Nitrogen oxides (NOx) are among the most widely emitted pollutants in the world, yet their impacts on agriculture remain poorly known. NOx can directly damage crop cells and indirectly affect growth by promoting ozone (O3) and aerosol formation. We use satellite measures of both crop greenness and NOx during 2018–2020 to evaluate crop impacts for five major agricultural regions. We find consistent negative associations between NOx and greenness across regions and seasons. These effects are strongest in conditions where O3 formation is NOx limited but remain significant even in locations where this pathway is muted, suggesting a role for direct NOx damage. Using simple counterfactuals and leveraging published relationships between greenness and growth, we estimate that reducing NOx levels to the current fifth percentile in each region would raise yields by ~25% for winter crops in China, ~15% for summer crops in China, and up to 10% in other regions.

**INTRODUCTION**

Improvements in agricultural productivity are needed in the coming decades to achieve many sustainable development goals, including reduced hunger and increased protection of forest area and biodiversity. Among the many strategies to achieve these gains are efforts to improve air quality (1). Although these efforts are primarily motivated by human health benefits, the potential agricultural effects are substantial. In some cases, levels of pollutants such as ozone are thought to suppress yields by as much as 30 to 40%, yet these estimates include wide uncertainties (2, 3). A better understanding of the agricultural impacts of air pollution would help to better assess both the potential benefits of air quality improvements and how prominent a role pollution reduction should have among efforts to raise agricultural productivity.

Historically, studies of air quality and crop productivity have been limited to small-scale experimental manipulations or observational analyses that rely on sparse ground measures of pollution. While these studies have provided a clear basis for further study, they are often plagued by large uncertainties associated with the difficulty of extrapolating beyond the experimental conditions (in the case of experiments) or the challenge of limited overlap between air monitoring stations and agricultural areas (in the case of empirical studies). These latter studies have also tended to focus on the secondary pollutants (ozone and particulate matter) that are most widely monitored because of human health concerns and have been limited to regions with available ground measures (4).

An alternative to using ambient measures of pollution has been to exploit yield variations in the vicinity of known pollution sources, such as power plants, including inspection of changes before and after the power plants are active (4–6). These approaches circumvent some of the drawbacks of relying on pollution monitoring stations, as they do not rely on direct pollution measures, can integrate the net effect of multiple pollutants, and can more readily assess the potential effect of removing specific pollution sources. However, approaches that rely on gradients near pollution sources can suffer from an inability to distinguish effects of different pollutants, are limited to regions that have reliable inventories of, e.g., power plant activity, and can be confounded if other sources (e.g., transportation) contribute significantly to local pollution levels.

Fortunately, recent progress in satellite observations is leading to rapid advances in global air pollution monitoring. The TROPOspheric Monitoring Instrument (TROPOMI) instrument, which was launched aboard the Sentinel-5 Precursor in late 2017, is especially novel in its ability to monitor tropospheric nitrogen dioxide (NO2) levels at daily frequency, with monthly aggregations of these measures available at spatial resolutions as fine as 0.01° (~1 km at the equator) (7). NO2 is itself a good measure of overall NOx [NOx, nitrogen oxide (NO) plus NO2] (8).

Plant health is affected by NOx via both direct and indirect pathways, some of which are illustrated in Fig. 1. NO and NO2 are themselves phytotoxins that can directly damage plant growth and reduce yields (9). In addition, NOx can operate through at least two indirect pathways. First, it is a key precursor to formation of ozone (O3) in the troposphere, another phytotoxin known to reduce crop yields (10). Especially in seasons and regions with high levels of volatile organic compounds (VOCs), variations in NO2 are tightly associated with variations in O3 levels (11, 12). Second, NOx is a precursor to particulate matter aerosols. In the presence of ammonia (often the case in agricultural regions from application of nitrogenous fertilizers such as urea), NOx can result in increased concentrations of ammonium nitrate aerosols (NH4NO3) (13) and can also oxidize sulfur dioxide (SO2) and drive formation of ammonium sulfate aerosols [(NH4)2SO4] (14, 15). These particles reflect and scatter incoming sunlight, changing the radiation environment experienced by crops and reducing access to photosynthetically active radiation (16, 17). Other pathways not depicted in Fig. 1 include additional interactions among NO2, nitrates, O3, and SO2 (18); the effects of NOx on secondary aerosol formation; and effects of NOx on the deposition of atmospheric nitrogen in agricultural fields.

Despite general understanding of NOx’s potential deleterious effects, few studies have attempted to quantify its impact on crops at scale. Several studies have examined measures of plant health or crop yield along gradients of pollution near urban areas (19, 20) or in fumigation experiments (21–24). In many of these cases, NOx was just one of several pollutants, and only the combined effects of
regimes on NO\textsubscript{2} is that it is measured with more precision than most pollutants yields. Our preferred greenness measure, near-infrared reflectance of which would not be possible using administrative records of crop conditions at a resolution commensurate with the NO\textsubscript{2} measures, is the degree to which the local de-meaned NO\textsubscript{2} variations are correlated with crop yields. Last, increased NOx in the presence of ammonia or SO\textsubscript{2} can lead to aerosol formation. These aerosols reflect and scatter incoming sunlight, reducing the amount of light available for photosynthesis and lowering yields. The net impact of NO\textsubscript{2} (NO\textsubscript{x}) on crop yields, i.e., the sum of direct, ozone, and aerosol pathways, thus depends on the local pollution regime. We leverage different ozone regimes around the world to evaluate the relative importance of ozone pathway.

In the current study, we combine the recent TROPOMI measures of NO\textsubscript{2} for 2018–2020 with satellite measures of crop greenness to elucidate the role of NO\textsubscript{2} in crop productivity. One benefit of focusing on NO\textsubscript{2} is that it is a primary pollutant (i.e., directly emitted from various sources). Another substantial benefit is that NO\textsubscript{2} is a primary pollutant (i.e., with the potential to cause both direct and indirect effects). Large-scale spatial variations in both pollution and crop yields (e.g., northern versus southern China) can provide meaningful information, they also greatly increase the risk of confounding from omitted variables (29). We find that, in all five regions, there is a highly significant negative association between the two (Fig. 4).

Robustness checks indicate that these relationships are unlikely to arise because of artifacts in the NO\textsubscript{2} retrieval algorithms, specifically the reliance on surface albedo, which is itself influenced by vegetation (28). Similarly, results are unlikely to result from the spatial correlation of NO\textsubscript{2} with other aerosols (of which nitrate aerosols are typically a small fraction) (30), given that results are robust to including controls for aerosol optical depth (fig. S2). Results are also robust to removing grid cells with a large fraction of non-cropland, which could potentially affect both NO\textsubscript{2} and greenness measures (fig. S5), using alternative sources of crop masks (fig. S4) and using alternate measures of crop greenness (fig. S4). These tests and the fact that estimated NO\textsubscript{2} effects were consistently negative across all study years (fig. S4) indicate that these estimates are very likely to reflect a true causal relationship between NO\textsubscript{2} and crop growth. However, these estimates alone cannot indicate the likely mechanism of impact.

To further distinguish between plausible pathways of impact, we partitioned each region into two subsets of observations. In the first subset, we identified points with a ratio of HCHO:NO\textsubscript{2} above 2,
which represents situations where $O_3$ formation is generally $NO_x$ limited (11) and, therefore, where an increase in $NO_x$ would be expected to lead to an increase in $O_3$. The second subset included all points with a ratio below 2, where $O_3$ is expected to be less responsive to variations in $NO_x$. For our study regions and seasons, only the winter season in China and Western Europe had a considerable fraction of points in both regimes, whereas in other cases, the cropped areas typically experience only the $NO_x$ limited regime, with a ratio above 2 (Fig. 5, A and B).

When examining the $NO_2$ sensitivity separately by $O_3$ regime, we found that (i) $NO_2$ sensitivity was considerably higher for locations where $O_3$ formation was likely to be $NO_x$ limited and (ii) $NO_2$ sensitivity was still significantly negative in regimes where $O_3$ formation was not $NO_x$ limited (Fig. 5, C and D). In both China and Europe, the sensitivity for $NO_x$-limited conditions was roughly double that for nonlimited conditions. These results suggest that $O_3$ is an important pathway for the impact of $NO_2$ but that other mechanisms including direct damage from $NO_2$ likely play an important role in suppressing crop growth, contributing perhaps as much as half of the total damage in some regions.

Table 1 presents an estimate of the total change in crop greenness ($NIRv$) that would be expected if all locations within a region...
were to achieve NO₂ levels equal to the fifth percentile of observed levels over the study period. This represents a simplistic scenario of aggressive actions to curb NO₂ and is not meant to substitute for a more detailed analysis of specific control measures but rather to bracket the total possible gain from reducing NO₂. A more extreme scenario, whereby all locations are reduced to zero, was not considered since this would extrapolate beyond the support of the data used to estimate the regressions.

Table 1 and Fig. 6 also estimate the total yield gain that would be associated with this increase in NIRv. To translate NIRv to yield gain, we rely on the fact that crop photosynthetic activity has been shown to be linearly related to NIRv (26) (see Materials and Methods). We estimate that reduction of NO₂ could contribute significantly toward yield gains in many cases, with the largest gains estimated for China: 28% in winter and 16% in summer. Western Europe would also experience substantial gains of nearly 10% for both winter and summer crops, with gains in India of roughly 8% in summer and 6% in winter.

**DISCUSSION**

The effects of NO₂ estimated in this study represent the net impact of myriad complex processes that govern both atmospheric chemistry (e.g., the conversion of NO₂ to other pollutants) and plant biology (e.g., the ability of plants to recover from exposure to high levels of...
5 of 9

Lobell, Sci. Adv. 8, eabm9909 (2022) 1 June 2022

SCIENCE ADVANCES | RESEARCH ARTICLE

Fig. 6. Reductions in NO\textsubscript{2} would lead to substantial yield gains in many regions. Bars show estimate of mean yield increase in each region and season associated with a hypothetical reduction of NO\textsubscript{2} levels to the fifth percentile observed for the respective region and season. Error bars indicate the 95% confidence intervals, which reflect the uncertainties in crop responses shown in Fig. 4.

Table 1. Summary of coefficients for NIR\textsubscript{v} regression, average and fifth percentile of NO\textsubscript{2} levels, and gains for reductions to fifth percentile for each region and season. Values in parentheses indicate 1 SE. Units of \(\beta\text{NO}_2\) are NIR\textsubscript{v} change per micromole/meter\(^2\) NO\textsubscript{2}, and units of NO\textsubscript{2} are micromole/meter\(^2\). Values shown in table assume NIR\textsubscript{v0} equal to 0.07.

| Region         | \(\beta\text{NO}_2\)       | NO\textsubscript{2} average | NO\textsubscript{2} fifth percentile | NO\textsubscript{2} difference | NIR\textsubscript{v} gain | Yield gain (%) |
|----------------|---------------------------|------------------------------|-------------------------------------|-------------------------------|---------------------------|----------------|
| Winter season  |                           |                              |                                     |                               |                           |                |
| China          | −0.0011 (0.0001)          | 57                           | 18                                  | 39                            | 0.042                     | 27.9 (2.2)     |
| India          | −0.0007 (0.0001)          | 33                           | 18                                  | 15                            | 0.011                     | 6.4 (1.2)      |
| South America  | −0.0020 (0.0003)          | 13                           | 8                                   | 5                             | 0.010                     | 7.4 (1.1)      |
| United States  | 0.0001 (0.0003)           | 18                           | 13                                  | 6                             | −0.001                    | −0.6 (1.8)     |
| W Europe       | −0.0014 (0.0001)          | 33                           | 19                                  | 13                            | 0.019                     | 8.7 (0.8)      |
| Summer season  |                           |                              |                                     |                               |                           |                |
| China          | −0.0014 (0.0001)          | 35                           | 15                                  | 20                            | 0.029                     | 17.1 (1)       |
| India          | −0.0008 (0.0002)          | 26                           | 15                                  | 11                            | 0.008                     | 5.3 (1.1)      |
| South America  | −0.0014 (0.0002)          | 11                           | 7                                   | 4                             | 0.005                     | 2.1 (0.4)      |
| United States  | −0.0033 (0.0002)          | 22                           | 16                                  | 7                             | 0.022                     | 8.7 (0.5)      |
| W Europe       | −0.0020 (0.0003)          | 31                           | 20                                  | 10                            | 0.020                     | 10.6 (1.4)     |

NO\textsubscript{2} or O\textsubscript{3}. This integration over many processes is both a strength and weakness of our study. By directly relating NO\textsubscript{2} to crop productivity, we capture the net effects of many pathways of impact and recovery in actual farmers’ fields, which encompass a diversity of conditions that would be impossible to recreate in controlled experiments. At the same time, the inability to fully disentangle mechanisms can limit the understanding of how effective different potential interventions would be at lowering impacts and can complicate comparisons with prior studies.

For example, comparison with the many prior studies that have considered the effects of O\textsubscript{3} on crop growth are difficult because (i) we are capturing effects of multiple pathways by which NO\textsubscript{x} can affect yields, with O\textsubscript{3} being just one of these pathways, (ii) we likely fail to fully capture O\textsubscript{3} effects because the longer residence time of O\textsubscript{3} means that O\textsubscript{3} concentrations are imperfectly correlated with NO\textsubscript{2}, and (iii) other studies may inadvertently capture some (but not all) NO\textsubscript{x} effects in their estimates of O\textsubscript{3} damages since NO\textsubscript{x} is correlated with O\textsubscript{3} and empirical studies that do not measure NO\textsubscript{x} will misattribute some direct NO\textsubscript{x} effects to O\textsubscript{3}.

Despite these caveats, comparison of our results with prior O\textsubscript{3} studies reveals several similarities. First, we find that the biggest estimated impacts among all locations and seasons are for winter crops in China. This result is similar to Mills et al. (31), who identified China as having the largest estimated wheat yield loss out of all wheat-producing countries on the basis of an analysis of exposure to O\textsubscript{3} above 40 ppb.

Second, similar to studies with O\textsubscript{3} (1, 2), our results indicate that reducing pollution would result in substantial yield gains. Here, we considered reducing NO\textsubscript{2} levels to the fifth percentile observed in the region. This scenario may be more conservative than studies that consider theoretically reducing O\textsubscript{3} exposure to zero, although, since O\textsubscript{3} exposure is often measured above some threshold (e.g., 60 ppb), reducing NO\textsubscript{2} by 50% could lead to far greater than 50% reduction in these O\textsubscript{3} metrics. In addition, reducing NO\textsubscript{2} levels to zero is unrealistic, given that lightning contributes a small but nontrivial fraction of global tropospheric NO\textsubscript{x} (32).
these to observed O₃ levels result in fairly wide ranges, given the uncertainty in both O₃ exposures and response functions. For example, Mills et al. (31) estimated between 12 and 25% yield loss for wheat in China depending on the ozone metric used. A recent analysis focused on China estimated potential gains from eliminating O₃ of 21 to 39% for winter wheat, 3.9 to 14% for rice, and 2.2 to 5.5% for maize (34). Thus, our estimate of ~28% gains possible from reduced air pollution is consistent with prior work focused on O₃. In addition, similar to other studies, we find that gains for summer crops would be roughly half as large as for winter, given that NO₂ levels are generally lower in summer.

In India, we estimate gains from NO₂ reductions that are ~6 to 8% for both winter and summer seasons (Fig. 6). A recent review of O₃ studies for India wheat estimates 21% yield gains for elimination of O₃ (35), roughly double our estimate for NO₂. One source of this disparity is likely the fact that the fifth percentile of NO₂ in India is roughly half the mean value, so our reduction scenario would likely leave a considerable amount of O₃ exposure.

In general, our estimated sensitivities to NO₂ are higher for summer than winter seasons (Fig. 4). Although there are many differences between the two seasons that could plausibly explain this pattern, it is likely that the indirect effects via O₃ are stronger in the summer, both because overall O₃ concentrations are typically higher in summer and the O₃ regime is more NO₂ limited in the summer (Fig. 5). Similarly, the indirect pathway via NH₄NO₃- driven formation of sulfate aerosols is plausibly higher when more NH₃ is present, although this relationship is complicated by meteorological factors and the presence of other aerosol precursors in the environment (e.g., SO₂) and likely varies by region. We thus do not attempt to isolate the role of the aerosol pathway, which would require assumptions about the proportion of NH₄NO₃ to overall aerosols and the direct effect of each aerosol type on the greenness measures. However, the fact that NH₃ levels are generally higher in summer (fig. S5) is consistent with enhanced aerosol formation in general. Temperature and radiation regimes also likely play some role, although previous work suggested that damage from NO₂ was smaller, not larger, under high radiation regimes (21).

Overall, we find a remarkably consistent negative association between NO₂ and crop growth in major cropping regions. The persistence of these negative effects across many conditions, including when NO₂ is not limiting O₃ formation, indicates a significant role for direct phytotoxicity of NO₂. At the same time, effects appear most negative in seasons and locations where NO₂ likely drives O₃ formation, indicating that indirect pathways are also important. These results indicate that reduction of NO₂ emissions could have important benefits for crop production, sometimes exceeding 30% of current yields. The magnitude of these effects have the potential both to alter overall yield growth rates (which are typically ~1% per year) and substantially change cost-benefit analysis for pollution mitigation measures (36, 37).

Maps of the spatial pattern of impacts (fig. S6) indicate that yield gradients from ambient NO₂ can be substantial within a region, with impacts differing by up to 50%. At first glance, the strong negative yield impacts in China and India may appear at odds with recent reports of substantial greening of vegetation in these countries, with much of that greening associated with croplands (38). However, trends in greenness should respond to trends in NO₂ rather than average levels, and the trends in greenness in China are highest in the same areas (around the North China plain) that have experienced significant declines in NO₂ since 2005 (39). Similarly, greenness trends in India were strongest in the northwest, which has experienced much smaller increases in NO₂ than the rest of the country (39). Thus, while detailed trend analysis is not possible with the short TROPOMI record, the estimated importance of NO₂ reported here is consistent with prior independent analyses of global greenness trends and NO₂ trends.

We anticipate several fruitful directions for future work. Incorporation of other spaceborne measures of crop activity, including measures of photosynthetic activity from solar-induced fluorescence (SIF) (40, 41), could help to probe the mechanisms of NO₂ effects and the differential sensitivity of crops throughout the growing season. More detailed examination of other pollutants, such as SO₂ and NH₃, and meteorological variables could help to understand variation in NO₂ sensitivity across different regions, years, and seasons. Notwithstanding these remaining research gaps, the consistent negative impact of NO₂ crops across diverse conditions reported here is an important advancement in our understanding of the widespread role that air pollution plays in crop production.

MATERIALS AND METHODS

Study regions
To link NO₂ measures to crop performance, we first define five regions of interest corresponding to major agricultural areas: the United States, China, India, Western Europe, and South America (Fig. 2). In each region, we separately analyze winter and summer crop behaviors.

MODIS greenness
To measure crop performance, we rely on two VIs calculated based on MODIS (Moderate Resolution Imaging Spectroradiometer) Terra MOD09A1 version 6 product (https://lpdaac.usgs.gov/products/mod09a1v006/), which represents 8-day composites of surface spectral reflectance at a 500-m resolution. The first is the commonnormalized difference VI (NDVI) (42), which is a conventional measure of plant greenness but often suffers from saturation for denser canopies. As a second measure, we use the NIRv, which is the product of NDVI and NIR reflectance (43). The NIRv has shown strong linear correlations with crop productivity at seasonal scales (26, 27), as well as final yields (28), and is therefore used as our primary measure of crop growth. All greenness measures were resampled to 1 km to match the TROPOMI resolution. Using VI time series for each region and crop, we identify the 2 months corresponding to the peak of the season for that crop (table S2). We opt for greenness measures rather than SIF measures that arguably more directly capture spatial and temporal variations in vegetation growth (44–46). This decision was based primarily on the availability of gridded data products and the relatively coarse spatial resolution of current SIF products compared to MODIS. We leave exploration of SIF to future work, which could particularly be useful for examining effects of subseasonal variations in pollution exposure.

TROPOMI NO₂ and HCHO
We use NO₂ measures from the TROPOMI aboard the Copernicus Sentinel-5 Precursor satellite. Specifically, we use the OFFL L3 (offline level 3)–processed data available in Google’s Earth Engine platform (47), which provides daily estimates at 0.01° × 0.01° (~1 km) resolution since late June of 2018. Following existing recommendations (8), only points
with a quality assurance (QA) value above 75% were used for analysis. Although the TROPOMI instrument is sensitive to the total column NO2, the baseline processing method uses model simulations to partition NO2 into stratospheric and tropospheric column densities. We use the TVCD band as a proxy for variation in surface NO2 concentrations.

The algorithm for separation of stratospheric and tropospheric NO2 subtracts stratospheric-modeled NO2 from the total observed column. This separation is feasible, both because there is not much exchange of NO2 from the troposphere to the stratosphere (except for volcanoes) (48) and the variations in stratospheric NO2 are driven by solar insolation at diurnal, annual, and multiannual scales (49), whereas lower tropospheric levels are driven by anthropogenic emissions. Although stratospheric concentrations can be of the same order as near-surface levels, their distinctive patterns and profiles facilitate the partitioning at the tropopause. Moreover, variations within the troposphere are mainly driven by surface variations, because surface concentrations are typically two orders of magnitude larger than in the upper troposphere (50, 51). For these reasons, the TVCD derived from the TROPOMI algorithm has shown strong agreement with surface station measurements, for instance, with TROPOMI capturing two-thirds of the variation in 2019 annual averages across sites in the United States (30). Regridding of TROPOMI from its native resolution to a 1-km resolution has also been shown to improve agreement with surface measurements (7), motivating our choice of using the 0.01° × 0.01° data in the current study.

For analysis of different O3 regimes, we also use TROPOMI measurements of HCHO column densities available in Earth Engine. These data are available starting in December 2018 and have the same spatial and temporal resolution as the NO2 data. We calculate the ratio of HCHO to NO2 as an indicator of the O3 regime, following Duncan et al. (11). Specifically, we first take bimonthly (2-month) averages of NO2 and HCHO and then calculate the ratio of HCHO:NO2 using the bimonthly averages. Negative daily values are included in the calculation of the averages, but the small number (129) of bimonthly averages that are negative are removed from further analysis.

**Weather**

To control for weather variation, which can influence both NO2 and greenness, we use TerraClimate monthly data (52) to retrieve early and late season precipitation and vapor pressure deficits.

**Crop area**

To ensure that the MODIS and TROPOMI measures used in this study correspond to agricultural locations, we require a globally complete map of areas for specific crops. For this, we use the Spatial Production Allocation Model 2005 (53), which has 10 km × 10 km spatial resolution, and create crop-specific masks, considering only cells with at least 2% of the area sown to the crop. For winter crop, we use the wheat mask, whereas for summer crops, we use the maize mask as our primary filter. Maize is a common summer crop in all regions, although it is typically sown in a landscape that includes many other crops, such as soybean, rice, or canola. Thus, maize is used as a proxy for the location and timing of summer crops. Because rice is also prevalent in India and China in many locations without maize, we repeated the analysis for these two regions using rice for comparison with the results for maize. In addition, we also vary the threshold on crop area from 2% to much higher values because of concerns that variation in land cover within grid cells could drive some of our results but find that this is not the case (fig. S3).

**Sampling points**

Using crop-specific crop masks, we sample a large number of cells within each region, with a density of sampling meant to ensure similar densities across the regions (table S2) and extract bimonthly NO2, VIs, and weather values for these cells for July 2018 to April 2020. We then remove cells for which the crop is likely not a major contributor to pixel greenness, retaining only cells for which the peak of the monthly NDVI values occurs in one of the 2-month window defined using MODIS time series (table S2).

**Other dataset used for robustness checks**

Some additional datasets were not used in the main specifications but for performing robustness checks or additional analysis. To examine possible influence of albedo on the NO2 retrieval algorithm, we used the OMI (Ozone Monitoring Instrument)/Aura Surface Reflectance Climatology L3 product, OMILER (OMI Lambert equivalent reflectivity) at 440 nm at a spatial resolution of 0.5° by 0.5° (downloaded at https://disc.gsfc.nasa.gov/datasets/OMILER_003/summary). To examine the potential pathway related to NH4NO3 aerosols or sulfate aerosol formation driven by NO2, we used the standard monthly L3 product (total column) for NH3 from IASI (infrared atmospheric sounding interferometer)/Metop-A at 1° × 1° (downloaded at https://iasi.aeris-data.fr/NH3/). To examine the potential for confounding from overall aerosol levels, we used MODIS Terra and Aqua combined Mult-angle Implementation of Atmospheric Correction Land Aerosol Optical Depth (MCD19A2 V6) based on gridded level 2 product produced daily at a 1-km resolution (https://lpdaac.usgs.gov/products/mcd19a2v006/).

**Regression model**

To estimate the effect of NO2 on greenness, we statistically relate colocated NO2 levels and VIs and estimate best-fit parameters for the following model separately for each region and season

\[
\text{VI}_{it} = \beta \text{NO2}_{2t} + \beta \text{W}_{it} + a_{it} + c_i + e_{it}
\]

Here \(\text{VI}_{it}\) refers to the observed peak VI for location \(i\) in year \(t\), \(\text{NO2}_{2t}\) is the observed average value of TVCD of NO2 during the peak months of the growing season, \(\text{W}_{it}\) is a vector of weather controls for the growing season, \(a_{it}\) represents a local intercept (fixed effect) for the area surrounding location \(i\) (e.g., for each 0.5° latitude × 0.5° longitude cell), \(c_i\) is a year fixed effect, and \(e_{it}\) represents the residual noise. The fixed effects for both the local area and the year are intended to control for the unobserved factors that might affect VI and be correlated with NO2, so that Eq. 1 relies on local spatial gradients (i.e., de-meaned values) for identification of \(\beta \text{NO2}\). Since weather is of particular concern, both because rainfall could stimulate crop growth and clean pollution from the air and because temperature could affect crop growth and ozone formation, we also include specific controls for weather, namely the total precipitation and average vapor pressure deficit during the same months as NO2. Removal of the weather controls has negligible effects on the results. SEs for coefficients were calculated using clustering at the 0.5° grid cell level.

Other potential sources of concern are that aerosol is correlated with NO2 and yet artificially lowers the estimated greenness or gradients in land use within grid cells lead to changes in both NO2 and greenness without a causal relationship between the two. We therefore test the sensitivity of results to inclusion of aerosol measures and to restricting our sample to grid cells with high percentages of cropland, finding the results robust to either change (figs. S2 and S3).
We pool data across all years to calculate a single regression for each region and season, although we also perform regressions by year to confirm that results are consistent across time (fig. S4). To assess the role of direct versus indirect pathways, we also estimate Eq. 1 for subsets of observations in each region based on the NO₃ regime, where the NO₂ regime is defined as either NO₂ limited if the ratio HCHO:NO₂ is above 2 or non–NOₓ limited if the ratio is below 2 (see Fig. 4) (11).

**Estimate of yield increases from NO₂ reductions**

To estimate the increase in canopy greenness for a counterfactual scenario of low NO₂, we calculate for each region and season

\[
\text{NO}_2_{\text{avg}} = \text{NO}_2_{\text{avg}} - \text{NO}_2_{\text{5th}}
\]

Where NO₂(avg) is the average level and NO₂(5th) is the fifth percentile of observed values over the study period over all locations (i.e., grid cells) and years for that region and season. We use the fifth percentile as a simple scenario of aggressive actions to curb NO₂, which we consider as an upper bound on the near-term potential to reduce NO₂. A more extreme scenario, whereby all locations are reduced to zero, was not considered, since this would extrapolate beyond the support of the data used to estimate the regressions.

The estimated best-fit coefficient \( \hat{\beta}_{\text{NO}_2} \) in Eq. 1 represents the expected change in canopy greenness (i.e., NIRv or NDVI) for a unit change in NO₂ TVCD. To translate these results into estimates of yield change per unit of NO₂, we consider crop yield (Y) to linearly increase with NIRv

\[
Y = \beta_{\text{NIRV}*}(\text{NIRV} - \text{NIRV}_0)
\]

where NIRV₀ is the NIRv value for which the crop growth is zero. This functional form is supported by several studies showing a clear linear relationship between NIRV and crop gross primary photosynthesis (GPP) as well as studies that show crop GPP to be linearly associated with yield (40, 54). We set NIRV₀ equal to 0.07 based on Badgley et al. (26).

The yield in current conditions can then be expressed as

\[
Y_{\text{cur}} = \beta_{\text{NIRV}^*}(\text{NIRV}_{\text{cur}} - \text{NIRV}_0)
\]

Where NIRV_cur is the current average of NIRV. The yield in a counterfactual low NO₂ scenario can similarly be expressed as

\[
Y_{\text{low} \text{NO}_2} = \beta_{\text{NIRV}^*}(\text{NIRV}_{\text{cur}} + \hat{\beta}_{\text{NO}_2} \text{NO}_2_{\text{dif}} - \text{NIRV}_0)
\]

The percent change in yield for the counterfactual low NO₂ scenario is then

\[
\%\text{yield change} = \frac{Y_{\text{low} \text{NO}_2}/Y_{\text{cur}} - 1}{(\text{NIRV}_{\text{cur}} + \hat{\beta}_{\text{NO}_2} \text{NO}_2_{\text{dif}} - \text{NIRV}_0)}/W/(\text{NIRV}_{\text{cur}} - \text{NIRV}_0) - 1
\]

Substituting NIRV₀ equal to 0.06 or 0.08 into Eq. 6 resulted in small changes in the estimated yield impacts, typically less than 2%.

**SUPPLEMENTARY MATERIALS**

Supplementary material for this article is available at https://science.org/doi/10.1126/sciadv.abm9909
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