# Leveraging Satellite Data to Address Air Pollution Inequities

by Susan C. Anenberg, Gaige H. Kerr, and Daniel L. Goldberg

This article describes advances in satellite remote sensing for exploring neighborhood-scale air pollution inequities, including recent applications, current limitations, and potential opportunities.

**Criteria air pollutant concentrations have decreased dramatically** in the United States since the passage of the 1970 U.S. Clean Air Act and its 1990 Amendments.[1] Air pollution inequality has also declined.[2] However, communities of color and those with lower household income and educational attainment still experience higher exposure levels.[3,4] With complete geographical coverage and relatively high spatial resolution, satellite remote sensing is opening new avenues for identifying communities that are experiencing disproportionate exposures and associated health risks.

## Actions to Advance Environmental Justice

Several U.S. states have recently implemented groundbreaking programs to address air pollution inequality in their air quality management programs. In 2017, California established the Community Air Protection Program to reduce exposures in the communities most impacted by air pollution by conducting community air monitoring and emissions reductions programs, targeting incentive funding and grants to deploy cleaner technologies that address localized air pollution, requiring accelerated retrofit of pollution controls on industrial sources, and enhancing transparency and availability of air pollution and emissions data. In 2020, New Jersey passed a new law requiring the New Jersey Department of Environmental Protection to only grant or renew permits for certain facilities if there are no disproportionate, cumulative environmental impacts on overburdened communities. Other states (e.g., Connecticut, Indiana, Minnesota, and Oregon) have also taken more limited steps to address disparities in environmental exposures.

At the federal level, in January 2021, the Biden Administration released Executive Order 14008, which directs federal agencies to integrate environmental justice (EJ) into their programs, policies, and activities. Among other actions, it sets a goal of delivering 40% of the benefits of relevant federal investments to disadvantaged communities and initiates the development of a national-scale Climate and Economic Justice Screening Tool. In April 2021, the U.S. Environmental Protection Agency (EPA) Administrator directed all EPA offices to integrate EJ considerations into their plans and actions.

## Approaches for Characterizing Neighborhood-Scale Air Quality

Addressing air pollution inequities requires information about air pollution levels within at-risk communities, which is beyond the intent and capability of the existing air monitoring network. Federal and state-level EJ mapping tools, including EJSCREEN developed by EPA and CalEnviroScreen developed by the California Office of Environmental Health Hazard Assessment, integrate environmental and sociodemographic data from many sources to identify disproportionately burdened neighborhoods and population sub-groups.[5]

The functionality of these tools depends on the quality and characteristics (e.g., spatial extent and resolution) of the data they use. Fortunately, a variety of new and maturing technologies can now provide high-quality, spatially complete, and granular information about various environmental exposures, including air quality.

Several studies have used portable air pollution sensors that are either wearable[6] or mounted on vehicles to capture concentrations at the street-level.[7,8] These approaches provide empirical measurements at scales that are meaningful for exposure at the individual or street-level, but are resource intensive and typically limited in temporal duration (e.g., campaigns lasting several weeks) and spatial coverage (e.g., within one neighborhood or city).

Distributed networks of "low-cost" sensors are another approach taken in several cities, including the Imperial Valley, CA, Los Angeles, CA, Portland, OR, Denver, CO, Chicago, IL, Baltimore, MD, and Pittsburgh, PA.[9–14] Some private companies (e.g., PurpleAir) also provide global, real-time maps of readings from their devices. These sensors are valuable for capturing variation within cities and during events such as wildfire smoke episodes. However, the results must be appropriately adjusted and used with caution as the sensors operate differently than federal reference monitors and are often limited by challenges with calibration and drift. EPA has developed guidance (https://www.epa.gov/air-sensor-toolbox) for setting up, maintaining, and interpreting results from low-cost sensors.

Both process-based models and statistical models are rapidly advancing in spatial resolution, speed, and accuracy, enabled by advances in computing power and scientific understanding. The range of models used to analyze exposure disparities includes chemical transport models[3,15,16] and statistical models such as land-use regressions.[17] These modeling approaches are valuable for filling the spatial gaps between monitors, but also have limitations. Chemical transport models often run at coarser spatial resolutions that preclude comparisons at the neighborhood scale. Land-use regression models are limited by the regionally representative monitor data used to train them, degrading their ability to capture

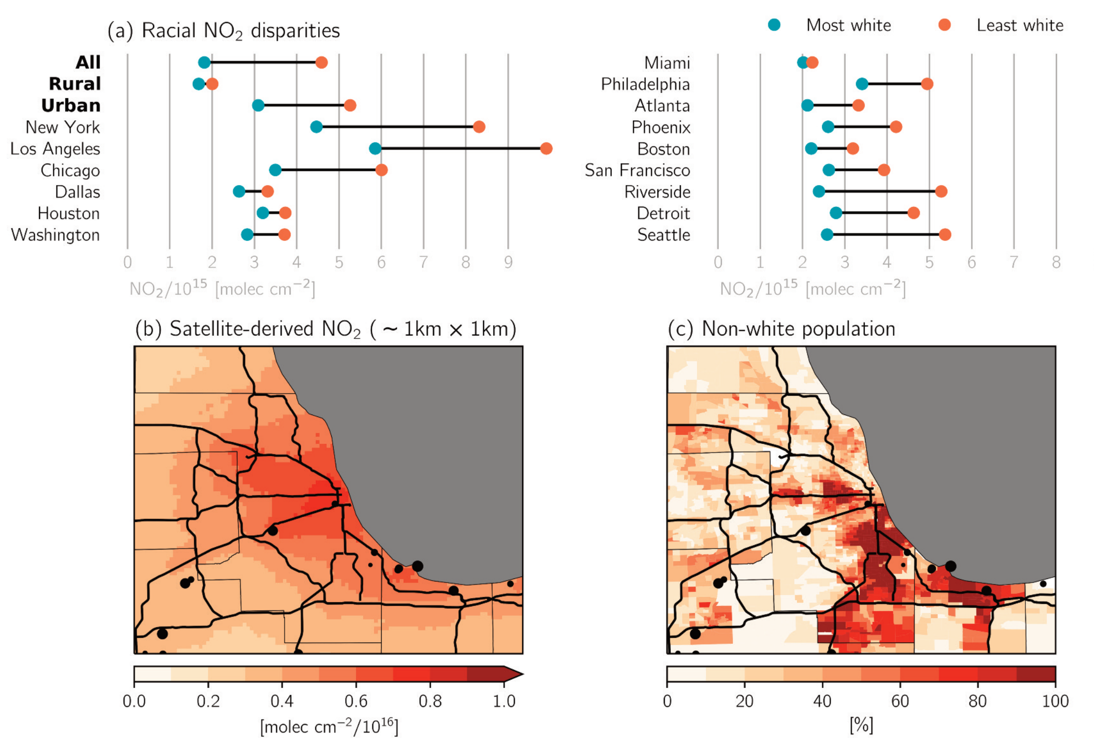


**Figure 1.** (a) Racial $NO_2$ disparities for all, urban, and rural census tracts in the contiguous United States and the 15 largest metropolitan statistical areas determined with annual average TROPOMI $NO_2$ for 2019 (adapted from Kerr et al.[26] with a different time period). Here, least (most) white corresponds to census tracts with their percentage of the white population in less than (greater than) the 10th (90th) percentile. (b) Annual average tropospheric column $NO_2$ from TROPOMI (~1km x 1km) for 2019 in the Chicago metropolitan area. (c) The percentage of non-white residents in each census tract from the 2014–2018 U.S. Census Bureau's American Community Survey. Interstates and point sources of NOx emissions (e.g., power plants, other industrial facilities) are denoted in (b)–(c) by the thick black lines and scatter points, respectively. The size of each scatter point represents the magnitude of NOx emissions in 2019. Thin black lines show county and state boundaries.

the highest (e.g., nearby large industrial facilities) or lowest (e.g., rural) concentrations.

Satellite remote sensing is emerging as a valuable information source for air quality surveillance, with key advantages from complete geospatial coverage and relatively high spatial resolution.[18,19] Unlike their polar-orbiting predecessors, new geostationary satellites will bring full daytime temporal coverage. Thus, new satellites such as the Tropospheric Emissions: Monitoring of Pollution (TEMPO) instrument launching in 2022, will offer the potential to analyze temporal and spatial variations in pollutant concentrations within cities.

## Leveraging Satellite Data

Several studies have begun using satellite data for analyzing environmental injustice, including for green space,[20] heat,[21] particulate matter ($PM_{2.5}$),[22,23] and nitrogen dioxide ($NO_2$).[24–26] Results demonstrate how disproportional environmental burdens are often linked with historical racially-biased policies, such as redlining and roadway placement.[20,21,27]

Satellite-derived $NO_2$ concentrations are particularly valuable for understanding the inequitable distribution of air pollutants and their health impacts. Compared with total $PM_{2.5}$ mass, $NO_2$ has a shorter atmospheric lifetime (i.e., hours compared with days) and less influence from regional pollution sources (e.g., agriculture, wildfire smoke, dust), leading to sharper gradients for $NO_2$ near emission sources. For these reasons, $NO_2$ is often considered to be an effective surrogate for urban combustion-related air pollution, including $PM_{2.5}$ components that exhibit more spatial variation than total $PM_{2.5}$ mass, such as black carbon (BC) and particle-bound polycyclic aromatic hydrocarbons (PAHs). In addition, while aerosol optical depth and surface $PM_{2.5}$ are more loosely associated, satellite $NO_2$ "column" observations (i.e., the number of molecules between the satellite instrument and the Earth's surface) are tightly correlated with $NO_2$ observed at ground monitors, providing an observational record of spatial patterns in urban combustion-related air pollution.[26]

Recent studies using data from the TROPOspheric Monitoring Instrument (TROPOMI) reveal that marginalized and minoritized populations still experience higher $NO_2$ levels, despite the fact that $NO_2$ concentrations have dropped and ethnoracial and socioeconomic disparities have narrowed in recent decades. For example, Demetillo et al.[25] showed that TROPOMI $NO_2$ levels (and on-road transportation, industrial, and petrochemical emissions) are disproportionately higher in low income, non-white census tracts in the Houston metropolitan area. Similarly, we found that TROPOMI $NO_2$ levels were substantially higher in census tracts with more diverse populations, lower income, and lower educational attainment across all urban areas throughout the continental U.S. (see Figure 1 and Kerr et al.[26]).

Mapping satellite-derived $NO_2$ levels with information on race and the location of NOx emitters (e.g., roadways, industrial facilities, power plants) can shed light on the reasons that marginalized populations experience higher levels of $NO_2$ than other demographic groups (Figure 1). For example, the highest concentration of industrial facilities in the Chicago metropolitan area and the convergence of Interstates 90, 94, and 65 are located in South Chicago and Gary, Indiana (Figure 1b–c). These sources lead to high levels of satellite derived $NO_2$ (Figure 1b), and this part of the city is home to a large percentage of non-white residents (Figure 1c). However, there are other parts of the city with high $NO_2$ concentrations or NOx sources but a predominantly white population, which underscores the nuance needed for understanding how patterns of injustice can also vary within cities.

Using the COVID-19 pandemic as a natural experiment, we also found that $NO_2$ levels in the least white census tracts during COVID-19 precautions exceeded those in most white census tracts prior to the pandemic, despite the unprecedented drop in emissions.[26] These studies add to the previous literature illustrating the power of space-based observations to understand neighborhood-scale $NO_2$ levels,[24] now with unprecedented sensitivity at fine spatial resolution

Satellite remote sensing is emerging as a valuable information source for air quality surveillance.

(1km x 1km).[28,29] As a whole, these studies provide empirical evidence of the persistent inequity in air pollution levels within individual cities and across the continental United States.

Moving beyond exposure to consider air pollution-related health risks, studies using satellite data for the Bay Area, CA, and Washington, DC, highlight how $PM_{2.5}$- and $NO_2$-related health risks vary dramatically within individual cities, resulting from disparities in both concentrations and population vulnerability.[30,31] These studies also found that street-level mobile monitoring captured more within-city variation compared with grid cell average satellite-derived concentrations, and that the spatial pattern of estimated air pollution-related health risks was driven more by the stark variation in disease rates compared with the relatively less resolved concentration estimates. These findings point to the need for increased spatial resolution and temporal coverage of satellite observations for understanding the contributions of emission source sectors (e.g., traffic) on disparities in air pollution-related health risks.

## Limitations and Future Opportunities

Satellite remote sensing is opening new opportunities for mapping EJ. However, some limitations remain. First, the limited temporal coverage of polar orbiting satellite observations (one snapshot per day) is unable to capture the full diurnal variation of pollution levels. $PM_{2.5}$ and $NO_2$ concentrations and their spatial heterogeneities are often largest in the early morning (6:00 a.m.–9:00a.m.), and current satellite instruments miss this timeframe. For now, early afternoon satellite measurements can be adjusted to daily averages using more temporally complete model simulations or surface observations. In the future, new geostationary satellites (e.g., TEMPO) will overcome this limitation by taking hourly U.S. air quality measurements throughout the daytime.

A second issue is spatial resolution. Post-processing techniques (e.g., averaging over many observations on different days) can yield surface concentration datasets with relatively high spatial resolutions (e.g., 1km x 1km), but native resolution of the satellite (3.5 x 5.5 km) tends to smear out pollution. Previous studies have shown that 1-km resolution can resolve $NO_2$ concentration differences within cities,[25,26] but even more granular information may be needed, particularly in dense urban areas where census tracts are small. Satellites are also unable to directly observe pollutants that may be of greatest concern for EJ, including black carbon and hazardous air pollutants. Satellite-derived $NO_2$ concentrations could potentially be used as a proxy for these spatially heterogeneous pollutants from fuel combustion, but methods have not yet been developed.

The recent, rapid proliferation of spatially explicit air quality assessment tools, including satellite remote sensing, mobile monitoring, and low-cost sensors, is opening new avenues for identifying air pollution inequities. Combining these tools with personal exposure measurements, federal reference monitor observations, and statistical techniques can leverage the strengths of each approach. In the future, these tools may provide more complete, refined, and accurate information to enable air quality management approaches that address inequities in exposure and associated health risks. **em**

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## Natural Emissions and Their Impacts on Air Quality

Emissions from natural sources can have important impacts on air quality. Examples of natural-source emissions include windblown dust; organosulfur, halogen, and sea-salt emissions from oceans; volcanic emissions; wildfires emissions; nitrogen oxides emissions from lightning; and biogenic/soil emissions. The October issue explores these natural emissions and their impacts on atmospheric ozone and particulate matter.