Daily Satellite Observations of Nitrogen Dioxide Air Pollution Inequality in New York City, New York and Newark, New Jersey: Evaluation and Application

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ABSTRACT: Urban air pollution disproportionately harms communities of color and low-income communities in the U.S. Intraurban nitrogen dioxide (NO₂) inequalities can be observed from space using the TROPOspheric Monitoring Instrument (TROPOMI). Past research has relied on time-averaged measurements, limiting our understanding of how neighborhood-level NO₂ inequalities co-vary with urban air quality and climate. Here, we use fine-scale (250 m × 250 m) airborne NO₂ remote sensing to demonstrate that daily TROPOMI observations resolve a major portion of census tract-scale NO₂ inequalities in the New York City–Newark urbanized area. Spatiotemporally coincident TROPOMI and airborne inequalities are well correlated (r = 0.82–0.97), with slopes of 0.82–1.05 for relative and 0.76–0.96 for absolute inequalities for different groups. We calculate daily TROPOMI NO₂ inequalities over May 2018–September 2021, reporting disparities of 25–38% with race, ethnicity, and/or household income. Mean daily inequalities agree with results based on TROPOMI measurements oversampled to 0.01° × 0.01° to within associated uncertainties. Individual and mean daily TROPOMI NO₂ inequalities are largely insensitive to pixel size, at least when pixels are smaller than ~60 km², but are sensitive to low observational coverage. We statistically analyze daily NO₂ inequalities, presenting empirical evidence of the systematic overburdening of communities of color and low-income neighborhoods with polluting sources, regulatory ozone co-benefits, and worsened NO₂ inequalities and cumulative NO₂ and urban heat burdens with climate change.

KEYWORDS: urban air pollution, environmental justice, nitrogen dioxide, satellite measurements, TROPOMI

INTRODUCTION

New York City, New York, and Newark, New Jersey, are populous U.S. cities with poor air quality, where there are documented inequalities in air pollution concentrations and health impacts affecting communities of color and low-income residents.¹–⁷ There have been decades of community organizing and activism around environmental racism issues, including air pollution and asthma, for example, in the South Bronx, West Harlem, and Ironbound.⁸–¹⁰ Air quality can vary substantially between neighborhoods in the same city, and recent observational and computational advances have improved quantitative estimates of intraurban inequalities across the U.S.¹¹–¹⁷ However, fine-scale pollutant mapping typically relies on measurements that are short-timescale snapshots or long-time averages, trading temporal information for enhanced spatial detail. As a result, we have less knowledge of temporal variability in neighborhood-level inequalities and relationships between inequalities, urban air quality issues such as ozone, and climate change.

Nitrogen dioxide (NO₂) is a criteria pollutant and surface ozone (O₃) precursor. NO₂ is a chemically reactive primary pollutant, and therefore, NO₂ concentrations are variable in space and time, with characteristic NO₂ distance decay gradients away from sources equaling hundreds of meters to 2 km.¹⁸–²⁰ NO₂ is emitted as NOₓ (≡NO + NO₂), with sources dominated by fossil fuel combustion in cities, especially traffic exhaust.²¹–²⁵ NO₂ exposure is associated with numerous adverse health effects,²⁶–²⁹ and roadway residential proximity has been linked to asthma-related urgent medical visits, pediatric asthma, cardiac and pulmonary mortality, and preeclampsia and preterm birth.³⁰–³⁵ NO₂
concentrations and NO₂ sources are unequally distributed with race, ethnicity, and income in U.S. cities, with urban NO₂ inequalities being large enough to cause health disparities.

To date, air pollution inequality analyses focusing on primary pollutants like NO₂ have typically prioritized spatial rather than temporal information, as observations and models must resolve length scales of atmospheric dispersion to fully describe disparities. Satellite NO₂ tropospheric vertical column densities (TVCDs) have been incorporated into regression models and other measurement-model hybrid surface NO₂ products relevant for health and environmental justice applications, with spatial resolutions ranging from 100 m to 0.01° (≈1 km). The TROPOSpheric Monitoring Instrument (TROPOMI) currently provides the highest-spatial resolution global satellite NO₂ TVCDs with TROPOMI describing NO₂ inequalities at census tract scales directly after TVCDs are oversampled to 0.01° × 0.01°, time averaging at least multiple months of measurements. For reference, the average area of census tracts in New York City and Newark is 2.1 km². Oversampled TVCDs have been shown to observe NO₂ inequalities equivalently to high-spatial resolution TVCDs. With TROPOMI describing NO₂ inequalities at census tract scales directly after TVCDs are oversampled to 0.01° × 0.01°, time averaging at least multiple months of measurements. For reference, the average area of census tracts in New York City and Newark is 2.1 km².

**MEASUREMENTS AND METHODS**

**GCAS and GeoTASO.** The Geostationary Coastal and Air Pollution Events (Geo-CAPE) Airborne Simulator (GCAS) and Geostationary Trace gas and Aerosol Sensor Optimization (GeoTASO) instruments are push-broom spectrometers that function as satellite analogs for NASA airborne missions. GeoTASO makes hyperspectral nadir-looking measurements of backscattered solar radiation in the ultraviolet (290–390 nm) and visible (415–695 nm) regions. GCAS makes similar observations at 300–490 nm (optimized for air quality) and 480–900 nm (optimized for the ocean color). Each of the two channels in both instruments uses two-dimensional charge-coupled device (CCD) array detectors, where one CCD dimension provides the spectral coverage, one provides the cross-track coverage across a 45° field of view, and the movement of host aircraft generates the along-track coverage. The GCAS and GeoTASO datasets used here have identical NO₂ retrieval algorithms, which are similar to those of major satellite instruments, including TROPOMI and eventually TEMPO. Briefly, NO₂ differential slant columns are produced by fitting the 425–460 nm spectral window using QDOAS and a measured reference spectrum collected over a nearby area away from NO₂ sources. Differential slant columns are converted to vertical column densities using an air mass factor (AMF), which is a function of viewing and solar
geometries, surface reflectance, and meteorological and trace-gas vertical profile shapes, among other variables (see Judd et al.\textsuperscript{41} and Judd et al.\textsuperscript{42} for details). NO\textsubscript{2} vertical profiles are calculated using bias-corrected PRATMO stratospheric NO\textsubscript{2} climatologies\textsuperscript{43–46} and hourly output from the North American Model-Community Multiscale Air Quality (NAMC-MAQ) model (12 km × 12 km) from a developmental analysis from the National Air Quality Forecasting Capability.\textsuperscript{47} The resulting GCAS and GeoTASO TVCDs have a spatial resolution of 250 m × 250 m.

During LISTOS, GeoTASO flew on the NASA LaRC HU-25 Falcon in June 2018, and GCAS flew onboard the NASA LaRC B200 from July to September 2018. On days when elevated regional air pollution was predicted (Table S1), a large rafter flight pattern spanning nearly the full New York City–Newark UA (Figures 1a and S1a) was mapped in the morning (9–11 am local time, LT) and afternoon (1:30–4:10 pm LT). On other days, aircraft followed a smaller rafter flight pattern (Figure S1b), sub-sampling the UA in the early morning (8:15–9:50 am LT), late morning (9:50–11:30 am LT), early afternoon (1:15–3:00 pm LT), and late afternoon (3:00–4:45 pm LT). During LISTOS, Judd et al.\textsuperscript{44} reported that GCAS and GeoTASO TVCDs agreed with coincident ground-based Pandora NO\textsubscript{2} column measurements to within ±25% with no apparent overall bias. Here, we focus on cloud-free observations from 37 large and small NO\textsubscript{2} TVCD flight rasters collected in 13 days having sampled at least 60% of census tracts in the New York City–Newark UA. On average, GCAS and GeoTASO sampled 79 ± 7% of UA census tracts. Compared to the full New York City–Newark UA, Black and African Americans, Hispanics and Latinos, and Asians were statistically overrepresented by 16–25% in census tracts sampled during the large and especially small raster patterns (Table S2).

**TROPOMI.** TROPOMI is a hyperspectral spectrometer onboard the sun-synchronous Copernicus Sentinel-5 Precursor (S-SP) satellite.\textsuperscript{48,49} S-SP has an equatorial crossing time of 1:30 pm LT, with observations collected over the New York City–Newark UA (Figure 1b) between 1 and 3 pm LT once or twice daily. NO\textsubscript{2} is retrieved by fitting the 405–465 nm spectral band based on an updated OMI DOMINO algorithm and work from the QA4ECV project.\textsuperscript{50–54} NO\textsubscript{2} TVCDs have documented low-bias overpolluted scenes, with uncertainties driven by spatially and temporally coarse inputs to the AMF,\textsuperscript{55} including the surface albedo (monthly 0.5° × 0.5° OMI climatology)\textsuperscript{56} and NO\textsubscript{2} profile shape (daily 1° × 1° TMS-MP output).\textsuperscript{57} We use level 2 NO\textsubscript{2} TVCDs reprocessed on the SSP-PAL system (qa value >0.75). From 1 May 2018 to 6 August 2019, encompassing the LISTOS period, the nadir spatial resolution of TROPOMI NO\textsubscript{2} TVCDs was 3.5 km × 7 km, with individual pixel areas of 27–63 km\textsuperscript{2} (mean ± 1σ). Subsequently, the spatial resolution improved to 3.5 km × 5.5 km at nadir,\textsuperscript{58} giving pixel areas of 21–49 km\textsuperscript{2} (mean ± 1σ) over the New York City–Newark UA. We focus on the individual daily TVCDs (an example is shown in Figure 1b) and observations over May 2018–September 2021 oversampled to 0.01° × 0.01° using a physics-based algorithm (Figure 1c).\textsuperscript{59}

**Census Tract NO\textsubscript{2} Inequalities.** We average NO\textsubscript{2} TVCDs within 2018 census tract polygons for the New York City–Newark UA. Individual airborne and TROPOMI TVCDs are spatially continuous but discretized to 0.001° × 0.001° at the pixel level prior to tract averaging without regridding or oversampling. NO\textsubscript{2} tract-averaged TVCDs are weighted using tract-scale populations of non-Hispanic/Latino Black and African Americans, non-Hispanic/Latino Asians, all races defined as those with household income-to-poverty ratios of >1. Tract-scale NO\textsubscript{2} TVCDs within both categories are population-weighted by residents at the given poverty status. We combine race-ethnicity and income metrics, categorizing census tracts as low-income and non-white (LIN), that is, people of color in low-income tracts, or high-income and white (HIW). In LIN tracts, NO\textsubscript{2} TVCDs are weighted using the population of Black and African Americans, Hispanics and Latinos, Asians, and/or American Indians and Alaska Natives in the lowest income quintile tracts (household incomes < $49,544.50). Because American Indians and Alaska Natives comprise less than 0.2% of the New York City–Newark UA population, we do not report results for this group separately. In HIW tracts, TVCDs are weighted using the population of non-Hispanic/Latino whites in the highest income quintile.

![Figure 2](https://example.com/figure2.png)

**Figure 2.** Fractional census tract populations for Black and African Americans (a), Hispanics and Latinos of all races (b), Asians (c), and non-Hispanic/Latino whites (d) and median household incomes (e) in the New York City–Newark UA (black line). Background map data: Landsat 8 composite January 2017–June 2020.
Airborne NO$_2$ inequalities for each of the 37 LISTOS flights for Black and African Americans (a), Hispanics and Latinos (b), and Asians (c) compared to those for non-Hispanic/Latino whites, below poverty vs above poverty tracts (d), and LIN compared to HIW tracts (e). Morning (8–11:30 am LT) (tan) and afternoon (1–5 pm LT) (brown) flights are shown separately. LISTOS mean inequalities with 95% confidence intervals are reported in each panel, for all flights (black) and separately in the morning (tan) and afternoon (brown).

We use NO$_2$* as the term NO$_2$ in acknowledgement of this interference, opting not to apply a correction factor as we are interested in the distance dependence of the correlations between surface NO$_2$* and overhead TVCDs rather than the surface NO$_2$ mixing ratios themselves. We use O$_3$ measurements from 17 monitoring stations within the UA (Figure S3b) converted to the policy-relevant metric of the daily maximum 8 h average (MDA8) O$_3$ mixing ratio. Temperature and wind speed measurements are collected at 14 stations throughout the New York City–Newark UA as part of the Automated Surface Observing System (ASOS) and the Automated Weather Observing System (AWOS) (Figure S3c), accessible through the Iowa State University Iowa Environmental Mesonet download service. Because of station-level variability in the data collection interval, we average individual station meteorological measurements from 12 to 3 pm LT prior to computing the UA-wide mean.

**NO$_2$ Emission Inventories: FIVE and NEI.** The Fuel-based Inventory of Vehicle Emissions (FIVE) tabulates monthly on-road and off-road gasoline and diesel mobile source emissions at 4 km × 4 km U.S. wide. FIVE is based on publicly available datasets of taxable fuel sales and road-level traffic and time-resolved weigh-in-motion traffic counts. We use emissions from the 2018, 2019, 2020 COVID-19, and 2020 business-as-usual (BAU) FIVE for 2018, 2019, 2020, and 2021, respectively. The 2020 COVID-19 inventory was developed using monthly scaling factors from U.S. Energy Information Administration fuel sales reports. In 2020 BAU FIVE, fuel use is assumed unchanged from 2019. See McDonald et al. and Harkins et al. for a detailed discussion of the uncertainties, which are ±24% for both gasoline and diesel vehicles. Annual NO$_2$ stationary source emissions are over a heated molybdenum catalyst, followed by the detection of NO using the chemiluminescence technique. The resulting NO$_2$ data have a known positive interference from higher-order nitrogen oxides and ammonia, which also decompose at non-unity efficiency in the presence of the catalyst. We use the term NO$_2$* in acknowledgement of this interference, opting not to apply a correction factor as we are interested in the distance dependence of the correlations between surface NO$_2$* and overhead TVCDs rather than the surface NO$_2$ mixing ratios themselves. We use O$_3$ measurements from 17 monitoring stations within the UA (Figure S3b) converted to the policy-relevant metric of the daily maximum 8 h average (MDA8) O$_3$ mixing ratio. Temperature and wind speed measurements are collected at 14 stations throughout the New York City–Newark UA as part of the Automated Surface Observing System (ASOS) and the Automated Weather Observing System (AWOS) (Figure S3c), accessible through the Iowa State University Iowa Environmental Mesonet download service. Because of station-level variability in the data collection interval, we average individual station meteorological measurements from 12 to 3 pm LT prior to computing the UA-wide mean.

**Measurements of Surface NO$_2$* and O$_3$ and Meteorology.** We use NO$_2$* surface observations collected at 11 stations across the New York City–Newark UA (Figure S3a). These measurements are made by decomposing NO$_2$ to NO over a heated molybdenum catalyst, followed by the detection of NO using the chemiluminescence technique. The resulting NO$_2$ data have a known positive interference from higher-order nitrogen oxides and ammonia, which also decompose at non-unity efficiency in the presence of the catalyst. We use the term NO$_2$* in acknowledgement of this interference, opting not to apply a correction factor as we are interested in the distance dependence of the correlations between surface NO$_2$* and overhead TVCDs rather than the surface NO$_2$ mixing ratios themselves. We use O$_3$ measurements from 17 monitoring stations within the UA (Figure S3b) converted to the policy-relevant metric of the daily maximum 8 h average (MDA8) O$_3$ mixing ratio. Temperature and wind speed measurements are collected at 14 stations throughout the New York City–Newark UA as part of the Automated Surface Observing System (ASOS) and the Automated Weather Observing System (AWOS) (Figure S3c), accessible through the Iowa State University Iowa Environmental Mesonet download service. Because of station-level variability in the data collection interval, we average individual station meteorological measurements from 12 to 3 pm LT prior to computing the UA-wide mean.

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taken from the 2017 National Emissions Inventory (NEI17),
including industrial and commercial facilities, power plants,
and airports. Uncertainties in power plant emissions are ±25%,
and uncertainties for industrial facilities and other stationary
sources are ±50%.

RESULTS AND DISCUSSION
GCAS and GeoTASO Census Tract-Level NO2 Inequalities during LISTOS. We report population-weighted census tract-scale NO2 inequalities measured during each of the 37 LISTOS flights within the New York City–Newark UA in Figure 3 and Table S3. Population-weighted NO2 TVCDs for Black and African Americans, Hispanics and Latinos, and Asians are 14 ± 3%, 14 ± 5%, and 15 ± 4% higher than those for non-Hispanic/Latino whites, respectively. NO2 TVCDs are on average 17 ± 4% greater in tracts below the poverty line compared to those above. When race-ethnicity and income metrics are combined, NO2 TVCDs are 24 ± 4% higher in LIN than those in HIW census tracts. Errors are defined as 95% confidence intervals for mean inequalities, derived from bootstrapped distributions sampled with replacement 104 times.

NO2 inequalities are more variable between days than by
time of the day during LISTOS. Although population-weighted
and/or income-sorted NO2 TVCDs for all groups are on
average 14–28% higher during morning (8–11:30 am LT)
than during afternoon flights (1–5 pm LT), corresponding
median relative and absolute NO2 inequalities are not
significantly different for any group (Mann–Whitney test, p < 0.050). Mean relative and absolute inequalities are also
similar during morning and afternoon flights, with exceptions
of relative inequalities for Hispanics and Latinos and absolute
inequalities for Asians and in LIN tracts. This suggests that
observations collected in the early afternoon by TROPOMI
capture daytime patterns in tract-scale population-weighted
NO2 TVCD (not surface mixing ratio) differences generally,
at least during LISTOS. The small number of flights limits our
ability to statistically infer relationships between NO2
disparities and environmental factors; however, we observe
moderate, negative correlations between absolute inequalities
and mean surface wind speeds and moderate, positive
correlations with UA-mean NO2* and NO2 TVCDs for
some groups (p < 0.050) (Table S4). This is consistent with
slower surface winds reducing the mixing of NO2 pollution
away from NOx sources and higher NO2 pollution worsening
absolute inequalities.

Evaluating Daily TROPOMI Observations. To deter-
mine the extent to which daily TROPOMI measurements
resolve census tract-level disparities, we compare NO2
inequalities for spatially and temporally coincident tract-
averaged GCAS, GeoTASO, and TROPOMI observations
within the New York City–Newark UA. We consider
measurements to be coincidental if the minimum and
maximum overfly times of airborne columns within a given
census tract occur within ±30 min of the TROPOMI overpass.

Daily relationships between airborne and TROPOMI inequal-
ities are fit using an unweighted bivariate linear regression
model (Figure 4). We infer the portion of NO2 inequalities
captured by TROPOMI from the slope of this line and assess
agreement between the airborne and TROPOMI-derived
results using Pearson correlation coefficients.

Daily TROPOMI observations capture most tract-scale NO2
differences and are well correlated with inequalities measured
by GCAS and GeoTASO. Correlation slopes are from 0.82 ±

Figure 4. Daily relative (%) (blue circles) and absolute (molecules cm−2) (green diamonds) inequalities measured by GCAS and GeoTASO vs TROPOMI during LISTOS for Black and African Americans (a), Hispanics and Latinos (b), and Asians (c) compared to those for non-Hispanic/Latino whites, below-poverty vs above poverty tracts (d), and LIN compared to HIW tracts (e). Fits are derived from an unweighted bivariate linear regression model. Slopes (m) and Pearson correlation coefficients (r) for each fit are reported for both relative (blue) and absolute (green) inequalities. One data point in panel d is out of frame (−119.5%, −136.4%).
Table 1. Influence of TROPOMI Pixel Area and Sampling Coverage on Both Mean and Individual Daily Relative Inequalities (May 2018–September 2021) and Comparison between Mean Daily and Oversampled Relative Inequalities for Black and African Americans, Hispanics and Latinos, and Asians Compared to Those for Non-Hispanic/Latino Whites, for below Poverty versus above Poverty Tracts, and for LIN Compared to HIW Tracts

| Pixel Area (km²) | Black and African Americans | Hispanics and Latinos | Asians | Below Poverty Tracts | LIN Tracts | Mean Daily Inequalities | Coefficient of Variation |
|-----------------|-----------------------------|-----------------------|-------|---------------------|-----------|------------------------|-------------------------|
| 20–25           | 31 ± 2                      | 30 ± 2                | 28 ± 2| 28 ± 2              | 40 ± 3    | 0.44                   | 0.52                    |
| 25–30           | 32 ± 3                      | 30 ± 3                | 28 ± 2| 26 ± 3              | 39 ± 3    | 0.45                   | 0.53                    |
| 30–35           | 31 ± 3                      | 29 ± 3                | 30 ± 2| 26 ± 2              | 38 ± 3    | 0.44                   | 0.42                    |
| 35–45           | 31 ± 2                      | 26 ± 3                | 28 ± 2| 25 ± 3              | 38 ± 3    | 0.37                   | 0.62                    |
| 45–60           | 30 ± 3                      | 27 ± 3                | 28 ± 2| 25 ± 2              | 38 ± 4    | 0.54                   | 0.60                    |
| >60             | 26 ± 3                      | 25 ± 3                | 23 ± 2| 22 ± 2              | 31 ± 3    | 0.47                   | 0.60                    |

**Mean Daily Inequalities and Coefficient of Variation**

| Pixel Area (km²) | Black and African Americans | Hispanics and Latinos | Asians | Below Poverty Tracts | LIN Tracts | Mean of Daily Inequalities | Mean of Oversampled Inequalities |
|-----------------|-----------------------------|-----------------------|-------|---------------------|-----------|--------------------------|--------------------------------|
| <30             | 12 ± 2                      | 11 ± 2                | 10 ± 2| 11 ± 4              | 18 ± 4    | 1.99                     | 2.00 |
| 30–60           | 30 ± 3                      | 29 ± 3                | 26 ± 3| 25 ± 3              | 37 ± 4    | 0.64                     | 0.62 |
| >60             | 30 ± 1                      | 28 ± 1                | 28 ± 1| 26 ± 1              | 38 ± 1    | 0.40                     | 0.53 |

“*The pixel area analysis only includes days with >30% UA coverage. Observations are grouped such that each category contains at least 80 observation days. Inequalities are binned by days with low (<30%), moderate (30–60%), and high (>60%) UA coverage. Daily inequalities are assessed using the coefficient of variation. Errors are 95% confidence intervals based on bootstrapped distributions sampled with replacement 10⁴ times. The oversampled TROPOMI TVCDs are oversampled to 0.01° × 0.01° prior to census tract averaging for all days, on days with >30% coverage, and on days with >60% coverage, with uncertainties as standard mean errors.

0.10 to 1.05 ± 0.07 for relative inequalities and from 0.76 ± 0.09 to 0.96 ± 0.06 for absolute inequalities, implying that TROPOMI detects at least 82% of relative and 76% of absolute inequalities, with slopes for many population groups being even higher. For comparison, the mean pixel area of coincident TROPOMI TVCDs is 44 ± 18 km² (±1σ), which is much larger than typical atmospheric NO₂ distance decay gradients of a few hundred meters. Although some precision is lost, our results suggest that measurements on the scale of these gradients, for example, GCAS and GeoTASO, are not required to constrain the majority of city-wide census tract-scale NO₂ inequalities. Airborne and TROPOMI inequalities are strongly correlated, with Pearson correlation coefficients ranging 0.82–0.97 for relative and 0.88–0.96 for absolute inequalities. Slopes and Pearson correlation coefficients do not improve significantly when inequalities are weighted by the number of coincident census tracts, mean TROPOMI pixel areas, UA-mean surface wind speeds, or mean TROPOMI NO₂ TVCDs, suggesting that these variables do not have a strong influence over the agreement, at least in the New York City–Newark UA during LISTOS.

We calculate daily census tract-scale NO₂ inequalities over May 2018–September 2021 and investigate the sensitivity of mean and individual daily results to the UA-mean TROPOMI pixel area and UA coverage percentage (Table 1). First, UA-mean daily TROPOMI pixel areas range ∼20–90 km² (Figure S4), providing an empirical test of the resolution dependence of NO₂ inequalities. We remove days from the analysis when TROPOMI observations cover less than 30% of census tracts across the New York City–Newark UA (justification below; see Table S5 for an analysis of all days). We find that relative inequalities are mostly insensitive to TROPOMI UA-mean pixel area, with significant differences in medians emerging when pixels are larger than ∼60 km², defined as p < 0.050 (Kruskal–Wallis test). Additionally, there is no clear influence of increasing UA-mean pixel area on the coefficient of variation of the individual daily inequalities. Substantial day-to-day variability limits our ability to identify an exact pixel area–sensitivity threshold, and because observation days with UA-mean pixel area >60 km² comprise less than 15% of the full dataset, their inclusion does not significantly affect our results. Relationships between inequalities and UA-mean pixel area suggest that key spatial scales for describing NO₂ inequalities are larger than those of atmospheric NO₂ dispersion gradients, which is consistent with recent work by Chambliss et al. and Demetillo et al., likely because NO₂ emission sources are ubiquitous and distributed, and tracts with similar population characteristics are spatially aggregated.

Second, we investigate the sensitivity of daily inequalities to TROPOMI observation UA coverage extent (Table 1). Reduced sampling coverage is largely caused by clouds, but snow accumulation can be important in the winter. In the New York City–Newark UA, snow cover accounted for 29% of missing pixels in winter months, with snow present on 43% of observations days in December–February and 12% of total observation days across May 2018–September 2021. Distributions of daily relative and absolute NO₂ inequalities for each group are shown in Figure S on all days, on days with at least 30% UA coverage, and on days with at least 60% UA coverage. Inclusion of days with sparse coverage (<30%) decreases mean relative NO₂ inequalities by 4–6% percentage points. Individual daily inequalities are more affected by missing data than means, with increasing coefficients of variation at UA coverage levels of <60% in comparison to days with >90% coverage. Effects of incomplete UA coverage are largely explained by insufficient sampling of key race-
This page discusses the impact of ethnicity, poverty, and income groups on environmental exposure, specifically using TROPOMI data from May 2018 to September 2021 across the New York City–Newark UA. The analysis focuses on three main groups: Black and African Americans, Hispanics and Latinos, and Asians, as well as tracts below and above the poverty line.

### Figure 5

Daily TROPOMI NO₂ inequalities over May 2018–September 2021 for Black and African Americans (a), Hispanics and Latinos (b), and Asians (c) compared to non-Hispanic/Latino whites, below-poverty vs above poverty tracts (d), and LIN compared to HIW tracts (e). Top panels depict relative inequalities (%) on all days (light blue), on days with at least 30% UA coverage (gray blue), and on days with at least 60% UA coverage (bright blue). Bottom panels depict absolute inequalities (molecules cm⁻²) on all days (light green), days with at least 30% UA coverage (yellow green), and on days with at least 60% UA coverage (dark green). The mean relative inequalities and 95% confidence interval are included in each panel for each coverage threshold: on all days (light blue), on days with at least 30% UA coverage (gray blue), and on days with at least 60% UA coverage (bright blue).

### Table 2

Mean Daily TROPOMI Inequalities (May 2018–September 2021) on Days with >30% Coverage across the New York City–Newark UA Based on the S5P-PAL NO₂ Product, as Used throughout the Analysis, on Days with >30% Coverage Based on the RPRO and OFFL Operational Products, Separately in New York City and Newark, and within the Large (30 June) and Small (15 August) LISTOS Flight Rasters

| Group                          | Mean Daily Inequalities (%) | New York City–Newark UA (S5P-PAL) | New York City–Newark UA (operational product) | New York City, NY | Newark, NJ | large LISTOS raster flight pattern | small LISTOS raster flight pattern |
|--------------------------------|-----------------------------|-----------------------------------|-----------------------------------------------|-----------------|-----------|------------------------------------|----------------------------------|
| Black and African Americans   | 30 ± 1                      | 26 ± 1                            | 22 ± 1                                        | 33 ± 2          | 22 ± 1    | 10 ± 1                             |                                  |
| Hispanics and Latinos          | 28 ± 1                      | 23 ± 1                            | 19 ± 1                                        | 43 ± 2          | 20 ± 1    | 11 ± 1                             |                                  |
| Asians                         | 28 ± 1                      | 25 ± 1                            | 25 ± 1                                        | 26 ± 2          | 19 ± 1    | 10 ± 1                             |                                  |
| below poverty tracts           | 25 ± 1                      | 22 ± 1                            | 20 ± 1                                        | 24 ± 1          | 22 ± 1    | 14 ± 1                             |                                  |
| LIN tracts                     | 38 ± 1                      | 32 ± 1                            | 30 ± 1                                        | 43 ± 1          | 32 ± 1    | 20 ± 1                             |                                  |

*Errors are 95% confidence intervals based on bootstrapped distributions sampled with replacement 10⁴ times.*

This analysis reveals greater coverage capturing more representative UA demographics and observations on lower-coverage days more likely to sample the population groups in the majority (Figure S5): non-Hispanic/Latino whites (44%) and tracts above the poverty line (73%). As a result, we remove days with <30% UA coverage from our discussion of mean NO₂ inequalities (323 days or 33% of the full dataset) and days with <60% coverage from our analysis of.
daily inequalities (457 days or 47% of the full dataset). Results are skewed toward clear sky conditions, corresponding to
daytime (12–3 pm LT) mean surface NO$_2^*$ mixing ratios of
8.1 ± 4.4 ppb (days with >30% UA coverage) compared to
daytime mean NO$_2^*$ ratios of 11.9 ± 6.6 ppb (days with <30%
coverage), likely biasing daily absolute NO$_2$ inequalities low
(discussion below).

Mean daily population-weighted NO$_2$ TVCDs over May
2018–September 2021 are 30 ± 1%, 28 ± 1%, and 28 ± 1%
higher for Black and African Americans, Hispanics and Latinos,
and Asians, respectively, compared to those for non-Hispanic/
Latino whites (Figure 5 and Table 1). NO$_2$ TVCDs are 25 ± 1% higher in tracts below the poverty line than above and 38 ± 1%
higher in LIN compared to those in HIW census tracts. We report results separately in New York City and Newark,
where mean daily NO$_2$ inequalities are 19–30% and 24–43%,
respectively (Table 2). Means and 95% confidence intervals are derived from bootstrapped daily NO$_2$ inequality distributions resampled 10$^3$ times. We repeat NO$_2$ inequality calculations by first oversampling the same subset of days to
a resolution of 0.01° × 0.01° using a physics-based algorithm prior to census tract averaging and find that oversampled and mean daily results are equal to within associated uncertainties for days with at least 30% UA coverage (Table 1). Finally, our analysis is based on recently reprocessed SSP-PAL TROPOMI TVCDs, which include improvements resolving some of the
low biases occurring over polluted northern midlatitude scenes and in the wintertime. Mean daily inequalities computed with the SSP-PAL TVCDs are 3–6 percentage points higher compared to those of the RPRO and OFL operational products (Table 2), indicating that TROPOMI NO$_2$ inequality estimates using previously available NO$_2$ products are biased low, as suggested by Demetillo et al. in their detailed evaluation of oversampled NO$_2$ TVCDs and census tract-scale inequalities in Houston, Texas.

Although inequalities based on spatially and temporally coincident airborne and TROPOMI TVCDs are in good agreement (Figure 4), mean daily TROPOMI NO$_2$ inequalities are significantly higher than those measured by GCAS and GeoTASO during LISTOS (Table 1). This is true both over the full May 2018–September 2021 period and on LISTOS flight days when all TROPOMI TVCDs, not just those coincident with airborne observations, are considered. Absolute inequalities are higher in the winter than in the summer; however, relative NO$_2$ inequalities exhibit little seasonal variation. Although LISTOS inequalities are within the distribution of daily TROPOMI inequalities, differences in mean disparities are explained by changes in UA observational coverage and corresponding demographic composition. Mean daily TROPOMI inequalities within a typical LISTOS large (30 June 2018) and small (15 August 2018) flight roster are 3–9 and 11–20 percentage points lower than those across the full New York City–Newark UA (Table 2), respectively. However, there are similarities; for example, mean inequalities for Black and African Americans, Hispanics and Latinos, and Asians are comparable to within associated uncertainties, as also observed by GCAS and GeoTASO during LISTOS, and inequality distributions for Hispanics and Latinos exhibit a heavy tail using both daily TROPOMI and aircraft TVCDs.

Finally, TROPOMI measures NO$_2$ atmospheric columns rather than surface mixing ratios. For satellite remote sensing to inform environmental justice decision-making, spatial and temporal patterns in TVCDs must reflect NO$_2$ distributions at the surface. To investigate NO$_2$ column–surface relationships, we calculate Pearson correlation coefficients between daily TROPOMI TVCDs (without averaging to underlying census tracts) and mean daytime (12–3 pm LT) NO$_2^*$ mixing

| Table 3. Correlation Coefficients between Daily Absolute Inequalities and UA-Mean NO$_2^*$ Mixing Ratios (12–3 pm LT), NO$_2$ TVCDs, Surface Wind Speeds (12–3 pm LT), Surface Temperatures (12–3 pm LT), Daily Maximum Temperatures, and MDA8 O$_3$ Mixing Ratios$^*$ |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
|                                | correlations with absolute daily inequalities | correlations with relative daily inequalities |                                |
|                                | surface wind | surface NO$_2^*$ | NO$_2$ TVCDs | MDAA8 O$_3$ | surface temperatures | daily maximum temperature |
|                                | speeds       |                  |             |               |                       |                               |
| Black and African Americans    | −0.31        | 0.56             | 0.61        | 0.41         | 0.19$^1$             | 0.19$^1$                  |
| Hispanics and Latinos          | −0.24        | 0.62             | 0.67        | 0.55         | 0.28                  | 0.33                      |
| below poverty tracts           | −0.34        | 0.59             | 0.68        | 0.51         | 0.30                  | 0.28                      |
| LIN tracts                     | −0.32        | 0.63             | 0.66        | 0.50         | 0.26                  | 0.30                      |

|                                | correlations with absolute daily inequalities | correlations with relative daily inequalities |                                |
|                                | surface wind | surface NO$_2^*$ | NO$_2$ TVCDs | surface temperatures |
| Black and African Americans    | −0.75        | 0.60             | 0.65        |
| Hispanics and Latinos          | −0.65        | 0.70             | 0.64        |
| Asians                         | −0.77        | 0.69             | 0.75        |
| below poverty tracts           | −0.71        | 0.63             | 0.54        |
| LIN tracts                     | −0.78        | 0.64             | 0.60        |

$^*$Relationships between daily NO$_2$ inequalities, surface NO$_2^*$, and NO$_2$ TVCDs are Pearson correlation coefficients (r). All other relationships are Spearman rank correlation coefficients (ρ). Correlations are separately analyzed in the winter (December–February) and summer (June–August) for days with TROPOMI observations with >60% UA coverage. Only statistically significant coefficients are reported, with r and ρ significant to 1% (p < 0.010) unless indicated as (*), which means significant to 5%.
ratios as a function of the distance between observations.\textsuperscript{15,17,72} We find the strongest mean correlations ($r = 0.61 \pm 0.03$; error is the 95% confidence interval) between NO$_x$ and directly overhead TVCDs, defined as TVCDs within 1 km of a monitor based on pixel center points. Mean daily column–surface correlations subsequently weaken with increasing distance, falling to 0.56 ± 0.03 at 1–2 km, 0.49 ± 0.02 at 2–5 km, and 0.43 ± 0.02 at 5–10 km. The distance dependence of mean Pearson correlation coefficients reflects typical NO$_x$ distance decay gradients,\textsuperscript{16–20} indicating that coarser-resolution daily observations resolve finer-scale NO$_x$ gradients, at least to some extent in the average. Column–surface correlations covary with wind speeds and overall NO$_x$ pollution levels in physically meaningfully ways. Daily $r$ values are significantly, although weakly, negatively associated with UA-mean surface wind speeds and positively associated with UA-mean NO$_x$ and NO$_2$ TVCDs. Lastly, we find no relationship between Pearson column–surface correlation coefficients and daily UA-mean pixel area (Table S6).

**Daily Variability in NO$_2$ Inequalities.** Here, we apply the daily TROPOMI NO$_2$ inequality observations, describing statistical relationships with overall NO$_x$ and O$_3$ pollution and climate-relevant atmospheric conditions (Table 3). We discuss the implications of each in turn. We report Pearson correlation coefficients among NO$_x$ inequalities, surface NO$_x$ mixing ratios, and NO$_2$ TVCDs. We compute Spearman rank correlation coefficients ($\rho$) among NO$_x$ inequalities, MDA8 O$_3$ surface wind speeds, and surface daytime and daily maximum temperatures, as these relationships are monotonic but nonlinear. Surface NO$_x$ mixing ratios, wind speeds, and temperatures are UA-wide means over 12–3 pm LT in correspondence with the TROPOMI overpass time. We calculate $r$ and $\rho$ values on days with $>$60% TROPOMI UA coverage, separately in the winter (December–February) and summer (June–August).

First, we find that absolute NO$_x$ inequalities are strongly associated with UA-mean surface NO$_x$ and NO$_2$ TVCDs. However, relative inequalities are mostly uncorrelated in the winter and only weakly or moderately associated with NO$_x$ pollution in the summer. Observed differences between absolute and relative inequalities are evidence that NO$_x$ sources are systematically located in communities of color and low-income neighborhoods, as variability in individual terms affecting the NO$_2$ mass balance will have a larger effect on absolute NO$_2$ concentrations than on relative differences city-wide. Therefore, while incremental NO$_x$ controls will decrease localized NO$_2$ burdens, any emissions above zero will drive continued disparities. Results from daily TROPOMI TVCDs are supported by predictions from FIVE and the NEI. We calculate inequalities in NO$_x$ source densities equivalently to those based on observations (Measurements and Methods), with point source emissions summed within census tracts and total NO$_x$ emissions (FIVE + NEI) divided by tract area. Inequalities in population-weighted NO$_x$ emission source densities are 90 ± 6% for Black and African Americans, 95 ± 5% for Hispanics and Latinos, 71 ± 6% for Asians, 88 ± 5% for below-poverty tract, and 113 ± 7% for LIN tracts.

NO$_x$ is a key reactant in the chemistry of O$_3$ production (PO$_3$); therefore, neighborhood-level NO$_x$ inequalities and urban O$_3$ are potentially coupled. In the New York City–Newark UA, there were 59 exceedances of the MDA8 70 ppb National Ambient Air Quality Standards (NAAQS) over May 2018–September 2021. Briefly, PO$_3$ is a nonlinear function of NO$_x$. At low NO$_x$ levels, NO$_x$ emission reductions decrease PO$_3$ (chemistry is NO$_x$-limited). At high NO$_x$ levels, NO$_x$ reductions increase PO$_3$ (chemistry is NO$_x$-suppressed), with decreases in gas-phase organic compounds being the most effective form of O$_3$ control, at least until NO$_x$ is sufficiently reduced to transition to NO$_x$-limited PO$_3$. Here, we find that absolute NO$_x$ inequalities are moderately, positively associated with summertime UA-mean MDA8 O$_3$ (Table 3), with similar results over the May–September O$_3$ season (Table S7). For comparison, correlation coefficients relating UA-mean surface NO$_x$ and column NO$_x$ TVCDs with MDA8 O$_3$ on >60% UA coverage days are 0.43 and 0.46, respectively. This suggests that there are regulatory O$_3$ co-benefits to reducing NO$_x$ inequalities and to strategies prioritizing NO$_x$ emission reductions in communities of color and low-income communities, consistent with recent work showing PO$_3$ in New York City and Newark trending toward NO$_x$ limitation.\textsuperscript{74} Because O$_3$ is an intermittently long-lived secondary pollutant, it is more evenly distributed and not generally associated with large intraurban exposure disparities.\textsuperscript{74} However, NO$_x$ concentrations are highly spatially heterogeneous, and NO$_x$ reductions in neighborhoods overburdened by NO$_x$ sources could potentially worsen O$_3$ locally. To investigate this, we compare population-weighted census tract-scale MDA8 O$_3$ NAAQS exceedance frequencies on weekdays and weekends based on surface O$_3$ measurements (Table S8). In the New York City–Newark UA, NO$_x$ TVCDs were on average 27% lower on weekends compared to those on weekdays over May 2018–September 2021. Across U.S. cities, weekday–weekend O$_3$ differences are a well-established test of the NO$_x$ dependence of PO$_3$, as substantial NO$_x$ decreases occur without comparatively large changes in other aspects of O$_3$ chemistry.\textsuperscript{3} We find that MDA8 O$_3$ NAAQS exceedances are more frequent on weekdays than weekends for all race, ethnicity, and/or income groups (Table S8), indicating that NO$_x$ reductions will not worsen O$_3$ where NO$_x$ emissions are greatest. This said, we add caution that our results may be influenced by the locations of the O$_3$ monitors.

Finally, atmospheric conditions influence intraurban NO$_x$ distributions in ways that inform how NO$_x$ inequalities may scale with climate change. The Northeast U.S. is expected to experience warmer surface temperatures and more frequent stagnation days in summer and winter months, with slower surface winds from reduced mid-latitude cyclone activity and a northward shift of the summer mid-latitude jet stream.\textsuperscript{76–81} We find that NO$_x$ inequalities exhibit moderate to strong negative associations with surface wind speeds, consistent with the accumulation of NO$_x$ pollution near NO$_x$ sources from reduced atmospheric mixing. This indicates that more frequent atmospheric stagnation events will exacerbate disparities. During summer months, NO$_x$ inequalities are weakly but significantly positively correlated with both daytime average and maximum daily temperatures. As a result, NO$_x$ inequalities and temperature may not scale together; however, people of color and low-income residents in New York City and Newark also bear disproportionate urban heat risks compared to non-Hispanic/Latino white and wealthy residents,\textsuperscript{81–84} suggesting that cumulative unequal climate-driven burdens will be greater without targeted NO$_x$ emission controls.

**Summary, Future Opportunities, and Implications.** We have demonstrated that individual daily TROPOMI observations capture a major portion of census tract-scale NO$_x$ inequalities in the New York City–Newark UA using
high-spatial resolution (250 m × 250 m) GCAS and GeoTASO remote sensing measurements as a standard of comparison. LISTOS airborne observations resolve length scales of dispersion, allowing for accurate representations of tract-averaged NO_{2} TVCDs. We show that spatially and temporally coincident TROPOMI and aircraft measurements are strongly correlated (0.82–0.97) with slopes of 0.82 ± 0.10–1.05 ± 0.07 and 0.76 ± 0.09–0.96 ± 0.06 for relative and absolute inequalities, respectively. Moreover, daily TROPOMI NO_{2} inequalities are generally insensitive to observation resolution for UA-mean pixel areas smaller than 60 km²; therefore, key spatial scales for measuring NO_{2} inequalities are larger than those of atmospheric NO_{2} gradients, as tracts with similar population characteristics are spatially aggregated, even in New York City and Newark where the structure of racial segregation is highly heterogeneous. As a result, fine-scale observations may not always be required to understand variability in intraregion air pollution disparities, especially if biases can be well characterized, opening new opportunities for satellite remote sensing and chemical transport modeling. We limit our conclusions to decision-making on city-wide NO_{2} inequalities, as we have not attempted to resolve near-field impacts of individual polluters in communities with air pollution-related environmental justice concerns, instead focusing on accumulated NO_{2} burdens from ubiquitous and overlapping urban NO_{2} sources. Daily TROPOMI observations cannot replace hyper-localized community-driven monitoring, but spatially comprehensive and temporally resolved satellite measurements offer complimentary information on spatiotemporal trends and in unmonitored locations.

We report mean daily NO_{2} inequalities of 28–30% for Black and African Americans, Hispanics and Latinos, and Asians and inequalities of 25% for residents of below-poverty census tracts. When race-ethnicity and income metrics are combined, we find 38% greater population-weighted NO_{2} TVCDs for people of color living in low-income tracts (LINs). These mean daily NO_{2} inequalities equal those based on TROPOMI NO_{2} TVCDs first oversampled to 0.01° × 0.01° to within associated uncertainties. Biases arise using individual observations with reduced UA coverage due to inadequate sampling of key race-ethnicity and income groups, affecting mean daily NO_{2} inequalities and the precision of individual daily results (Figure S5). The dependence of city-level inequalities on sampling coverage has relevance for other measurement approaches for which it is difficult to collect observations city-wide, for example, mobile monitoring. Reliance on clear sky measurements likely biases absolute NO_{2} inequalities low, and relative inequalities to a smaller extent, as UA-wide mean surface NO_{2} mixing ratios are 40% higher (3.8 ppb higher) on low- (<30%) than on high-coverage (>30%) days and as TROPOMI absolute inequalities are strongly, positively associated with overall NO_{2} pollution, at least in the New York City–Newark UA.

Observations of daily NO_{2} inequalities offer new insights into the causes and countermeasures of neighborhood-level disparities through their statistical relationships with other factors. We present empirical evidence for the systematic placement of NO_{2} sources in communities of color and low-income neighborhoods across the New York City–Newark UA. Specifically, absolute NO_{2} inequalities are strongly correlated with overall NO_{2} pollution, while relative NO_{2} inequalities are not. The issue of source placement has been long identified by community organizations and residents, with TROPOMI providing space-based accountability of whether the promises of recent legislation in both states to consider cumulative burdens during permitting are kept. Municipalities have several tools for addressing existing siting disparities: establishing penalties; eliminating nonconforming uses; using environmental reviews, impact analyses, and comprehensive planning; and tightening existing zoning codes in polluted neighborhoods with marginalized and vulnerable populations. Daily TROPOMI observations enable approaches to prioritize affected communities where and when NO_{2} burdens are highest. We find that frequent stagnation conditions in the coming decades will exacerbate neighborhood-level NO_{2} inequalities, and warming summer surface temperatures will increase cumulative disparities from overlapping NO_{2} and urban heat burdens. Thus informed, municipalities have opportunities for targeted interventions focused on redressing harms and eliminating disparities by preventing the arrival of new sources and decreasing existing NO_{2} emissions in overburdened communities. In addition, because NO_{2} inequalities are positively associated with high MDA8 O_{3} in the New York City–Newark UA, targeted NO_{2} emission reductions in communities of color and low-income neighborhoods have the potential to improve O_{3} city-wide.

### ASSOCIATED CONTENT

#### Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c02828.

Study area maps, including example large and small LISTOS rasters, UA population density, surface monitoring station locations, figures displaying the distribution of TROPOMI pixel areas and variability in population demographics with different TROPOMI coverage levels, tables describing LISTOS flight patterns, detailed LISTOS inequality results, correlations between LISTOS inequalities and various surface conditions, effect of pixel area on daily TROPOMI inequalities, influence of various factors on TROPOMI column–surface correlations, relative weekday–weekend MDA8 O_{3} NAAQS exceedances, equation for population weighting, and relationships between daily TROPOMI inequalities and various factors over O_{3} season (May–September) (PDF)

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Notes
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