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Viewpoint

Monitoring Compliance in Pandemic Management with Air Pollution Data: A Lesson From COVID-19

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The use of nonpharmaceutical interventions (NPI) by governments to help curb the spread of the coronavirus (COVID-19) epidemic before effective vaccines became globally available have been important measures. These measures are highly sensitive to compliance.[1] To effectively manage pandemics, policy makers need to know the degree of compliance of containment measures and whether such measures are effective in containing the pandemic. Unlike NPI measures, such as facial masking and social distancing, the measures imposed, like restricting mobility and closing nonessential factories, led directly to a reduction in air pollutant emissions (Supporting Information Table S1). Such changes can be used as an early global indicator of the compliance of mandatory lockdown measures.[2,3]

Measuring the compliance to containment policies is challenging, varying locally as individuals decide not to comply with governmental advice.[4] Compliance has become an inevitable uncertainty factor when predicting the effectiveness of containment measures. However, air pollution, with the help of machine learning, may become a more useful general predictor of the potential spread of a virus than currently used tools, as the data can be a more informative measure of the actual behaviors of people in reducing their activities (e.g., staying at home). Unlike these reported indicators such as the government response trackers[5] and the human mobility data,[6] levels of air pollution can be monitored irrespective of the willingness of human behaviors (Figure 1), with air pollution levels providing details on how much activity is actually reduced. For example, spaceborne NO_2 data provided a better correlation with the rate of deceleration of the reported daily COVID-19 cases (Figure 1) than the coded NPIs.[3] Spaceborne observations have a better coverage than in situ monitoring networks, despite some limitations due to the impact of clouds and satellite orbits.[7,8] Widely used monitoring instruments

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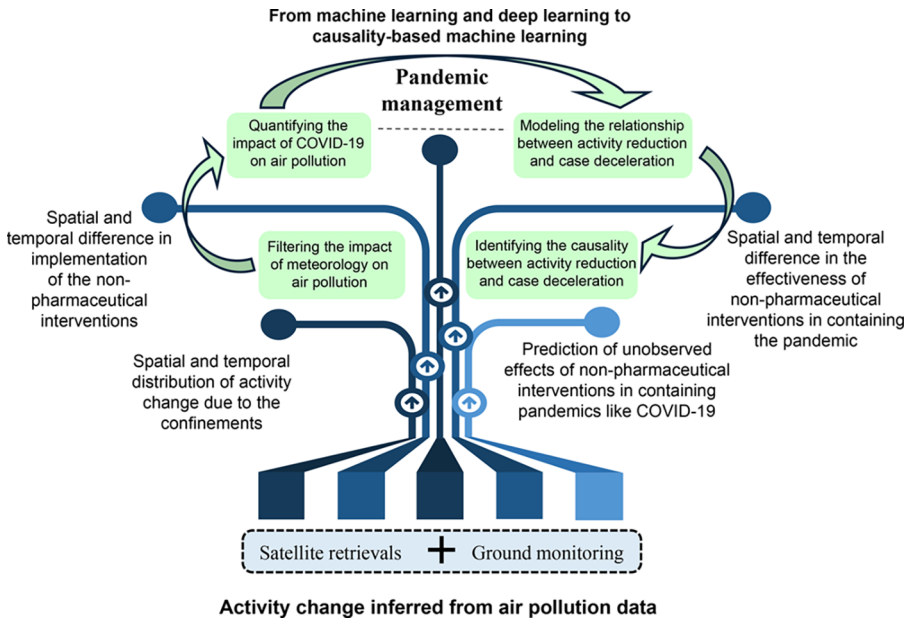

Figure 1. Application of air pollution data for pandemic management. Atmospheric monitoring for pandemic management was applied in four steps. First, the spaceborne or ground-based data for air pollution, such as daily concentrations of tropospheric nitrogen dioxide (NO_2) measured by the Ozone Monitoring Instrument or the Tropospheric Monitoring Instrument on satellites, are used to trace changes in activity. Second, differences in concentrations of air pollutants such as NO_2 are attributed to containment measures after filtering the impact of confounding factors. Third, temporal changes in activities inferred from air-pollution data are correlated with the rate of the reported daily COVID-19 cases to examine the effectiveness of confinements. Fourth, technologies such as machine learning, deep learning or causality-based machine learning are applied to predict the rate of deceleration of COVID-19 cases.

include those that determine the concentrations of nitrogen dioxide (NO_2) and ozone (O_3) in tropospheric columns from backscattered solar radiation (Supporting Information Table S1),for example, the Ozone Monitoring Instrument (OMI) on board the U.S. NASA Aura satellite at a resolution of 0.25 × 0.25°[7] and the Tropospheric Monitoring Instrument (TROPOMI) on board the European Copernicus Sentinel-5 Precursor satellite at a resolution of 0.01 × 0.01°.[8] After filtering the effects of confounding factors,[3] these products measured a decrease in NO_2 concentrations in 2020 relative to the same period in 2016−2019 for China in February and for Europe and North America in March−April at the beginning of the pandemic, which is defined as the first 3 weeks after the week detecting >100 cases. By contrast, there is a remarkable increase in NO_2 concentrations worldwide except for South Asia in November 2020, coincident with reopening the economy and lifting controls due to economic stress.

Inferring changes in activity using air pollution data should, however, consider all confounding factors. For example, air pollutants with short lifetimes in the atmosphere (<1 week), such as NO_2, are sensitive to meteorological conditions such as wet scavenging, atmospheric advection and chemical conversion (e.g., from NO_2 to nitrate). The unstable relationship between the lifetime of air pollutants like NO_2 and their concentrations[9] leads to a nonlinear relationship between air concentrations and rates of emission. In addition, the interannual trend in emissions is an important factor responsible for interannual variation in air pollution for developing countries like China and India. For example, air pollution in China has decreased sharply since 2013 due to stringent policies to mitigate emissions, which should be considered when observing changes in NO_2 concentrations due to lockdown. The use of machine learning allows us to consider these factors together in a nonlinear form.[3]

Clearly, the spread of a virus such as COVID-19 also depends on many socioeconomic and environmental factors such as population aggregation and heterogeneity, with crowded and ethnically diverse cities being more at risk than less densely populated cities;[10] on local weather conditions and seasonal effects, influencing people's behavior to stay indoors and affecting the risk of viral transmission among people.[11] In addition, epidemiological data may be available at local or regional level in some countries, but not globally at a subnational scale, making reported daily cases difficult to assess due to insufficient testing capacity resources. All of these limitations make it challenging to evaluate the true effects of reduced activity and lockdown confinement on viral spread. In fact, more than 50% of the variations in the rate of case deceleration[3] and the speed of viral transmission,[10] have not been explained.

However, machine learning could be a more powerful tool than traditional regression techniques[10] in identifying the relationship between changes in activity inferred from NO_2 concentrations and virus spread. Most machine-learning techniques can identify correlated data but lack explanatory ability without a causal structure. However, applications such as deep learning with causality may provide the necessary causal structure in the relationship of a decelerated spread of the virus with the reduced activity. A deep-learning method using the speed of adaptation to a supported distribution as a meta-learning objective is capable of returning a simple "cause-and-effect" relationship under a single degree of freedom.[12] Full dynamics of COVID-19 transmission will provide the ground truth validation for such training distribution. Achieving this step is tantalizing, because it allows the prediction of unobserved effects of the best actions against the containment of COVID-19, which in turn helps to calibrate parameters in epidemiological models.

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Future studies should aim to establish a global real-time system to trace changes in activity from observations of air pollution and develop a deep-learning method to identify the causal relationship between activity reduction and deceleration of the viral spread. Tracing changes in human activity using data for air pollution provides a tool to monitor the willingness of people to follow rules and governmental advice. Releasing such information protects public confidence in the ability of governments to impose mandatory regulation by inducing voluntary actions to disrupt the path of viral transmission in the management of future pandemics.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c03818.

Table S1 (PDF)

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Notes

The authors declare no competing financial interest.

Biographies

Rong Wang is a professor in Fudan University. He is leading a group dedicated to modelling global environmental change by focusing on the interactions between air pollution and climate change. He has more than 90 papers published in peer-reviewed journals and 18 papers published as the first or corresponding author in journals like Environ. Sci. & Technol. (4), Joule, Nature Geos., Nature Commun., Proc. Natl. Acad. Sci. USA. (2), Global Chang. Bio., Geophys. Res. Lett. (2) and Atmos. Chem. Phys. (2). He is the winner of the UNIDO Global Science and Technology Outstanding Contribution Award in 2020, the AARA Asian Young Aerosol Scientist Award in 2019 and the European Commission Marie Curie Fellowship Award in 2015.

Prof. Josep Penuelas is the Director of the Global Ecology Unit CREAF-CSIC-UAB-UB Barcelona. He is Highly Cited scientist in ecology/environment and in plant and animal sciences. Professor Josep Penuelas has published 6 books on ecology, more than 1.500 papers in scientific journals and books (ca. 1000 in journals of the Science Citation Index; 93 in Nature journals, 8 in Science journals, 13 in PNAS, 1 in National Science Review, 18 in Trends in Plant Science, 7 in Trends in Ecology and Evolution, as well as in highest profile scientific journals in ecology and environmental sciences: 79 in Global Change Biology, 26 in Global Ecology and Biogeography, 7 in Ecology Letters; remote sensing: 15 in Remote Sensing of Environment; and plant biology: 39 in New Phytologist), and more than 300 articles on popular science. He is also generating several influencing studies to develop science and policy for a sustainable planet, including use and recycling of resources, food security, and mitigation of pollution and climate change. He has been awarded many international prizes and recognitions, among which National Research Prize of Catalonia 2010; ERC-Synergy 2013; King Jaime I 2015; Ramon Margalef's Prize in Ecology 2016; Marsh Award for Climate Change Research, British Ecological Society (2018), Elected American Geophysical Union 2020 Fellowship.

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