correlation matrix between the weather parameters (Fig. 6c). A strong correlation pattern was observed between temperature, specific humidity, and dew point. Another high correlation pattern was recorded between sea level pressure, surface pressure, and surface net solar radiation. Also, a smaller significant pattern was observed between temperature, specific humidity, and dew point.

Similarly, during April 2020, there were two highly significant patterns and another of lesser intensity in the matrix (Fig. 6d). The same pattern of high correlation was detected between temperature, specific humidity, and dew point. Another high correlation pattern was recorded between sea level pressure, surface pressure, and surface net solar radiation. In this case, however, a minor pattern was observed between temperature, specific humidity, and dew point.

These results support what is indicated by the overall significant
correlation percentages between the two sets of observations evidencing that the meteorological parameters varied minimally between April 2019 and 2020 and, by implication, it is impossible to derive from this minimal covariance the near-surface NO\textsubscript{2} decline.

4.3. HIAPDI and relative change of NO\textsubscript{2}

HIAPDI was calculated based on the HII, plus the APDS derived from Hotspot-Coldspot analysis of the relative change in tropospheric NO\textsubscript{2}.

APDS revealed the intensity of the change phenomenon in the regions of France indicating the decrease levels in near-surface NO\textsubscript{2} pollution (Fig. 7). The APDS results evidenced a high reduction in the north of the country on a west-east line, having Ile-de-France in the epicenter and extensive areas of decline in Grand Est, Centre-Val de Loire, and Normandie. In the extreme north of the Hauts-de-France region, near the Belgian border, another point of maximum reduction score was observed. Furthermore, the second-largest center of NO\textsubscript{2} decrease was detected in Auvergne-Rhône-Alpes, basically on two lines that correspond to two densely populated river valleys: Saône-Rhône and Isère. Other reduction spots in the south were around the city of Nice and along the Arles-Nîmes-Montpellier axis. There were also significant declines in isolated areas surrounding large cities: Nantes, Limoges, Clermont-Ferrand, Lille, Béziers, Poitiers, Angers. The smallest decline in NO\textsubscript{2} was observed in the south-western part (Aquitaine Basin), in the axis of the Alps, and on the island of Corsica. In these parts, the population density and anthropogenic influence are also lower.

The HIAPDI spatial index was calculated for two levels of territorial administration: departments and regions of Metropolitan France. HIAPDI indicated for a given administrative-territorial unit the degree of decrease in near-surface NO\textsubscript{2} air pollution due to human influence in the context of confinement (Fig. 8). A HIAPDI value equal to 0 means no significant human implication; also, the index’s values around 0 indicate a small human influence on reducing air pollution concentrations (NO\textsubscript{2} density in this case). Contrarily, a large HIAPDI value reveals a highly significant anthropogenic influence on the decrease in air pollution. Accordingly, as the value of the index increased, the greater was the anthropogenic influence on the confinement-induced air pollution reduction.

The results of the HIAPDI based on the departments evidenced two opposite territorial tendencies in Metropolitan France. The findings of this analysis demonstrated that in the northern, northeastern, and eastern parts of the country, the human influence was more decisive in reducing NO\textsubscript{2} air pollution during the applied anti-COVID-19 measures (Fig. 8). Only a few departments were excepted from this general trend where the relative change in NO\textsubscript{2} concentration concerning the reference period was generally not statistically significant. Contrariwise, in the southern, southwestern, and western parts of the country, HIAPDI indicated that in these areas the human influence was less intense or insignificant in decreasing NO\textsubscript{2} during confinement. Consequently, based on the results, a diagonal line could be drawn over the territory of

![Fig. 7. APDS indicating the degree of statistically significant NO\textsubscript{2} decrease attributed to confinement.](image-url)
Fig. 8. HIAPDI and its NO$_2$ diagonal in the departments of Metropolitan France.

Fig. 9. Scatterplot showing the relationship between HIAPDI and relative change in tropospheric NO$_2$ concentration during April 2020 (COVID-19 lockdown) in French regions.
Metropolitan France: the HIAPDI diagonal, which had its vertices on the axis of the cities of Rennes and Grenoble, approximately.

The results of the regression and correlation analysis using T-test revealed that there was an inverse and statistically significant relationship between HIAPDI and decrease in tropospheric NO\textsubscript{2} during the COVID-19 confinement in the regions of France (Fig. 9). The correlation coefficient between HIAPDI and dNO\textsubscript{2} was R = −0.918. The coefficient of determination using a quadratic function curve was R\textsuperscript{2} = 0.939. The result of the T-test for the correlation between the variables established that: t(10) = -6.531 > CV = 2.228, α = 0.05, p = 0.000; H\textsubscript{1}. The result supported with reliable statistical evidence that as the HIAPDI value increased, the greater the reduction in air pollution. This result demonstrated that HIAPDI is an adequate measure to estimate NO\textsubscript{2} decrease under confinement conditions. As being an outlier in the dataset, in this correlation and regression analysis, the region of Corsica (Corse) was not considered because only in this territory an average dataset, in this correlation and regression analysis, the region of Corsica decreases under confinement conditions. As being an outlier in the ship between HIAPDI and decrease in tropospheric NO\textsubscript{2}.

4.4. Validation of satellite dNO\textsubscript{2} results with CAMS CTM

Based on in-situ NO\textsubscript{2} concentration measurements from 214 stations across the French territory, the relative NO\textsubscript{2} change results obtained from TROPOMI satellite data were validated using the CAMS chemical transport model. This CAMS CTM model was developed to estimate the NO\textsubscript{2} changes attributed to the COVID-19 lockdown during April 2020 (Fig. 10a).

Validation was performed using regression and correlation analysis with T-test. The results indicated a direct and statistically significant connection between dNO\textsubscript{2} measured by the Sentinel-5P satellite and dNO\textsubscript{2} estimated by the CAMS CTM in the regions of France (Fig. 10b). The correlation coefficient between the two variables was R = 0.706. The coefficient of determination describing the points with a quadratic function curve was R\textsuperscript{2} = 0.672. The output of the T-test for the correlation between the variables returned: t(11) = 2.820 > CV = 2.201; α = 0.05; p = 0.017; H\textsubscript{1}. This validation result demonstrated statistically significant evidence that the changes detected using TROPOMI data were in concordance with those estimated by on-site monitoring stations on the ground. The CAMS CTM was found to estimate a greater decrease in air pollution than satellite measurements. This happened mainly because the data resulting from point measurements were influenced by merely local conditions and by the CAMS interpolation model (see also: Schulz et al., 2020; Ştefan et al., 2013; Virghileanu et al., 2020).

5. Discussions

The findings of this research support the theory that territorial human influence was decisive in the phenomenon of near-surface NO\textsubscript{2} pollution decrease during COVID-19. This study revealed a significant NO\textsubscript{2} reduction phenomenon during April 2020 when a total lockdown was in force in France. As compared with previous concentration levels, reductions of −35% to −50% and lower were detected in several areas. A notable exception was the Corsica region where there was a slight increase (4.07%) over the entire island region due to the presence of elevated tropospheric Saharan dust during the analysis period (Ndour et al., 2009). The results indicated that these changes cannot be explained by simple temporal variations in atmospheric conditions. The study found a correlation between human influence measured with a precalculated spatial index (HII) and the decrease in NO\textsubscript{2} attributed to confinement. Besides, this study evaluated the degree of anthropogenic influence on air pollution reduction in different administrative-territorial units of France by using a novel spatial index (HIAPDI).

In line with the research hypothesis, the study revealed through the HII and HIAPDI indices that the greater the human influence within a geographical territory, the more significant the decrease in NO\textsubscript{2} air pollution attributed to lockdown. Therefore, the human impact is decisive in the evolution of pollution under control measures and policies. This fact provides a new perspective in the context of research that revealed strong decreases in NO\textsubscript{2} and PM during similar lockdowns (Cameletti, 2020; Kumari & Toshniwal, 2020; Rugani & Caro, 2020; Saha et al., 2022; Zambrano-Monserrat et al., 2020). Moreover, this study, by adopting a meteorological approach, focuses on a large national territory rather than on changes in and around urban areas (Sokhi et al., 2021). Considering recent research, it can be generalized that the correlation between territorial anthropogenic influence and decrease in air pollution was also linked to the level of economic development of particular areas of France (Kovacs & Haidu, 2021; Magazzino et al., 2021; Mele & Magazzino, 2021). It is evident that the anti-COVID-19
measures slowed down human activity to a greater extent in the regions with the greatest economic potential. However, HI reflects more information on man’s territorial impact than certain economic indices, such as GDP, gross value added at basic prices (GVA), or employment. Additionally, the HIAPDI diagonal also appears to be influenced by France’s territorial inequalities based upon economic and population factors. This happens mainly due to the higher population density and greater concentration of the national economy in the north-northeast and east.

Additional causes, such as topography, can influence population density, air pollution, and certain types of anthropogenic activities, although in this case, it did not represent a direct cause of the observed changes in NO2 between localities (Fig. S1), since the measures against COVID-19 were not directed for exclusive areas of the territory. Across Metropolitan France, the decrease in NO2 air pollution during the COVID-19-induced total confinement was, in fact, produced by potential interactions between meteorology and territorial human influence. Locally, different interactions between weather conditions, NO2, and anthropogenic activities may have occurred, however, this differential influence between localities was minimal because during April 2020 a nationwide total lockdown was implemented by all levels of French administration, reducing significantly most human activities related to economy and mobility (Galeazzi et al., 2020; Gouvernement Français, n.d.; Salje et al., 2020).

In the context of mitigation measures in large urban areas, the experiments of this study and the HIAPDI spatial index provide new insight into the relationship between human influence on the territory and changes in air pollution (Coudon et al., 2021; Dahech et al., 2022). Anti-COVID-19 measures were not intended as a way to reduce air pollution; however, they mitigated large extents of air contamination in France, Europe, and several other countries (Fan et al., 2021; Ikhlasse et al., 2021; Jiang et al., 2021; Magazzino et al., 2020; Piazzola et al., 2021; Sbai et al., 2021). Consistent with other studies on air pollution change under lockdowns using satellite data (Hashim et al., 2021; Potts et al., 2021; Prunet et al., 2020; Stasielé et al., 2021), this study also validated the results obtained remotely with in-situ data from stations located throughout the territory (Bar et al., 2021; Biswal et al., 2021; Chan et al., 2021). The validation contributed to the consistency of the correlation analysis between HII/HIAPDI and dNO2.

The results of this research contribute to a clearer understanding of the correlation between air pollution changes and anthropogenic influence. Although, in the framework of the pandemic, research in France previously focused on the phenomenon of dramatic reductions in air pollution and their impact on health (Adelaida et al., 2021; INERIS, 2020; Pazzino et al., 2021), these results emphasize another aspect of decontamination. Namely, the intrinsic link between the degree of human environmental impact on a certain territory and the magnitude of the atmospheric pollution change that may occur. In this vision, the importance of the effectiveness of pollution mitigation policies becomes clearer, which – regardless of the COVID-19 context – must be very specific and aimed at having a positive impact on the urban environment (Schneider et al., 2022).

Moreover, this study also addressed the question of influential meteorological biases and PBLH differences affecting air pollution during lockdowns, pointed out by recent research (Chen et al., 2020; Kovács & Hádik, 2021; Menut et al., 2020). In this paper, the analysis of ten atmospheric parameters and PBLH found that the meteorological conditions during the confinement were statistically similar to those in the reference period, i.e. in the circumstances without anti-COVID-19 measures. This evidenced that meteorological variations could not affect NO2 pollution. Consequently, the observed decreases were caused by anti-COVID measures.

The methodological options were limited by the current low temporal resolution of Sentinel-5P data accessible since mid-2018. For this reason, the equivalent reference period of the confinement was limited exclusively to April 2019. Nevertheless, this did not pose an obstacle since the relative NO2 change between a period under confinement measures and another period under no anti-COVID restrictions could be calculated. Furthermore, it is beyond the scope of this study to address the particular types of anthropogenic influence that determine the phenomenon of NO2 decrease during lockdown. More research is needed to establish these particular correlations between human influence types and changes in air pollution.

6. Conclusions

As the effect of total and partial lockdowns demonstrate the relevance of human involvement in changing air pollution, it becomes important to understand the degree of human influence in these dynamics.

This study investigated the effect of human influence on the relative decrease in near-surface NO2 concentration during a period of confinement induced by the COVID-19 pandemic. The research focused on Metropolitan France, which was one of the countries most affected by the coronavirus in Europe. Results revealed that the greater the human influence, the greater the NO2 reduction during the April 2020 lockdown.

The measure of anthropogenic influence on the reduction of air pollution — the HIAPDI spatial index — was found to be reliable in determining the link between human involvement and NO2 concentration change. HIAPDI revealed that France was divided into two distinct spatial patterns by a diagonal. In one part, larger human involvement was observed in the reduction of NO2, while in the other less. This occurred due to territorial inequality between the north-northeast and south-southwest in terms of population density and concentration of the national economy.

In the context of mobility control measures, future research on the role of human influence in declining air pollution should be aimed at improving our understanding of how different types of human influences/activities may affect the change in air pollution. Furthermore, although this experiment measured the relative change of NO2 under anti-COVID-19 measures, observational studies are required to obtain more information on other polluting gases and their correlation with territorial human influence.

Declaration of competing interest

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

Acknowledgments

Acknowledgment is expressed to the data providers, especially the Wildlife Conservation Society and Center for International Earth Science Information Network, the European Environment Agency, and NASA Giovanni. Credit is also given to the developers of the open-source QGIS software.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2022.119441.
Appendix A

Fig. A1. Frequency distributions of ten meteorological factors during confinement (April 2020) and in its corresponding period in 2019 (see also Table 2). H0 (homogeneity) is maintained if $\chi^2 \leq CV$ (critical value) and $p > 0.01$ at the given significance level $\alpha$. H0 is rejected by accepting the H1 (difference) if $\chi^2 > CV$ and $p < 0.01$. Mean surface temperature and dew point are given at 2 meters height. U and v components of wind and near-surface wind speed are given at 10 meters height.
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