

Review

COVID-19 Pandemic as an Environmental Health Indicator: Lessons Learned from Air Pollution Changes and Climate Implications

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Abstract

The most crucial environmental issue threatening public health is air pollution, which is strongly associated with respiratory, cardiovascular, and infectious diseases. Increased concentrations of air pollutants, particularly from industrial activities, fossil fuel combustion, and transportation, have become a major global concern. Fine particulate matter emitted from diesel vehicles, biomass burning, and coal combustion has been identified as one of the most important contributors to adverse health outcomes. Previous studies have demonstrated that meteorological conditions and air pollutant concentrations may influence the transmission dynamics and severity of respiratory viral infections, including COVID-19. The COVID-19 pandemic provided a unique global-scale environmental experiment by temporarily reducing anthropogenic activities, including transportation and industrial processes, through lockdown measures. These restrictions resulted in short-term improvements in outdoor air quality and reductions in greenhouse gas emissions in many regions. However, these temporary improvements also highlighted the need for long-term structural strategies rather than short-term reductions in human activities to mitigate climate change. In this critical narrative review, peer-reviewed original research and review articles, with particular emphasis on studies published during and following the COVID-19 period, were critically evaluated to examine the interactions among air pollution, climatological parameters, and COVID-19 transmission, as well as the effects of COVID-19-related lockdown measures on outdoor air quality. Furthermore, the implications of the pandemic for climate change mitigation and future environmental health preparedness are discussed, with particular attention to healthcare capacity, technological and surveillance infrastructure, public education, and integrated environmental and public health monitoring. Methodological limitations related to spatial mismatch between environmental exposure and epidemiological data, as well as delayed and nonlinear exposure–response relationships, are also critically considered. Overall, the evidence highlights the need to translate the temporary environmental improvements observed during the pandemic into long-term strategies integrating environmental monitoring, public health preparedness, technological capacity, and climate action.



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1. Introduction

There is no doubt that the most important environmental problem threatening the whole world today, and over the next century, is global climate change, particularly that

caused by the increase in the concentrations of greenhouse gases (GHGs) such as carbon dioxide (CO₂), methane (CH₄), nitrous oxides (NO_x), and other fluorinated gases released into the atmosphere as a result of the burning of fossil fuels, especially during energy production. Fuel-fired thermal power plants and industries, urbanization, deforestation, land degradation, and agricultural and mining activities are all sources of GHG emissions that contribute to this global environmental phenomenon [1–3]. Global climate change has numerous negative effects on human beings, and its effects on public health have gained great attention [2,4,5]. Considering the increased exposure to air pollutants including carbon monoxide (CO), nitrogen dioxide (NO₂), sulfur dioxide (SO₂), ground-level or tropospheric ozone (O₃), and particulate matter (PM₁₀: aerodynamic diameter smaller than 10 µm and PM_{2.5}: aerodynamic diameter smaller than 2.5 µm) due to global climate change, there has been an increase in important diseases, such as asthma, lung inflammation, heart ischemic, and vector-borne infectious diseases affecting the cardiovascular and respiratory system and immune system ([5,6].

In recent years, increasing attention has been given to the interactions between environmental changes and public health risks, particularly after the COVID-19 pandemic, which demonstrated the vulnerability of societies to environmental and biological stressors. The pandemic has also provided a unique opportunity to evaluate the connection between anthropogenic activities, environmental changes, and public health outcomes, highlighting the importance of integrated environmental health strategies for future global challenges. In this context, many previous studies indicated that outdoor air pollutant concentrations, such as CO, NO₂, SO₂, O₃, PM_{2.5}, and PM₁₀, and climatological parameters, including ambient temperature, atmospheric pressure, relative humidity, wind speed, gust, and cloud conditions, were associated with the transmission of COVID-19 [7–12]. To prevent the spread of this virus, which caused significant global health impacts, many strict lockdown measures restricting human mobility, such as public, airport, and ship transport limitations, were implemented on regional or national scales by decision-makers. These measures, although primarily introduced as public health interventions, also provided an unprecedented opportunity to evaluate the relationship between anthropogenic activities and environmental quality. Previous studies examined the effects of COVID-19-related lockdown measures on regional air pollution by comparing air pollutant concentrations obtained from monitoring stations or remotely sensed data with previous years' observations. Ground-based air-quality monitoring stations provide direct measurements of pollutant concentrations at specific locations and are essential for evaluating temporal variations in ambient air quality. However, the spatial representativeness of these measurements depends on monitoring-site characteristics, pollutant type, averaging period, and the spatial variability of pollutant concentrations; therefore, measurements obtained at individual stations may not fully represent air-quality conditions across larger or heterogeneous geographical areas [13]. Remote sensing provides complementary spatial information by enabling repeated observations of atmospheric constituents such as NO₂, CO, O₃, aerosols, and GHGs over regional to global scales, while recent geostationary platforms have further improved the temporal resolution of atmospheric observations [14,15]. For example, the TEMPO geostationary mission demonstrates the value of high-spatial-resolution, hourly satellite observations for capturing suburban pollution patterns and diurnal variability that may be missed by once-daily low-Earth-orbit observations [16]. In addition, high-resolution a priori information and the use of a common spatial grid can improve the consistency and comparability of satellite NO₂ retrievals derived from datasets with different spatial resolutions [17]. Nevertheless, satellite-derived quantities and ground-level measurements represent different spatial and vertical characteristics and should not be interpreted as directly equivalent. For example, aerosol optical depth represents particle loading through

the atmospheric column and requires additional modeling or statistical relationships to estimate surface $PM_{2.5}$ concentrations, while satellite-derived tropospheric NO_2 is affected by spatial resolution, vertical-profile assumptions, and retrieval characteristics [18,19]. Thus, ground-based monitoring and satellite observations provide complementary evidence, and their respective spatial, temporal, and measurement characteristics should be considered when comparing air-quality findings across studies. Despite these methodological differences, evidence obtained using these complementary observational approaches has provided important insights into the changes in atmospheric pollution associated with COVID-19-related restrictions.

Most of these studies demonstrated improvements in air quality during quarantine periods, highlighting the strong influence of transportation and industrial activities on atmospheric pollution [4,20–23]. More recent systematic reviews and global-scale assessments have further confirmed that COVID-19-related restrictions resulted in significant reductions in major pollutants, particularly NO_2 , $PM_{2.5}$, PM_{10} , CO, and NO_x , while also emphasizing the role of mobility reduction and industrial activity changes in improving air quality [24,25]. Correspondingly, this review paper critically evaluates the associations among climate parameters, air pollutants, and SARS-CoV-2 transmission, as well as the impacts of COVID-19-related lockdown restrictions on outdoor air quality. Furthermore, this review highlights the lessons learned from the pandemic by examining the interactions among human activities, environmental quality, respiratory health, and climate change, while considering their implications for future environmental health preparedness. The current state of knowledge is discussed from four main perspectives: (i) the influence of air pollutants and climatological conditions on COVID-19 transmission and broader respiratory health outcomes, including spatial and temporal considerations in exposure assessment; (ii) the impacts of COVID-19-related lockdown measures on outdoor air quality, with attention to meteorological variability and differences across pandemic periods; (iii) the implications of pandemic-related changes in anthropogenic emissions for climate change mitigation; and (iv) integrated environmental health strategies for future public health challenges, including healthcare capacity, technological and surveillance infrastructure, public education, and the integration of environmental and health data. The conceptual framework illustrating the scope and main components of this review is presented in Figure 1.

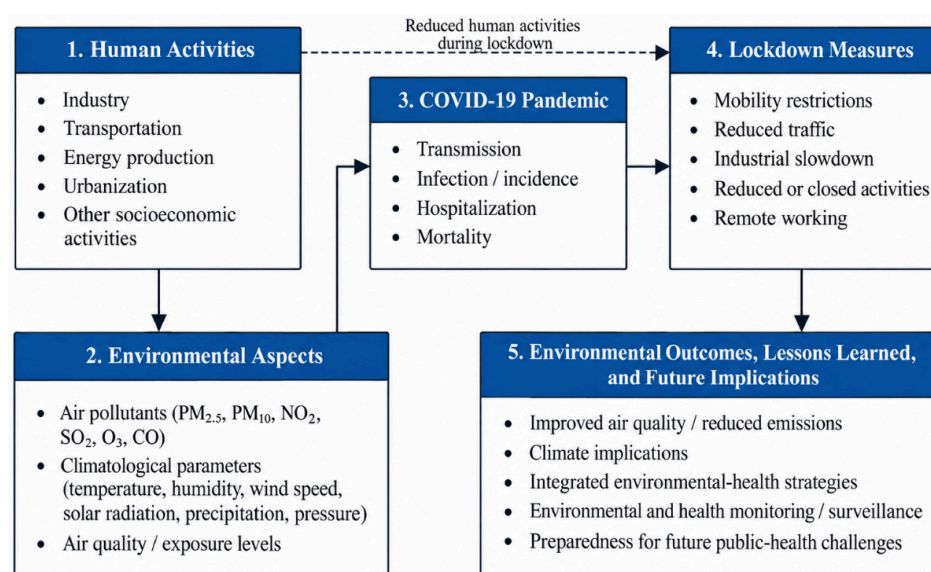


Figure 1. Conceptual framework illustrating the relationships between COVID-19, air pollution, climate parameters, and environmental health implications.

Figure 1 shows how human activities influence environmental conditions through emissions, air pollution, and climatological factors, while the COVID-19 pandemic triggered lockdown measures that temporarily reduced many anthropogenic activities. These restrictions resulted in short-term environmental improvements, particularly in air quality and emissions. The framework also highlights how these observations can inform longer-term environmental health strategies, integrated monitoring systems, and preparedness for future public health challenges.

2. Methodology

This study was conducted as a critical narrative review to synthesize evidence on the interactions among air pollution, climatological conditions, COVID-19 transmission, pandemic-related changes in outdoor air quality, and their broader climate and environmental health implications. The literature was identified primarily through Web of Science, Scopus, and Google Scholar. No predefined publication-year restriction was applied; however, particular attention was given to studies published during and following the COVID-19 period to capture both the immediate environmental effects of the pandemic and subsequent evidence evaluating their longer-term implications. Peer-reviewed original research articles and review papers constituted the principal evidence base. The literature search was conducted using combinations of keywords reflecting the main themes of the study. Search terms included “COVID-19” OR “SARS-CoV-2” combined with “air pollution”, “air quality”, “meteorological parameters”, “climatological parameters”, and “respiratory health”. For studies examining the environmental consequences of pandemic restrictions, combinations of “COVID-19” OR “pandemic” with “lockdown”, “air quality”, “air pollution”, “anthropogenic emissions”, “mobility”, “transportation”, “industrial activity”, “greenhouse gas emissions”, “CO₂ emissions”, and “climate change” were used. Additional targeted searches were performed when necessary to examine methodological issues relevant to the interpretation of the evidence, including meteorological variability, remote sensing, satellite observations, ground-based monitoring, temporal lag effects, and spatial differences in exposure assessment.

Studies were considered for inclusion when they directly addressed at least one of the principal themes of the review: (i) relationships between air pollutants or climatological parameters and COVID-19 transmission or related health outcomes; (ii) changes in outdoor air quality associated with COVID-19-related lockdowns or reductions in anthropogenic activity; or (iii) changes in greenhouse gas emissions and their implications for climate change and environmental health. Studies conducted at local, regional, national, and global scales were considered to capture geographical variability in the reported environmental responses. Studies were excluded when their primary focus was unrelated to the air–climate–health relationships addressed in this review, when they did not provide sufficient information to interpret the environmental or health relationships reported, or when they duplicated evidence already reported in the same study population and period without providing additional relevant information.

Given the substantial heterogeneity of the available evidence in terms of geographical scale, observation period, environmental variables, data sources, exposure metrics, lockdown intensity, meteorological conditions, and statistical or modeling approaches, quantitative pooling of effect estimates was not considered appropriate. The evidence was therefore synthesized narratively, with particular attention to methodological and contextual factors that could explain differences among studies. Findings obtained from ground-based monitoring, satellite and remote-sensing observations, and modeling approaches were interpreted according to their respective spatial and temporal characteristics. Similarly, apparently inconsistent pollutant responses among regions, particularly for O₃

and SO₂, were interpreted in relation to differences in local emission sources, atmospheric processes, meteorological conditions, seasonality, and study design. This approach enabled the review to evaluate both consistent patterns and sources of heterogeneity across the available evidence while avoiding direct quantitative comparison of methodologically non-equivalent effect estimates.

3. Associations Among Air Pollution, Climatological Parameters, and the COVID-19 Outbreak

COVID-19 has been one of the most influential global health challenges in recent years, affecting various aspects of human life due to the substantial changes in social, economic, and environmental systems following the emergence of the SARS-CoV-2 virus. Since its first identification in December 2019 and subsequent rapid global spread, the COVID-19 pandemic has not only placed significant pressure on healthcare systems but also caused considerable socioeconomic impacts, particularly on trade, production, manufacturing, air and land transportation, shipping, and service sectors associated with social activities [26]. Investigations into the factors influencing SARS-CoV-2 transmission have demonstrated that environmental conditions, including meteorological parameters and air pollution levels, together with demographic, socioeconomic, behavioral characteristics, and non-pharmaceutical interventions, played important roles in the spread and severity of the pandemic across different regions [27,28]. Many previous studies have revealed that climatic parameters, such as temperature, relative humidity, wind speed, precipitation, atmospheric pressure, gusts, clouds, sun hours, and air pollutants, including CO, NO₂, SO₂, O₃, PM_{2.5}, and PM₁₀, have a significant contribution to the spread of respiratory infectious diseases [29,30]. Faruk and co-workers (2022) [31] evaluated the associations between meteorological factors and COVID-19 transmission considering previously published manuscripts. They stressed that the most significant associations with the spread of COVID-19 are mostly based on two environmental factors: temperature and humidity. Moreover, air pollution leads to an increase in the number of COVID-19 confirmed cases depending on PM₁₀, PM_{2.5}, and O₃ concentrations. Han and co-workers (2022) [32] explored globally the factors affecting the transmission of COVID-19, examining data from 188 countries related to meteorological parameters, outdoor air pollutants, and socioeconomic aspects for the period between March and November 2020. They found that the spread of the SARS-CoV-2 virus was negatively correlated with meteorological variables and positively correlated with air pollutants and socioeconomic characteristics. In another study, Aboura (2022) [27] evaluated the relationship between climate parameters including ambient temperature, relative humidity, precipitation, and wind speed, and the number of cases and deaths in 134 countries related to the SARS-CoV-2 virus for the period 1 January 2020 to 23 March 2021, considering control parameters, such as government interventions, total population, and population density. The results obtained on a global scale have shown that relative humidity causes a decrease in case and death rates in both high and low regimes, while temperature and wind parameters decrease mortality rates. Another remarkable result of the study is that relative humidity is more effective in confirmed cases and wind is more effective for death rates. Moreover, another study conducted by Sun and co-workers (2022) [33] evaluated the effects of meteorological factors including air temperature, relative humidity, wind speed, and surface pressure on the epidemic using regression models. They stated that ambient temperature is both significantly and positively correlated with the transmission of the COVID-19 outbreak. Multiple studies have reported associations between air pollutant concentrations, meteorological conditions, and COVID-19 transmission, suggesting that populations exposed to elevated air pollution and unfavorable atmospheric conditions, such as low wind speeds that limit pollutant dis-

person, may experience increased environmental exposure relevant to respiratory infection risk [7,34–36]. Although this review primarily focuses on COVID-19, these environmental associations should also be considered within the broader context of respiratory infectious diseases. Air pollution and meteorological conditions have been associated with the incidence and severity of other respiratory infections, including influenza, although the magnitude and direction of these relationships vary according to pathogen characteristics, population susceptibility, environmental conditions, and study design [28,30]. Therefore, COVID-19 should not be considered a direct surrogate for all respiratory infections; rather, the pandemic provides an important case for examining how environmental exposures may interact with respiratory infectious disease dynamics. Within this broader respiratory health context, selected studies examining the effects of meteorological parameters and air pollutant concentrations on SARS-CoV-2 transmission across different countries are summarized in Table 1.

Table 1. Studies on associations between environmental parameters and the spread of COVID-19.

Reference	Country	Parameters	Main Findings
[37]	Russia	Meteorological Parameters: temperature, relative humidity, temperature seasonality, sunshine, wind speed, diurnal temperature range, mean temperature of driest quarter	The results show that the relationship between COVID-19 transmission and meteorological parameters is based on the climatic conditions of the region. In other words, temperature seasonality has a vital significance on COVID-19 transmission in both the humid continental and the sub-arctic regions; the diurnal temperature range is an important parameter only in the sub-arctic region.
[7]	Turkey	Meteorological Parameters: dew point, relative humidity, atmospheric pressure, ambient temperature, wind speed, gust, precipitation, and cloud Air Pollutants: CO, NO ₂ , SO ₂ , O ₃ , PM _{2.5} and PM ₁₀	The results showed that air pollution and weather parameters are significantly associated with the spread of the SARS-CoV-2 virus. In particular, regions with high air pollution and low wind speed have been identified as more favorable places for virus spread.
[36]	South Africa	Air Pollutants: CO, NO ₂ , SO ₂ , O ₃ , PM _{2.5} and PM ₁₀	The findings reveal that there is a significant and positive correlation between all air pollutants and COVID-19 infection.
[38]	Romania	Climate Parameters: air temperature, relative humidity, atmospheric pressure, wind speed, surface solar irradiation Air Pollutants: CO, NO ₂ , SO ₂ , O ₃ , PM _{2.5} and PM ₁₀	The results showed that air pollution at a high level increases the risk of COVID-19 incidence and mortality. Positive correlations were observed for all air pollutants except for tropospheric O ₃ with COVID-19 rates during the entire pandemic period.
[39]	Iran	Air Pollutants: NO, NO ₂ , NO _x , CO, SO ₂ , O ₃ , PM _{2.5} and PM ₁₀	The results show that air pollution resulting from high concentrations of CO, NO, and NO _x triggered COVID-19 cases during the short-term period; PM _{2.5} during the long-term period but O ₃ , SO ₂ , PM ₁₀ , and NO ₂ did not show significant correlations with the COVID-19 incidence for both short- and long-term periods
[40]	China	Air Pollutants: CO, NO ₂ , SO ₂ , O ₃ , PM _{2.5} and PM ₁₀	They concluded that PM _{2.5} , PM ₁₀ , and NO ₂ pollutants were positively correlated with confirmed cases of COVID-19.

Table 1. *Cont.*

Reference	Country	Parameters	Main Findings
[41]	Bangladesh	Climatological Parameters: average temperature, wind speed, and relative humidity Air Pollutants: particulate PM _{2.5} , and carbon emissions	The results indicated that wind speed, temperature, and carbon emissions were positively correlated with the transmission of the SARS-CoV-2 virus but PM _{2.5} showed a negative association with widespread COVID-19.
[42]	Germany, United Kingdom, Spain, France	Air Pollutants: NO ₂ , O ₃ , PM _{2.5} , PM ₁₀ and aerosol optical depth (AOD)	The results indicated that aerosol-related pollutants (PM _{2.5} , PM ₁₀ , and AOD) showed positive associations with COVID-19 spreading and severity. Meteorological factors, including temperature, humidity, and wind conditions, influenced the variability of COVID-19 transmission among metropolitan regions.
[43]	39 cities worldwide	Climatological Parameters: temperature, humidity Air Pollutants: NO ₂ , PM _{2.5} , PM ₁₀ , CO, O ₃	Using causal analysis approaches, the study demonstrated nonlinear relationships between environmental factors and COVID-19 cases and mortality. Temperature and humidity showed dominant causal effects, while NO ₂ , PM _{2.5} , and O ₃ were associated with increased COVID-19 cases and deaths.

The studies summarized in Table 1 demonstrate that the association between environmental parameters and COVID-19 transmission is complex and influenced by multiple interacting factors. Although several studies have reported significant relationships between air pollutants, particularly particulate matter and NO₂, and COVID-19 incidence, the magnitude and direction of these associations differ depending on geographical location, meteorological conditions, population characteristics, and implemented control measures. Spatial compatibility between environmental exposure measurements and epidemiological data is also important when interpreting these associations. Ground-based monitoring stations provide pollutant concentrations at specific locations, whereas COVID-19 cases, hospitalizations, or mortality are often reported for entire cities, districts, or regions. Therefore, assigning measurements from one or a limited number of monitoring stations to a broader population may not adequately represent spatial variations in exposure and may introduce exposure misclassification, particularly in heterogeneous urban environments [13]. Spatial comparability can be improved by using multiple monitoring stations, spatially averaged or population-weighted exposure estimates, satellite-derived observations, spatial exposure models, or environmental and epidemiological data aggregated at comparable geographical scales. Accordingly, findings based on local monitoring data combined with broader regional health indicators should be carefully interpreted. To further illustrate how spatial differences between environmental exposure and epidemiological data have been addressed in the literature, Table 2 compares selected studies in terms of their spatial data configuration and the methods used to improve spatial alignment.

Table 2. Comparison of spatial data configurations and spatial treatment methods in selected air-pollution epidemiology and environmental COVID-19 studies.

Reference	Spatial Data Configuration	Spatial Treatment Method
[44]	Gridded environmental data vs postal-code COVID-19 data	Interpolation and aggregation to postal-code scale

Table 2. Cont.

Reference	Spatial Data Configuration	Spatial Treatment Method
[45]	Central-monitor exposure vs metropolitan health data	Comparison of multiple spatial exposure metrics
[46]	Regional pollution estimates vs regional COVID-19 outcomes	Matched regional-scale analysis
[47]	Monitor-based exposure vs aggregated health data	Spatial prediction modeling
[48]	Point pollution data vs area-level health outcomes	Spatiotemporal calibration

The studies summarized in Table 2 demonstrate that spatial mismatch can be addressed at different stages of exposure assessment, ranging from statistical correction of point-to-area misalignment to direct harmonization of environmental and epidemiological data at a common geographical scale. Peng and Bell (2010) [48] showed that comparing point-based exposure measurements with aggregated health outcomes can bias health-risk estimates, particularly when the exposure exhibits substantial spatial heterogeneity, and proposed spatiotemporal calibration approaches to reduce this error. Keller and Peng (2019) [47] further demonstrated that spatial exposure-prediction models generally produced lower area-level exposure error than simple averaging of monitoring-station measurements, supporting the use of model-based area-wide exposure estimates when health outcomes are spatially aggregated. However, the comparison by Ebelt et al. (2023) [45] indicates that more complex exposure metrics are not necessarily superior in every application. Most non-central-monitor metrics reproduced central-monitor-based health associations, although inverse-distance weighting strengthened or detected associations for spatially heterogeneous pollutants such as NO₂ and SO₂, while some CMAQ- and LUR-based estimates produced less consistent results. These findings suggest that the appropriateness of an exposure-assignment method depends not only on its spatial resolution but also on pollutant characteristics, monitoring-network density, and the geographical scale of the health outcome. More recent studies illustrate the value of explicitly harmonizing environmental and epidemiological datasets before estimating exposure–response relationships. Hoffmann et al. (2025) [44], for example, addressed the mismatch between 0.1° × 0.1° environmental grids and postal-code-level COVID-19 data by applying bilinear interpolation and subsequently aggregating environmental estimates to postal-code polygons; the data were also temporally aggregated to match the resolution of the health dataset. At a broader scale, Solimini et al. (2021) [46] combined approximately 10 km satellite/model-derived air-pollution data with COVID-19 outcomes defined for 730 administrative regions, thereby maintaining analysis at a consistent regional level. From a geospatial analytics perspective, each spatial treatment approach has specific advantages and limitations. Aggregating monitoring data to administrative units is relatively simple and facilitates direct comparison with area-level health outcomes, but it may mask within-area exposure variability. Spatial interpolation and prediction methods can provide more continuous exposure surfaces and improve spatial coverage, although their performance depends on monitoring density, spatial distribution, input-data quality, and model assumptions. A common-grid approach provides an additional option for harmonizing heterogeneous geospatial datasets. Mak et al. (2018) [17], for example, addressed differences in the native array structures of satellite and model datasets by projecting them onto a common 0.1° × 0.1° rectangular grid. Satellite pixels were assigned to grid cells according to their overlapping area, enabling consistent spatial projection and comparison among datasets. Such harmonization facilitates the joint interpretation of environmental datasets with different native spatial structures, although resampling to a common grid does not increase the intrinsic spatial resolution of

the original data. Future environmental health studies should therefore report the spatial resolution of both exposure and health data explicitly and justify how these scales are aligned. Where possible, environmental exposures should be aggregated or modeled to the same geographical units used for epidemiological outcomes, while population-weighted exposure estimates, spatial interpolation, and high-resolution exposure surfaces should be considered when substantial within-area variability is expected. Sensitivity analyses comparing alternative spatial exposure-assignment methods would also be valuable, particularly for pollutants with pronounced intra-urban gradients. Overall, reducing spatial misalignment should be treated as an integral component of exposure assessment rather than as a secondary limitation considered only after epidemiological associations have been estimated.

In addition to spatial compatibility, temporal alignment between environmental exposure and reported health outcomes is equally important for accurately interpreting exposure–response relationships. Recent investigations have further emphasized the importance of considering nonlinear relationships, delayed effects, and potential causal mechanisms when evaluating the influence of environmental factors on infectious disease dynamics. In particular, delayed effects are important because changes in environmental exposure may not be reflected in reported COVID-19 outcomes on the same day. Several studies have therefore examined different lag periods or applied Distributed Lag Nonlinear Models (DLNMs), which allow delayed and nonlinear exposure–response relationships to be evaluated simultaneously. DLNMs are particularly useful because they represent the exposure–response and lag–response dimensions simultaneously through a cross-basis function, allowing the effect of an exposure to vary both with its magnitude and with the time elapsed after exposure [49]. Selection of an appropriate maximum lag period is therefore a key modeling decision and should reflect the biological and reporting processes underlying the health outcome. In COVID-19 studies, lag windows commonly extend beyond the incubation period to account for delays between infection, symptom development, testing, and case reporting. Model specification also requires appropriate control for temporal trends and potential confounders, because the estimated lag structure may otherwise reflect seasonality, autocorrelation, concurrent meteorological conditions, air pollution, or changes in non-pharmaceutical interventions rather than the exposure of interest. Studies applying lag-based approaches, including DLNMs, to environmental exposures and COVID-19 health endpoints are summarized in Table 3.

Table 3. Studies evaluating lagged and nonlinear effects of environmental exposures on COVID-19 health endpoints.

Reference	Study Area	Environmental Exposure	Health Endpoint	Lag/Analytical Approach	Main Findings
[50]	USA	PM _{2.5} , AQI, temperature, wind speed, precipitation	COVID-19 cases	DLNM; 3-day moving temperature (df = 6), PM _{2.5} (df = 3), and wind speed (df = 3); maximum lag of 14 days	Temperature and PM _{2.5} showed no significant effects on COVID-19 cases, whereas wind speed showed a positive association with COVID-19 transmission. Cumulative effects were evaluated at lag 0–4 days for temperature and PM _{2.5} and lag 0–7 days for wind speed.

Table 3. *Cont.*

Reference	Study Area	Environmental Exposure	Health Endpoint	Lag/Analytical Approach	Main Findings
[51]	12 cities, Italy	Air temperature, relative humidity, air pressure, PM _{2.5}	Daily COVID-19 incidence	DLNM; city-specific delayed temperature effects followed by random-effects meta-analysis to obtain pooled exposure–lag response estimates	Temperature showed nonlinear and delayed associations with COVID-19 incidence. Low-temperature effects returned toward the null by lag day 10, whereas high-temperature effects appeared more delayed and could extend beyond 10 days.
[52]	455 cities in 20 countries	Daily mean air temperature, relative and absolute humidity, and UV radiation	COVID-19 incidence	DLNM; city-specific time-series models with a 15-day lag period, followed by multilevel random-effects meta-regression	Low temperature and low absolute humidity were associated with higher COVID-19 incidence. Temperature-related risk appeared after approximately 3 days, peaked at lag days 8–9, and declined toward the end of the 15-day lag period.
[53]	Belgium, 581 municipalities	Black carbon, NO ₂ , O ₃ , PM _{2.5} , and PM ₁₀	COVID-19 cases	Spatiotemporal DLNM fitted to COVID-19 incidence data; cumulative lagged effects evaluated over 8 weeks	Black carbon was strongly associated with increased COVID-19 risk, with the greatest effect during the first few weeks after exposure and almost no effect remaining at an 8-week lag. DLNM revealed nonlinear exposure–lag relationships.

The studies summarized in Table 3 demonstrate that the relationship between environmental exposures and COVID-19 outcomes can vary substantially according to the lag period considered. Delayed effects were observed over time scales ranging from several days to several weeks, and the strongest associations were not always observed on the day of exposure.

For example, Zhou et al. (2022) [50] applied a DLNM with a maximum lag of 14 days, using natural cubic spline functions to model the exposure–lag structure and controlling for long-term temporal trends and day-of-week effects. In their analysis, cumulative effects were evaluated over lag 0–4 days for temperature and PM_{2.5} and lag 0–7 days for wind speed; temperature and PM_{2.5} showed no evident effect on COVID-19 cases, whereas a wind speed of approximately 2 m/s was significantly positively associated with COVID-19 transmission. Fong and Smith (2022) [51] reported a nonlinear cumulative temperature–incidence relationship across 12 Italian cities, with the highest risk at approximately 15.1 °C and a cumulative relative risk of 0.72 (95% CI: 0.56–0.91) at 0.2 °C relative to the temperature associated with the highest risk; temperature-related effects

were distributed over approximately 10 days or longer. Nottmeyer et al. (2023) [52], using data from 455 cities, found that low temperature (7.5 versus 17.0 °C) and low absolute humidity (6.0 versus 11.0 g/m³) were each associated with a pooled relative risk of 1.33 for COVID-19 incidence over a 15-day lag period (95% CI: 1.08–1.64 and 1.12–1.57, respectively). Rutten et al. (2025) [53] further demonstrated that, at the median black-carbon concentration, the cumulative COVID-19 risk over eight weeks was 1.66 (1.57–1.74) relative to the 5th-percentile exposure level. These findings demonstrate that same-day estimates may substantially underrepresent or mischaracterize an exposure–health relationship when effects accumulate or vary across subsequent days or weeks. The use of DLNMs allowed these studies to capture both delayed and nonlinear exposure–response patterns that may be overlooked in analyses based only on concurrent or linear associations. Therefore, the temporal structure of exposure should be considered when interpreting relationships between air pollution, meteorological conditions, and COVID-19 outcomes, particularly when comparing results across studies using different lag periods and analytical approaches.

In addition to these temporal considerations, the health effects associated with environmental exposures are not limited to COVID-19 transmission and may also include morbidity and mortality. Juarez et al. (2022) [54] reported that the available evidence predominantly indicated positive relationships between PM_{2.5}, other air pollutants, meteorological conditions, and COVID-19 risk and outcomes, while also emphasizing geographical variability in the reported associations. The review further indicated that morbidity and mortality associated with these environmental exposures were more frequently observed among socially disadvantaged and vulnerable populations. Beyond COVID-19-specific outcomes, air pollution also contributes to a broader mortality burden in urban populations. In Hong Kong, Mak and Ng (2021) [55] reported positive correlations between district-level traffic-related NO_x and PM_{2.5} emissions and mortality rates, with correlation coefficients ranging from 0.371 to 0.783 for NO_x and from 0.509 to 0.754 for PM_{2.5}. More broadly, exposure to major air pollutants contributes to disease burden and premature mortality, emphasizing the importance of reducing population exposure as part of long-term environmental health strategies [56]. Overall, these findings highlight the close interaction between atmospheric conditions, human activities, and public health risks, supporting the consideration of COVID-19 as an important environmental health indicator.

4. Impacts of Lockdown Measures Based on COVID-19 Outbreak on Outdoor Air Quality

To prevent the transmission of the COVID-19 virus from person to person on a national scale, countries implemented various measures to reduce human activities in society across different regions and periods while controlling the health impacts of the epidemic and improving urban air quality [57–60]. While strict lockdown measures imposed by governments to combat the transmission of COVID-19 impact the countries' economies adversely, they can also improve air quality by reducing anthropogenic emissions from sources such as diesel-fueled vehicles, power plants, cement and iron-steel factories [61]. COVID-19-based restrictions have shown that reductions in human activities can temporarily decrease GHGs and atmospheric pollution, providing valuable insights into the relationship between societal activities and environmental quality [62].

Akan and Coccia (2022) [4] explored globally how lockdown measures taken by governments to prevent the spread of the COVID-19 outbreak influenced air quality levels by evaluating average changes in air pollutant concentrations across 300 cities in 19 countries of five geoeconomic regions. They concluded that air pollutant concentrations generally decreased during the lockdown periods, but the variation in each country was different from one another, especially due to their differences in geographical, economic, and in-

dustrial characteristics. Another study performed by Skirienė and Stasiškienė (2021) [26] investigated how lockdown strategies influenced air quality changes during three periods: (i) pre-lockdown from Jan to Feb 2020, (ii) the period from Mar to Apr 2020 including lockdown measures applied nationally, (iii) the period covering only May 2020, when countries started to relax measures by comparing the data with the same periods from 2018 to 2019 for five European countries: the United Kingdom, Spain, France, and Sweden, as well as the Northern Italy region. The results showed that NO_2 , $\text{PM}_{2.5}$, and PM_{10} emissions were reduced by 20–40% in 2020 because of the decline in industrial and mobility activities. A study carried out in the Kolkata Metropolitan Area, India, to determine the possible influence of the reductions in mobility activities based on lockdown restrictions on air pollutant concentrations indicated that the concentrations of air pollutants showed significant reductions, contributing to improvements in the air-quality index (AQI) by 54.94% during the lockdown months [63].

In another study carried out in cities of India, including Delhi, Mumbai, Kolkata, and Chennai, enforced lockdown measures from 24 March 2020 to May 17, 2020 were analyzed to comprehend the influence of restrictions on air quality improvements; it was found that air pollutant levels and aerosol concentration were reduced across all examined cities compared to previous years, with reductions ranging from −37.13% to −54.94%. Moreover, the variation in $\text{PM}_{2.5}$ concentration in these megacities demonstrated the highest decline, directly related to restricted vehicular movement [64]. In the study conducted in Wuhan during the COVID-19 pandemic lockdown and the post-pandemic period, it was observed that $\text{PM}_{2.5}$ concentrations were reduced by 9.57–18.67% from a momentum effect and by 7.07–27.60% from a spillover effect through the spatiotemporal model [65]. On the other hand, another study conducted by Jakob et al. (2022) [66] evaluated the variations in the concentration of air pollutants based on lockdown restrictions in Jakarta, Indonesia. Since the results indicated that the concentrations of PM_{10} and $\text{PM}_{2.5}$ did not change significantly because of the lockdown measures, meteorological factors impacting air quality should also be considered. Furthermore, in a study conducted in downtown Toronto, Canada, it was found that even if a significant reduction in traffic density was observed, the reduction in the concentration of $\text{PM}_{2.5}$ remained negligibly low [67]. Moreover, Das et al. (2022) [68] compared the effects of lockdown measures applied on a regional and national scale on air quality. They indicated that regional lockdown in 2021 improved air quality by 32% more than the national lockdown in 2020. In another study focusing on the impact of the lockdown imposed in India nationally from March 25, 2020, to prevent the spread of COVID-19 disease on the anthropogenic emission sources by analyzing a multi-scale (national-regional-city), it was found that there was a significant reduction in surface measurements of NO_2 (46–61%) and fine particulate matter (42–60%) during the lockdown period. Other species, namely coarse particulate matter (24–62%) and ozone (22–56%), also showed a substantial reduction, whereas CO exhibited a moderate decline in the range of 16–46%. However, SO_2 levels did not exhibit any defined reduction trend but increased in Mumbai, Bengaluru, and Kolkata [69].

Lockdown measures generally improved air quality by reducing transportation and industrial emissions; however, the magnitude of these improvements varied significantly among regions depending on emission sources, meteorological conditions, and local characteristics. To stress the influence of lockdown measures applied regionally or nationally by countries on air quality improvements, Table 4 demonstrates significant results from previous studies from different countries.

Table 4. A literature review showing the impact of lockdown measures on countries' air quality.

Reference	City/Country	Parameters	Periods	Main Findings
[70]	Global (China, USA, Europe and other regions)	NO ₂	2020 lockdown period; comparison with the same period of 2019	Lockdown measures substantially reduced NO ₂ concentrations worldwide. The study estimated an approximately 20% reduction in global NO ₂ emissions in 2020.
[71]	Mexico, Latin America	CO, NO ₂ , O ₃ , SO ₂ , PM ₁₀ , and PM _{2.5}	The lockdown (Apr–May) and pre-lockdown (Jan–Mar) periods.	Concentrations of NO ₂ , SO ₂ , and PM ₁₀ were reduced in the range of −11% and −55%, while CO, PM _{2.5} , and O ₃ showed an increase between +1.1% and +63%.
[60]	Chandigarh, India	NO ₂ , NO, NO _x , SO ₂ , O ₃ , NH ₃ , CO, PM ₁₀ , PM _{2.5} and volatile organic carbons (VOCs)	Four lockdown periods: (i) before lockdown, (ii) the first phase of lockdown, (iii) the second phase of lockdown, (iv) the third phase of lockdown	Concentrations of all pollutants showed significant reductions during the first two phases, while they increased during the third phase. The concentrations of SO ₂ , O ₃ , and m,p-xylene showed increasing trends.
[72]	Lyon, France	NO ₂ , NO, PM ₁₀ , PM _{2.5} , O ₃ , VOC, CO, SO ₂ , and isoprene	17 Mar–11 May 2020	NO ₂ , NO, and CO levels decreased in the range of 62–78% due to a significant decrease in traffic emissions, while O ₃ , PM ₁₀ , and PM _{2.5} increased in the range of 23% and 105%.
[73]	Bangkok, Thailand	CO, O ₃ , NO ₂ , SO ₂ , and PM _{2.5}	The period from Jan 2020 to Jun 2020	During the lockdown period, PM _{2.5} , O ₃ , and CO concentrations showed decreasing trends, while NO ₂ and SO ₂ concentrations showed increasing ones.
[74]	Riyadh, Saudi Arabia	NO, NO ₂ , NO _x , SO ₂ , CO, O ₃ , PM ₁₀ , and PM _{2.5}	Three measurement periods: (i) between Apr 2020 and Jun 2020, (ii) from Mar 2020 to Jun 2020, (iii) from Mar 2019 to Jun 2019	The average concentrations of NO, NO ₂ , NO _x , and CO decreased during the lockdown period, with the highest at 73%, 133%, and 222% at the work site, traffic site, and residential site, respectively, but O ₃ showed an increasing trend.
[75]	Istanbul, Turkey	PM ₁₀ , SO ₂ , CO, NO ₂ , NO, NO _x , and O ₃	Two different periods: from Mar 2019 to May 2019 and Mar 2020 to May 2020	A remarkable decrease in concentration levels of PM ₁₀ , NO ₂ , NO, and NO _x was recorded during the pandemic compared to the pre-lockdown periods in Istanbul. On the other hand, a partial increase in O ₃ concentration is obtained by comparing before and during the partial lockdown period.

Table 4. *Cont.*

Reference	City/Country	Parameters	Periods	Main Findings
[76]	Barcelona, Catalonia, Spain	NO ₂ , O ₃ , and PM ₁₀	Two periods: (i) from 15th Feb to 31st Aug and (ii) the month of April for the 3 years (2018, 2019, and 2020)	NO ₂ levels and PM ₁₀ showed a reduction in rural areas, but O ₃ levels increased in urban ones due to the decline in NO _x during the lockdown
[77]	South Asia	AOD, CO, NO ₂ , O ₃ , SO ₂ , PM ₁₀ , and PM _{2.5}	March and April 2020	Results indicated reductions in the concentration of pollutants including NO ₂ , SO ₂ , and PM _{2.5} , especially in regions with a high level of air pollution.
[78]	Canada	PM _{2.5}	2000–2021; COVID-19 lockdown and post-lockdown analysis focused on 2020	Reduced anthropogenic emissions during COVID-19 lockdowns resulted in significant PM _{2.5} reductions in major Canadian cities. Peak reductions ranged between 42% and 53% compared with long-term reference conditions, indicating the sensitivity of urban air quality to changes in human activities.
[79]	Mexico, Chile, Peru, Ecuador (Mexico City, Santiago de Chile, Lima, Quito)	NO ₂ , SO ₂ , O ₃	December 2018–December 2023; pre-lockdown, lockdown, and post-lockdown periods	Lockdowns generally resulted in decreased NO ₂ concentrations, whereas the effects on SO ₂ and O ₃ were inconsistent. Considerable spatial variability was observed among the four cities, with local weather patterns and urban characteristics influencing pollutant levels.

Overall, the studies summarized in Table 4 demonstrate that COVID-19-related lockdown measures generally resulted in short-term improvements in outdoor air quality, particularly through reductions in transportation, industrial activities, and other anthropogenic emissions. However, the magnitude and direction of these changes varied considerably among regions and pollutants, depending on local emission sources, geographical characteristics, meteorological conditions, and the intensity and duration of lockdown measures. Recent studies have further demonstrated that these effects should be interpreted cautiously, as observed changes in pollutant concentrations may also reflect seasonal variability, atmospheric processes, and natural emission sources. Therefore, the environmental improvements observed during the pandemic should not be interpreted as evidence of a permanent reduction in air pollution, but rather as an important environmental health lesson demonstrating the sensitivity of air quality to changes in human activities.

Although many studies have reported that lockdown measures improved air quality, Jakob et al. (2022) [66], on the other hand, stated that the decrease in pollutant concentrations observed during the quarantine period was not necessarily related to the restrictive measures, as seasonal changes may also have contributed to the observed variations. This methodological concern is further supported by studies applying meteorological normalization to distinguish emission-related changes from weather-driven variability. Lv et al. (2022) [80], using a Random Forest-based meteorological normalization approach in Beijing,

Wuhan, and Urumqi, demonstrated that meteorological conditions substantially influenced the observed changes in pollutant concentrations during the lockdown period. In Beijing, adverse meteorological conditions contributed approximately 33.5% to the variation in PM_{2.5}, partially offsetting the reduction associated with lockdown measures. Nevertheless, the analysis identified lockdown-related emission reductions as the dominant driver of the overall decline in pollutant concentrations, whereas the reductions in SO₂ and CO were relatively limited and were influenced primarily by their underlying temporal trends [80]. In a subsequent study covering North China, Lv et al. (2023) [81] combined machine learning-based meteorological normalization with Theil–Sen regression to accurately evaluate meteorological effects and long-term emission trends in lockdown-related changes. Their analyses showed that meteorological conditions contributed to a 9.8% increase in PM_{2.5} during the lockdown period, while reduced anthropogenic emissions resulted in a much larger decrease of 32.2%. After accounting for the long-term emission trend, the lockdown was associated with decreases of 30.8% in NO₂ and 27.6% in PM_{2.5}, whereas O₃ increased by 10.0%. The study also showed that the effect of lockdown on air pollutant concentrations could be overestimated by up to twofold if meteorological conditions and long-term emission trends were not considered [81]. These findings indicate that lockdown-related improvements in air quality may be overestimated when meteorological variability and underlying long-term emission trends are not explicitly accounted for, particularly in studies based on short observation periods or simple year-to-year and pre-lockdown/post-lockdown comparisons. In this context, considering that quarantine restrictions may provide insights for future policy actions, such as the preparation of national strategies and the development of new technologies to combat air pollution and climate change, future studies should not only evaluate changes in pollutant concentrations using empirical measurements, various models, and remote sensing data, but also examine seasonal variations in pollutant concentrations over longer periods.

5. The Impacts of the COVID-19 Pandemic on Climate Change

To reduce human-to-human transmission of COVID-19, temporary lockdowns at various scales were imposed during different periods of the pandemic to control the spread of the virus. The considerable reductions in economic production and transportation activities contributed to a sharp decline in major GHG emissions, particularly CO₂ [82,83]. In China, CO₂ emissions were reduced by 23% due to lockdown measures applied nationally, limiting industrial, commercial, and transportation activities by February 2020 [84]. According to a report published by the International Energy Agency in 2020, in the first quarter of 2020, CO₂ emissions were reduced by 5%, depending on the decrease in energy demand compared to the previous year's data [85]. Considering the reductions in CO₂ emissions across several areas, they were in the range of 1.4–19.3%, depending on the countries and regions in the power sector, and were recorded as 5.5% in heavy industry and manufacturing sources [83,86]. In the transportation area, by the end of March 2020, due to the reduction in flights by 85%, global aviation emissions recorded remarkable drops compared with 2019 [82,86].

In another study conducted by Kumar et al. (2022) [87] investigating how international air transportation and industrialization restrictions based on the COVID-19 pandemic impact CO₂ emissions, comparisons of daily CO₂ emission data between 2019 and 2020 for 69 countries indicated a 17% reduction. The studies conducted by Liu et al. (2020) [83] explored how the diminishing of human activities due to COVID-19 lockdown measures affects energy demand and CO₂ emissions. They found that the COVID-related decreases in CO₂ emissions (a total of 938 Mt CO₂) were as follows: 15.5%, 6.4%, 4.4%, 28.9%, 2.7%, and 15% caused by road transportation, power, industry, aviation, residential buildings,

and international shipping, respectively. A study conducted by Gillingham et al. (2020) [88] explored the importance of limitations based on COVID-19 incidence associated with reduced traffic- and industry-based emissions on the air quality of the USA. The results pointed out that CO₂, NO_x, and PM emissions were reduced by 15, 12, and 1%, respectively.

Monteiro (2022) [89] aimed to determine the changes in GHG emissions, including CO₂, CH₄, and air pollutant (CO) concentration, by comparing lockdown-period impact with data from previous years for North American cities. The results indicated that CO₂ and CO emissions showed much greater reductions because of a decrease in traffic density rather than CH₄ emissions associated with city characteristics. The mitigation in the concentration of air pollutants is significantly attributed to changes in traffic trends compared to changes in meteorology and biology. Ray et al. (2022) [61] investigated how COVID-19 lockdown measures affect carbon emissions by evaluating data from different countries on a global scale. Following their results, the strict lockdown measures have been playing a significant role in the mitigation of carbon emissions.

Hickman et al. (2023) [90] investigated how the atmospheric composition and climate impacts of COVID-19 pandemic responses depend on background emissions, climate conditions, and the season in which lockdowns occurred. Using the ModelE Earth system model, they evaluated atmospheric and climate responses to lockdown-related emission perturbations occurring in different decades and seasons. The results showed that global COVID-19-related anomalies in aerosols and trace gases differed by up to an order of magnitude or more when lockdowns occurring in 1980, 2008, 2020, and 2051 were compared. Regional atmospheric composition anomalies were generally largest when emissions were close to their historical peak, with the largest responses occurring in different periods depending on the region. Regional aerosol direct-effect anomalies were almost always below 0.1 W/m² during the first pandemic year, whereas larger anomalies were obtained in some historical scenarios. The study also demonstrated that shifting the onset of COVID-19 by 3, 6, or 9 months could alter global atmospheric composition by approximately 2–25%. However, changes in surface temperature and precipitation were not systematically related to local changes in atmospheric composition. These findings indicate that the atmospheric and climatic consequences of temporary emission reductions are strongly dependent on the background emission conditions, timing, season, and regional characteristics.

In summary, strict measures, including lockdowns and reductions in industrial activities and traffic density, resulted in substantial short-term reductions in CO₂ and other greenhouse gas emissions at regional, national, and global scales. However, these reductions were primarily associated with temporary decreases in economic and transportation activities and therefore should not be interpreted as evidence of a sustained reversal in global climate change trends.

Liang et al. (2023) [91] examined the spatiotemporal characteristics and co-effects of changes in air quality and CO₂ emissions during the COVID-19 lockdown in China. The study analyzed 324 prefecture-level cities during the period from January 24 to April 30, 2020, using a regression discontinuity in time approach. During the major lockdown period, SO₂, NO₂, and CO₂ concentrations decreased by 5.6%, 16.6%, and 25.1%, respectively, at the national scale. The reductions in CO₂ and NO₂ were particularly pronounced in southern regions, indicating considerable spatial heterogeneity in the response to lockdown measures. However, from March onward, the improvement effects on air quality and CO₂ emissions weakened, and pollutant concentrations began to rebound. These findings demonstrate that lockdown measures can produce substantial short-term reductions in CO₂ emissions, although such effects may diminish as economic and human activities resume.

Wang et al. (2024) [84] reviewed the responses of short-lived atmospheric pollutants and climate forcers to the large-scale emission reductions associated with COVID-19 lock-

downs. The review focused particularly on aerosols, ozone (O₃), nitrogen oxides (NO_x), and methane (CH₄), providing an assessment of their atmospheric and climatic responses at regional and global scales. The authors reported that reductions in transportation-related emissions generally decreased near-surface particulate matter and ozone concentrations, although the magnitude and even the direction of these changes varied among regions because of atmospheric oxidation capacity and anomalous meteorological conditions.

Zeppini and van den Bergh (2025) [92] investigated the long-term climate implications of the COVID-19 pandemic by developing a global energy competition model that jointly considered lockdown measures, economic stimulus programs, climate policies, and CO₂ emissions. Unlike studies focusing primarily on the short-term emission reductions observed during lockdown periods, their analysis examined how the pandemic could influence long-term emission pathways. The results indicated that, in the absence of countervailing climate policies, the COVID-19 pandemic could increase long-term emissions. In contrast, when a carbon tax was already in place, the pandemic scenario resulted in lower emissions than scenarios without the pandemic or without climate policy. The combination of economic stimulus and carbon taxation produced the strongest long-term emission reductions, indicating that the climatic consequences of a pandemic depend not only on temporary changes in human activities but also on the policy framework implemented during the recovery period.

Taken together, the evidence indicates that the COVID-19 pandemic provided a unique opportunity to observe how rapid changes in human activities can influence greenhouse gas emissions and atmospheric composition. Although lockdown measures resulted in substantial short-term reductions in CO₂ and other emissions, these reductions were insufficient to produce a sustained reversal in long-term climate change trends. The subsequent recovery of economic, industrial, and transportation activities further demonstrated the limitations of temporary restrictions as a climate mitigation strategy. Therefore, one of the most important lessons from the pandemic is that lasting climate benefits require structural changes in energy systems, transportation, industrial production, and climate policy rather than temporary reductions in human mobility and economic activity.

6. Integrated Environmental Health Strategies for Future Public Health Challenges

The COVID-19 pandemic demonstrated that short-term environmental improvements resulting from restrictions on human activities should not be interpreted as permanent environmental gains. During the initial lockdown periods, substantial reductions in transportation, industrial activity, and other anthropogenic sources contributed to improvements in air quality in many regions [93,94]. However, these benefits were not reproduced to the same extent during later pandemic waves. In Delhi, for example, air-quality improvement during the second lockdown was reported to be 39% lower than during the first nationwide lockdown, which was attributed partly to changes in human behavior, partial relaxation of industrial restrictions, and adaptation to pandemic conditions [95]. Similarly, Saharan et al. (2022) [96] reported substantially higher concentrations of several pollutants during the 2021 lockdown than during the corresponding 2020 lockdown period and identified regional emissions, crop-residue burning, long-range transport, and meteorological conditions as important contributing factors. These observations indicate that the environmental effects of pandemic restrictions were strongly dependent on the intensity and geographical extent of restrictions, behavioral responses, emission sources, and prevailing environmental conditions. Consequently, the main environmental lesson of the pandemic is not the feasibility of maintaining lockdown-like restrictions, but the need to translate the temporary

improvements observed during periods of reduced anthropogenic activity into sustainable environmental and public health strategies [93,94].

The pandemic also demonstrated that environmental conditions cannot be considered independently of the capacity and resilience of healthcare systems. Cross-country evidence indicates that healthcare capacity, healthcare financing, availability of medical personnel and hospital beds, population coverage by health insurance, and testing and tracing capacity can influence health outcomes during large-scale public health emergencies. In an analysis of 86 countries, Khan et al. (2020) [97] found that greater multidimensional healthcare capacity was significantly associated with lower COVID-19 case fatality, whereas healthcare expenditure alone was not a statistically significant predictor. In contrast, an analysis of 79 countries by Kapitsinis (2021) [98] found that healthcare underfunding was associated with higher excess mortality, whereas greater health expenditure, availability of doctors and hospital beds, health-insurance coverage, and test-and-trace capacity were negatively associated with excess mortality. These findings suggest that financial resources alone should not be regarded as an adequate measure of preparedness; rather, expenditure must be translated into accessible healthcare infrastructure, trained personnel, diagnostic and surveillance capacity, and effective public health services. Differences in socioeconomic conditions and national preparedness may further modify health outcomes, emphasizing that environmental exposure, economic capacity, healthcare resources, and public health responses should be considered as interacting rather than isolated determinants [99].

Technological capacity represents another important component of such preparedness. During the pandemic, digital technologies including mobile applications, location-tracking systems, wearable devices, temperature-scanning technologies, and other digital tools were widely applied to public health surveillance. However, their effectiveness depended on population uptake, technological infrastructure, data validity and accuracy, legal frameworks, and institutional capacity [100]. Similar considerations apply to environmental surveillance. A One Health perspective emphasizes that environmental monitoring can complement conventional clinical surveillance by detecting pathogens or environmental conditions relevant to human health; wastewater surveillance during COVID-19 provides a prominent example of this complementary approach [101]. At the same time, technological infrastructure cannot replace public participation and health literacy. Environmental health-based educational interventions have been shown to improve public knowledge, attitudes, and preventive practices, although improvements in actual practices may be smaller than improvements in knowledge and attitudes [102]. Thus, future preparedness strategies should combine technological surveillance and healthcare resources with public education, transparent risk communication, and community engagement rather than relying exclusively on technological solutions.

These requirements increasingly converge within the concepts of healthy and smart cities. Smart-city technologies can support the acquisition, processing, storage, integration, and dissemination of information required for the early detection and management of public health emergencies [103]. Recent evidence also indicates that neighborhood- and city-scale monitoring systems can support real-time air-quality mapping, environmental pollutant management, identification of community-level health risks, and faster emergency responses. However, implementation is accompanied by challenges related to technological performance, usability, privacy, equity, and unequal monitoring capacity between regions [104]. Similarly, the integration of smart technologies within healthy-city frameworks remains incomplete; sensors, web applications, and machine learning approaches are increasingly used for urban environmental and infrastructure monitoring, while human-centered participation remains comparatively underrepresented [105]. These findings support a broader One Health perspective in which human and environmental

health are treated as interconnected components of urban systems rather than as separate policy domains [106].

Accordingly, one important direction for future environmental health policy is the development of integrated data infrastructures that connect environmental monitoring with public health and urban-system information. The assessment of five East Asian cities by Mak (2021) [107] highlighted the importance of data openness and identified needs for centralized big-data systems, public education, website centralization, and improved integration of healthcare and environmental datasets. Such an approach could bring together air-quality and meteorological observations, transportation and mobility information, environmental surveillance, healthcare capacity indicators, and epidemiological data within interoperable platforms. This concept is consistent with health-centered smart-city approaches in which heterogeneous urban data streams are integrated to support detection, risk assessment, communication, and timely intervention [100,103,104]. However, data integration should be accompanied by appropriate governance, privacy protection, equitable access, and mechanisms for public participation [100,104,107]. The broader lesson from the COVID-19 experience is therefore that environmental quality, healthcare capacity, technological infrastructure, public awareness, and urban governance should not be addressed independently. Integrating these components offers a more resilient framework for responding to future infectious disease outbreaks and other environmental health challenges.

7. Concluding Remarks

Climate change remains one of the most significant environmental challenges affecting public health in the twenty-first century. While there is a need to understand how and to what extent climate change is affecting public health, from respiratory diseases, heart diseases, and mental illnesses to infectious diseases, it is necessary to urgently identify and take the necessary measures at the individual and societal levels, as well as to put into effect the laws and policies to be implemented by states. The positive effects of partial and full quarantine measures applied during the pandemic on air quality, which were explained in detail in this review paper by presenting an extensive and comprehensive literature review, provide valuable evidence for understanding how changes in human activities can influence environmental quality and may inform the scope of countries' commitments to combat global climate change. However, these improvements were largely temporary and were not reproduced uniformly during later pandemic waves, demonstrating that short-term restrictions on human activity cannot substitute for structural changes in transportation, energy systems, industrial activity, and environmental policy. Consequently, the pandemic experience supports long-term strategies that combine emission reduction, cleaner technologies, sustainable mobility, and climate mitigation with broader environmental health preparedness.

The findings further demonstrate that environmental quality and public health preparedness should not be considered independently. Healthcare capacity, diagnostic and surveillance infrastructure, technological resources, public education, and community awareness influence the ability of societies to respond to large-scale health emergencies. Future environmental health strategies should therefore promote integrated monitoring systems that connect air-quality and meteorological observations with mobility, environmental surveillance, healthcare capacity indicators, and epidemiological information. Such integration may improve early identification of environmental health risks and support more timely and evidence-based interventions during future public health challenges.

This review has several limitations. First, considerable heterogeneity was observed among the reviewed studies in terms of study periods, geographical coverage, environ-

mental parameters, data sources, and statistical or modeling approaches, which limits direct quantitative comparisons among their findings. Second, many studies conducted during the early stages of the pandemic relied on short observation periods and were therefore potentially influenced by seasonal variations, meteorological conditions, and other confounding factors. Accordingly, studies that did not apply meteorological normalization or long-term emission-trend adjustment may have overestimated the apparent effect of lockdown-related reductions in human activity on air quality. Third, the reviewed literature predominantly focused on the initial lockdown periods, whereas fewer studies evaluated the longer-term environmental consequences following the relaxation of restrictions. Additional methodological limitations arise from differences in the spatial resolution of environmental exposure and epidemiological data. In particular, assigning measurements from one or a limited number of monitoring stations to broader city-, district-, or regional-level populations may introduce exposure misclassification. Temporal differences should also be considered because environmental exposures may influence reported health outcomes after a delay, and studies based only on same-day associations may fail to capture nonlinear and lagged exposure–response relationships. Finally, because this review did not perform a formal meta-analysis, the magnitude of associations reported across individual studies should be interpreted in the context of their respective methodological approaches and study settings. Future studies should therefore prioritize spatially harmonized exposure and health datasets, appropriate lag structures, meteorological adjustment, and longer observation periods to improve comparability and causal interpretation.

Overall, the evidence reviewed in this study highlights that the COVID-19 pandemic should be regarded not only as a global public health crisis but also as an important environmental health indicator, providing valuable lessons for developing integrated and long-term strategies to address air pollution, climate change, and future environmental health challenges. The central lesson is that temporary environmental improvements can reveal the sensitivity of air quality and emissions to changes in human activity, but sustained benefits require integrated environmental, climate, technological, and public health strategies rather than temporary behavioral restrictions.

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