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Current Benefits of Wildfire Smoke for Yields in the US Midwest May Dissipate by 2050

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Abstract

Wildfires throughout western North America produce smoke plumes that can stretch across the agricultural regions of the American Midwest. Climate change is likely to increase the number and size of these fires and subsequent smoke plumes. These smoke plumes change direct, diffuse, and total sunlight during the crop growing season and consequently influence yields of both corn and soybeans. The analysis in this paper uses a twelve-year panel of county-level yields from all counties east of the 100th meridian combined with measures of exposure to smoke plumes of low and high density during the growing season. It shows that low-density plumes enhance yields, likely by increasing in the fraction of diffuse light, while high-density plumes decrease yields. Because there are more low-density plumes today, the net effect is a slight increase in yields on average. As climate change makes wildfires larger and more frequent, the overall impact of smoke on yields is expected to be substantially more negative.

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Current Benefits of Wildfire Smoke for Yields in the US Midwest May Dissipate by 2050

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1 Introduction

Smoke from wildfires is increasingly common across North America. To date, research on the impacts of wildfire smoke has focused largely on how smoke increases particulate air pollution and causes negative consequences for human health.[1,2,3] But increases in particulate pollution have impacts that extend beyond health. Air pollution from both anthropogenic and non-anthropogenic sources is known to affect crop yields, due to the ability of particulates to scatter sunlight.[4,5,6,7] These effects can be sizeable, with black carbon particulates reducing yields of rice and wheat in India by up to 35%.[4] This suggests that wildfire smoke may exert a meaningful influence over crop yields across the American Corn Belt; however, this relationship has not yet been studied empirically at a landscape scale.

As other sources of particulate pollution have declined, due at least in part to regulation, wildfires have become a major source of summertime particulate pollution in the Midwestern United States. As much as 25% of the particulate pollution in the upper Midwest in recent years can be attributed to wildfire smoke.[1] As climate change leads to earlier springs and drier summers throughout western North America, fires are expected to be larger and fire season longer.[8,9,10] Current estimates suggest the area burned in western North America by 2050 will increase by between 27%–1000% relative to today.[11,12,13,14,15] An increase in burned area will likely lead to increases in the number of smoke plumes that North American farmland is exposed to, with the number of days under a smoke plume potentially increasing faster than the total area burned.[1,14] As the Midwest contains some of the world's most productive corn and soybean farmland, the impact of wildfire smoke on agricultural yields is likely to be an important component of the impact of climate change on global food production and security.

The anticipated sign of the impact of smoke plumes on yields is theoretically ambiguous. The main impact, operating via smoke plumes' effect on the amount of sunlight available for photosynthesis, depends on the extent to which smoke plumes block sunlight versus refract that light. In general, decreasing the total radiation reduces yields, while increasing the fraction of radiation that is diffuse can raise yields.[7,16,17,18,19] A secondary effect arises from ground-level aerosols and particulate pollution, particularly ozone, interfering with photosynthetic pathways within the plants.[20,21] The net impacts of smoke plumes depend on the particular plants and their photosynthetic pathways as well as the baseline level of direct versus diffuse radiation.[22]

Existing work on clouds and aerosols support this theory. Clouds, which are relatively effective at blocking radiation, tend to result in net declines in primary production because the reduction in direct light outweighs the benefits of increased diffusion.[16] However, this effect is sensitive to baseline levels of cloudiness; areas receiving frequent direct sunlight can see improvements in yields if the optical depth of clouds is increased.[22] The impacts of aerosols are more mixed. Several studies examining the impact of the release of stratospheric aerosols from volcanic eruptions have found improvements in photosynthesis and carbon sequestration in natural ecosystems.[17,19] Work specifically examining the impact of these eruptions on crop yields, however, suggests that both C3 (e.g. soybean) and C4 (e.g. maize) crops suffered yield declines as the reduction in total sunlight dominated the increase in diffuse light.[7]

While the role of wildfire smoke in changing crop yields has received less attention than clouds or aerosols broadly, available evidence suggests that the effect is similar to other sources of aerosols. The 2018 wildfire season, a particularly intense season, led to large increases in the fraction of light that was diffuse in California's Central Valley, a location that typically has few clouds and receives mostly direct sunlight.[23] This led to increases in daily integrated gross ecosystem productivity of between 1.2 and 4.2%. These effects were concentrated in alfalfa and corn and were substantially larger than reductions in productivity due to associated increases in surface level ozone.[23] These estimates come from a single research plot and one especially intense fire season in an area with relatively high levels of direct radiation. It remains unquantified how wildfire plumes impact yields at a landscape level, in areas with higher average cloud cover, and across many years.

This study examines how North American smoke plumes have affected corn and soybean yields in the Midwestern and eastern United States over the period 2008–2020. This region experiences frequent exposure to smoke plumes over our sample period (Figure 1). We obtain data on smoke plumes from the National Oceanographic and Atmospheric Agency's (NOAA) Hazard Mapping System (HMS) and data on the location and yield of corn and soybean crops from the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS). Smoke plumes are divided into "low density" and "high density" categories, because we hypothesize that different smoke densities may have different signed impacts.

To identify the impact of smoke plumes on crop yields, we leverage the quasi-random variation in exposure to smoke plumes within a county from year to year. We estimate a standard two-way fixed effects model that examines how quasi-random exposure to smoke plumes in a given county and year impacts yields in that year. To isolate the impact of smoke plumes operating through the amount and type of sunlight available for photosynthesis, we control for a range of weather conditions that might influence yield including temperature, precipitation, and cloud cover.

Lastly, we estimate the impact of smoke plumes on crop yields in 2050, taking into account the current state of knowledge about future burned area and smoke exposure. Because there is large uncertainty in the future quantity and density of smoke plumes, we analyze how crop yields will be impacted under a wide range of changes in smoke exposure.

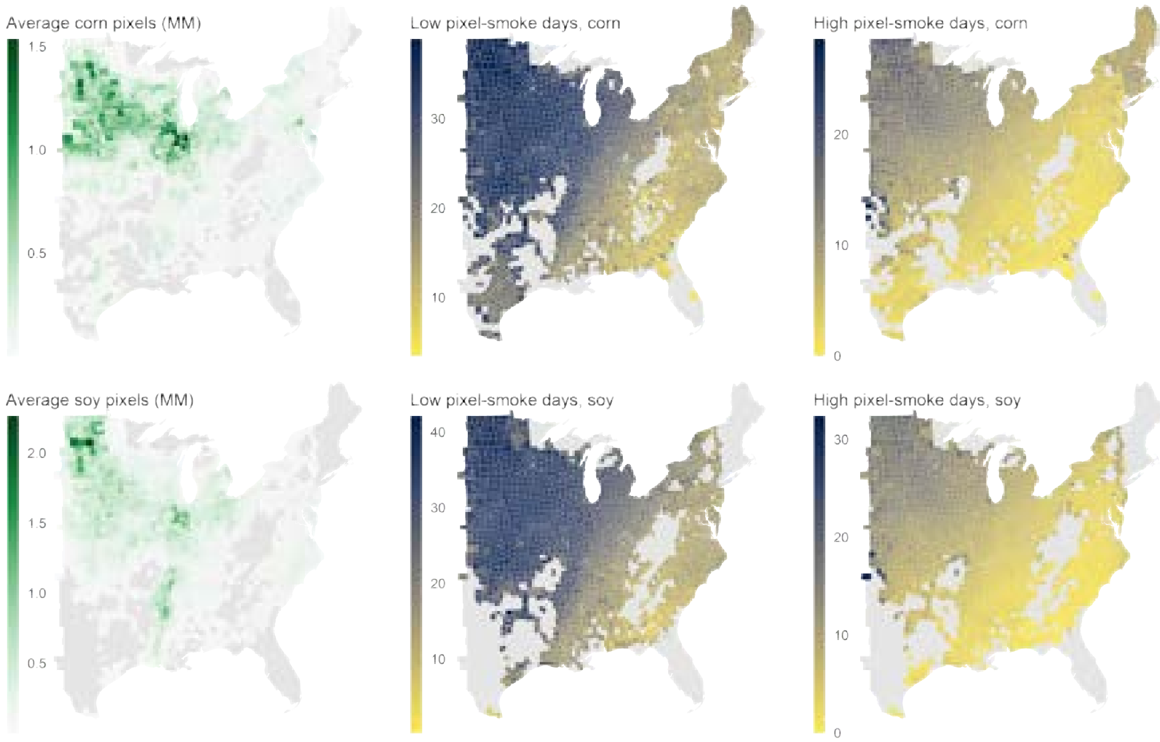

Figure 1: Average annual smoke days by county and smoke density. The first row shows data for corn and the second row shows data for soybeans. From left to right, we show the average total pixels planted in each crop by county from 2008–2020, the average number of pixel-days under a low-density smoke plume, and the average number of pixel-days under a high-density smoke plume.

2 Results

2.1 Impacts of current smoke exposure

We find that low-density smoke plumes increase yields and high-density smoke plumes decrease yields. Low-density plumes appear to have a small positive impact on soybean yields and a noisily-estimated small positive impact on corn yields (Figure 2 panel **A**). A growing season with one additional day under a low-density smoke plume, relative to a clear sky day, increases soy yields by 0.1%. High-density plumes have the opposite effect on both crops. Days under a high-density plume decrease yields by between 0.1% and 0.2% relative to clear sky days. The pattern of these results is broadly consistent with existing work that finds larger positive effects of diffuse light for C3 crops (e.g. soybeans) and negative effects on yield for both C3 and C4 crops (e.g. corn) when the reduction effect dominates the refraction effect.[7,16] The different signs of the effects also highlight the importance of distinguishing between plumes of different densities. Our results are robust to alternative clustering of standard errors that allow for spatial auto-correlation.[24,25]

What do our marginal estimates imply about total yield losses from exposure to wildfire smoke plumes in the American Midwest? In panels **B** and **C** of Figure 2, we show the total impact of exposure to smoke on yields in an average year for every county in our sample. In an average year, crop-growing counties in our sample are exposed to approximately 24 days under a low-density smoke plume and 7 days under a high-density plume. The larger number of days under low-density smoke plumes, combined with the positive impact that these days have on yields, results in a positive impact on yields for both soy and corn across nearly all of the counties in our sample.

Because of the larger positive effect of diffuse light on soy yields, the overall effect is more positive for soy. On average, soy yields increase 1.7% in a typical year as a result of smoke exposure, although in counties with the smallest impacts the effect is only slightly greater than zero. Corn yields increase by an average of 0.5%, but because of the smaller positive impact of diffuse light and subsequently smaller positive impact of days with low-density smoke plumes, there are some counties that experience yield losses in corn in an average year. In the most negatively impacted counties, corn yields appear to decline by approximately 0.5% in a typical year. The absolute impact of these yield changes on production, measured in bushels, is highly concentrated in counties in Illinois, Iowa, and Nebraska as these are the states with the largest levels of absolute production (Figure SI2).

2.1.1 Mechanisms

To test the hypothesis that wildfire smoke plumes affect crop yields by changing the amount and type of sunlight available for photosynthesis rather than changing meteorological determinants of yield, we examine the extent to which smoke plumes impact weather inputs directly and how smoke plumes change aerosol optical depth (AOD).

We use satellite-derived measures of the AOD to verify that plumes of both types increase AOD relative to no plumes and that the effect of a high-density plume on daily AOD is roughly $3\times$ greater than that of a low-density plume (Table SI2). Turning to impacts on meteorological variables, we do not find evidence that smoke plumes of either density meaningfully impact the number of growing degree days or extreme degree days during a growing season (Figure SI1).

We do find some evidence that there is less precipitation on days with plumes of either density. We also see that cloud cover is lower on days with smoke plumes, which suggests that the impact on daily precipitation may be an artifact of the construction of the smoke plume data—it is more difficult for analysts to draw smoke plumes on days with dense cloud cover, which are the same days when precipitation is most likely. At the same time, there is evidence from the Amazon that smoke plumes can directly impact cloud formation, with the specific mechanics depending on local weather conditions.[26] It is not clear whether the mechanics observed in the Amazon would be present in the American Midwest. If smoke plumes do influence cloud formation and precipitation, then our estimated effects, which include controls for precipitation and cloud cover, will be net of any secondary impact that smoke plumes have on cloud formation. To the extent that smoke plumes reduce precipitation, as suggested by our weather tests, our estimates will underestimate the total negative impact that smoke has on yields by only estimating the impact operating via changes in sunlight. However, robustness checks omitting both precipitation and cloud cover controls (column 2 of Table SI5) result in point estimates that are very similar to those in our primary specification. This suggests that, if smoke plumes do indirectly influence yields via a precipitation pathway, the effect is small relative to the primary impact operating via changes in sunlight. As a further check of the extent to which meteorological conditions are driving our results, we drop the year 2012 from our analysis because it saw an unusually severe drought across much of the country. In Table SI8, we show that this exclusion does not meaningfully change our conclusions, and actually suggests a slightly more negative impact of smoke.

The beneficial effects of low-density smoke plumes may be due to a relatively high number of days with less than the optimal level of diffraction from cloud coverage (Figure SI6).[22] As a result, low-density smoke plumes that occur on what would be otherwise clear days may be generating a similarly beneficial diffraction effect as clouds do on a day with optimal cloud coverage.

To test this hypothesis, we divide counties into terciles based on their average level of cloud cover during the growing season over our full sample. We then run our primary specification within each tercile of cloud cover to examine how the impact of smoke changes. We find some evidence that the negative impact of smoke is concentrated in the third of counties with the highest average levels of cloud cover, while those with lower average cloud cover experience more positive impacts of smoke plumes (Table SI9). Understanding how smoke plumes interact with clouds is a subject for future work.

We also examine how our results change when we control for ground-level pollutants shown to influence crop yields directly and whose level may be increased by wildfire smoke.[20,21,1] Broadly, our results are also robust to including controls for annual average levels of various pollutants, including $PM_{2.5}$, SO_4, and NH_4 (Table SI6), as well as growing season averages (for further discussion see SI Section SI1.3).

2.2 Impacts of future smoke exposure

If trends in the number of smoke plumes from 2008–2020 continue, the increased smoke exposure by 2050 will substantially reduce the positive impacts of smoke on yields of both corn and soy

(Figure 3 panels **A** and **B**). Projecting changes in smoke plumes is highly uncertain despite substantial work projecting large increases in the number of fires and area burned by mid-century. In the absence of precise estimates, we focus here on linear projections of current trends in the number of smoke plumes. Relative to projected changes in the number and intensity of fires in existing literature, our projected increase in plumes appears somewhat conservative.[8,9,10]

In nearly all counties in our sample, exposure to linearly extrapolated estimates of smoke days in 2050 will reduce yields relative to the counterfactual where present-day levels of exposure continue. On average, soy-growing counties will experience yields that are 1.8% lower than today, while corn-growing counties will see declines of 1.5%. The most negatively impacted counties will experience yield losses of more than 4%.

Of course, smoke days of either density may not continue to increase at the same rate as they have over the period 2008–2020. We therefore also compute how yields will change by mid-century for both corn and soy if low- and high-density smoke days increase equally by 50%, increase equally by 200%, and increase unequally by 50% and 200% (Figure 3 panels **C**-**J**). This exercise highlights that the reduction in yields that we obtain when assuming current trends continue is driven by the fact that high-density smoke days are currently growing faster than low-density smoke days. Of the four combinations shown in panels **C**-**J**, only panels **G** and **H**, which show the impacts of low-density days growing by 50% while high-density days grow by 200%, show widespread reductions in yields.

To illustrate this point more clearly, we explore how the average impact in 2050 across all counties varies based on different percent increases in days under each type of plume (Figure 4). We estimate the change in yields for changes in low-density days from -100% to 320% and for high-density days from -15% to 570%. This range captures the full range of the uncertainty bounds around our linear projections of how smoke days will change by 2050 (Figure SI3).

For corn, we observe reductions in average yields relative to today whenever high-density days increase at least half as fast as low-density days. In other words, changes in exposure to smoke plumes will result in reductions in corn yields unless low-density smoke days grow at least twice as fast as high-density days. The patterns for soy yields are similar, but the ratio is different. For soy, low-density days must grow roughly $1.5\times$ faster than high density days to prevent reductions in yields in the future relative to today's levels.

These results assume that low-density smoke days continue to have the same beneficial effects as their number increases. This may not be true if, as discussed above, the benefits of low-density smoke days depend on smoke increasing the number of days with optimal levels of light diffraction. It may be the case that, as the share of growing days under low-density smoke plumes increases, the benefits of each additional low-density smoke day declines, because a greater share of growing season days already have close-to-optimal level of diffraction, either from clouds or smoke. If the beneficial effects of low-density smoke do decline as low-density smoke days increases, then our estimates would underestimate smoke's future harm to yields.

Our projected future impacts are uncertain, in large part because of substantial uncertainty in how the number of days under low- and high-density smoke plumes will evolve in the future. However, our qualitative results—that yields will be negatively impacted by future increases in exposure to smoke plumes—will occur unless low-density days increase 1.5× faster than high-density days for soy and twice as fast as high density days for corn. Current work projecting the change in the number of fires, the area burned, total biomass burned, and total particulate matter produced all suggest that high-density days will increase at least as fast as low-density days, even if the increase is different from what our linear extrapolations suggest. As a result, it is likely that future changes in smoke exposure will reduce yields relative to today.

2.3 Interaction with crop expansion

Farmers respond to changing conditions by changing what they plant, and these adaptations may be important for the future impacts of smoke plumes on crop production.[27] We do not have enough data to determine whether farmers have changed their planting practices in response to smoke plumes specifically, but we do examine how changes in where crops are planted have impacted our results.

We do so in two ways. First, we examine the correlation between expansion in corn or soy area and yield impacts of smoke across all counties in our sample. In Figure SI4, we show the relationship between changes in planted area relative to the national trend and the average impact that smoke had on yields over our time period. For corn, there is a slight but insignificant positive relationship between impact and increases in area planted relative to the national average. For soybeans, this relationship is larger and significant. That suggests that, on average, production shifted between 2008 and 2020 from areas with lower impacts from smoke to areas with higher impacts.

We find further evidence for this when we compare the total production of each crop that occurred in the lowest and highest deciles of smoke impact from 2008–2011 vs. 2018–2020. For corn, we find that the share of production that occurred in the top decile increased by 14.4% vs. 6.5% in the lowest decile. For soybeans, the highest decile of impact increased its share of production by 5.2% compared to a −11.2% reduction in the lowest decile (Figure SI5).

Taken together, it appears that production of soybeans has shifted towards counties where yields have been more affected by smoke. This trend may also be true for corn but to a lesser degree. Over our sample, because smoke has had a broadly positive impact on yields, this suggests that the shifts in production towards more smoke-impacted areas have led to increases in production relative to what would have occurred absent changes in the location of production.

We compute that the actual pattern of planting from 2008–2020 led to a 3% increase in total production compared to a baseline where every county increased its production at the national average trend over our sample period.

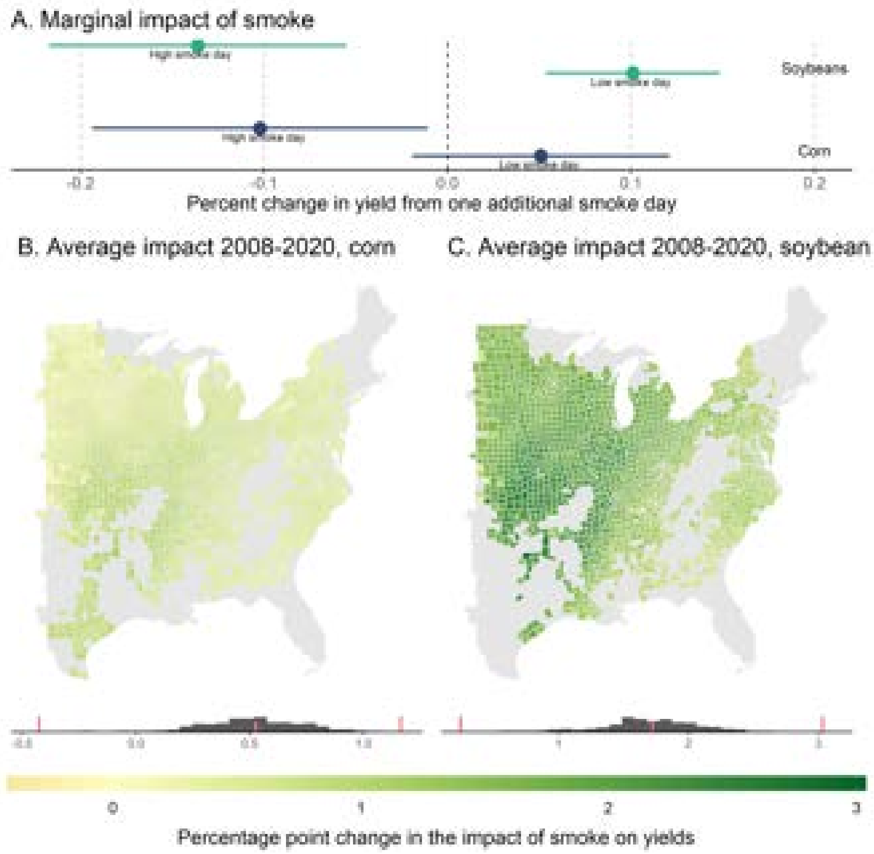

Figure 2: Impact of smoke on current yields. **A** shows the marginal impact of an additional day under a low- or high-density smoke plume on corn or soybean yields estimated with a panel fixed effects model using all counties east of the 100^{th} meridian for the years 2008–2020. We drop counties whose cropped area is in the the bottom 1% of the overall distribution of crop pixels for each crop. All regressions include county and year fixed effects as well as controls for growing season temperature, growing season cloud cover, a quadratic in pre-season precipitation, and a quadratic in growing season precipitation. Error bars indicate the 95% confidence interval of our estimates. **B** and **C** show the estimated total impact of smoke on corn and soybean yields based on the number of smoke days that each county experiences in an average year in our data. Histograms show the distribution of impacts across counties. The red lines on the histogram indicate the minimum, mean, and maximum impact. Full results are reported in Table SI7.

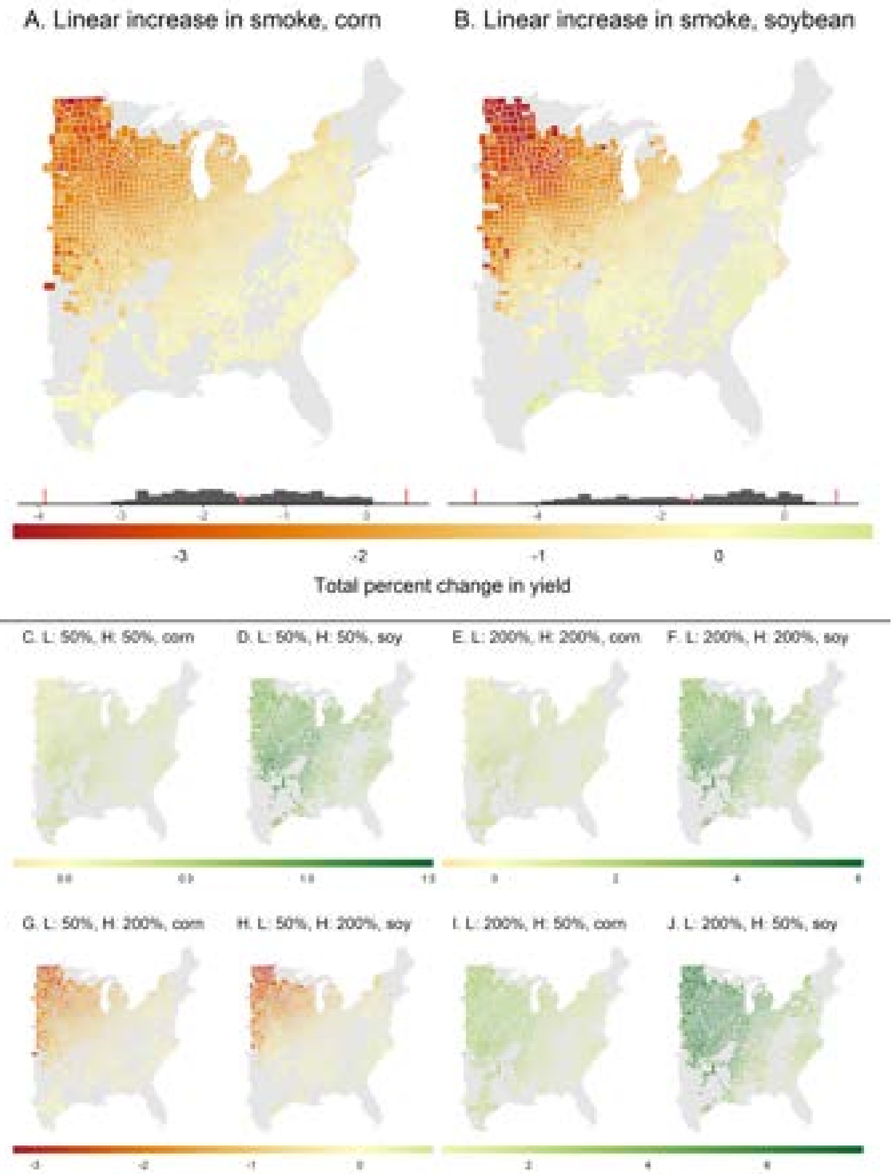

Figure 3: Yield impacts in 2050 relative to today, under five scenarios. In **A** and **B**, we show how 2050 yields will change relative to today for corn and soybeans if low- and high-density smoke days evolve linearly following the 2008–2020 trend. The linear extrapolation implies an increase in low-density smoke days of approximately 60% and an increase in high-density smoke days of approximately 250%. These estimates are uncertain, so panels **C-J** show predictions for changes in yields for a variety of increases in low- and high-density smoke days. In each panel, the change in low- and high-density days is indicated by "L:X%" and "H:X%." In all cases, the first figure shows the impacts on corn and the second on soybeans. All predictions are based on applying the marginal estimates from panel **A** of Figure 2 to the predicted number of low- and high-density days. Histograms show the distribution of counties over the range of impacts. The red lines on the histogram indicate the minimum, mean, and maximum impact.

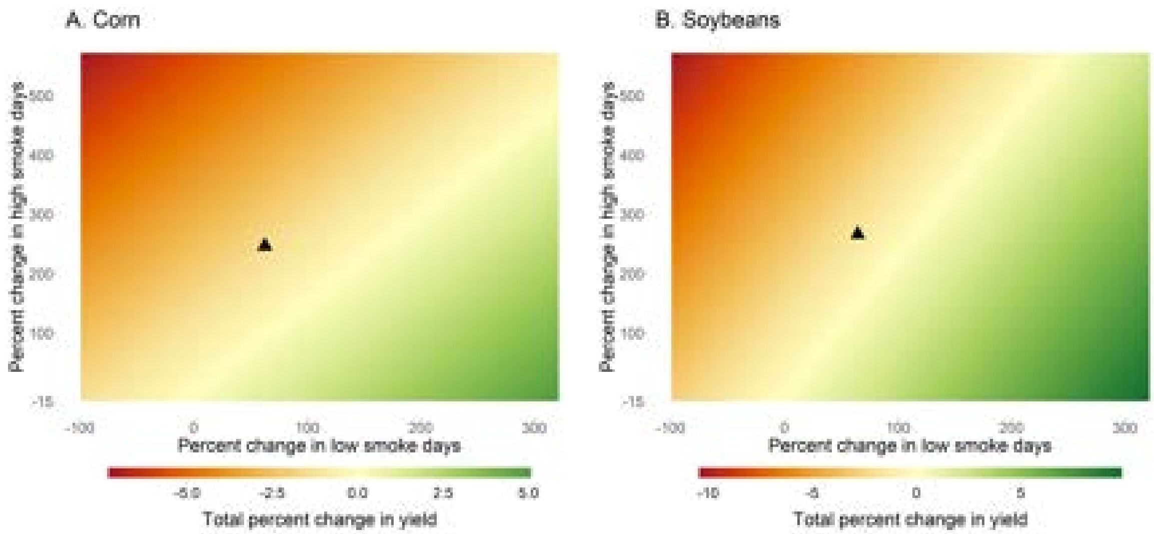

Figure 4: Variation in 2050 impact by growth in smoke days. Panel **A** shows how the total impact on corn yields in 2050, averaged across all counties in our sample, changes based on different percentage increases in low- and high-density smoke days. **B** shows the same but for soybeans. Each cell reports the average across all counties of the sum of the impact on yields of low- and high-density smoke days. The percentage increase in low-density smoke days is shown on the x-axis while the percentage increase in the high-density smoke days is shown on the y-axis. Percentage increases are calculated relative to counties' 2008–2020 average. The triangles indicate impact calculated based on our linear projections of the change in smoke days of each type.

3 Discussion

Using twelve years of data from across the Midwestern and Eastern US, we show that exposure to low-density smoke plumes increases both corn and soybean yields relative to days without smoke plumes. Days with high-density smoke plumes, however, have a negative impact that is roughly double the positive impact estimated for low-density smoke days.

This difference in marginal effects is consistent with the expectation that low-density smoke plumes increase the fraction of light that is diffuse and slightly reduce the total available light, so that the gains in photosynthetic efficiency from the increase in diffuse light dominate. High-density plumes, on the other hand, absorb more light than they diffract, so the reduction in available light dominates the increase in diffuse light. We are unable to test this hypothesis directly (see SI Section SI1.4), but we find that high density plumes substantially increase AOD while low density plumes have only a mild impact (Figure SI2). Our effects do not appear to be driven by changes in ground-level pollutants induced by wildfire smoke plumes, but we cannot rule out that some of our measured effect may be due to these changes.

Our estimates suggest that, if current trends in the number of low-density and high-density smoke days continue, the present positive impacts on yield will be substantially reduced by 2050. Projections of the number of low- and high-density smoke days by mid-century suggest that, for soy, the average county will experience a positive impact on yields roughly a third of today's impact. The impact on the average corn-growing county will be a substantial reduction in yield relative to that under today's smoke conditions. If low-density smoke days grow 1.5–2$\times$ faster than high-density smoke days, however, the effects will be reversed, and smoke will have an even higher yield-boosting effect.

The reduction in yields due to future smoke exposure may impose significant costs on farmers. Using 2020 production and price data from the USDA, combined with our estimated yield losses, we can conduct a back-of-the-envelope calculation of lost revenue. Based on the total tonnage of corn and soybeans produced and the price of corn and soybeans in 2020, we estimate that the combined yield losses due to increased smoke exposure in 2050 would reduce farm revenue by roughly $1.5 billion annually in 2020 dollars. This is comparable to the reduction in farm revenue due to decreased sulfur fertilization after the implementation of the Acid Rain Program.[28] This calculation is a rough approximation of the costs and ignores how prices and production will evolve over time—although, as we discuss below, changes in the location of production may increase these damages. The point is not to provide a precise dollar estimate, but rather to highlight that, while the percent change in yields may be small, the lost revenue could be substantial.

Over our sample period, crop production has shifted towards counties that are more impacted by smoke. This is especially true for soybeans. The result of this shift to-date has been an increase in yields relative to a counterfactual in which counties' share of production stayed constant, because we find that smoke has had a positive impact on yields. However, if smoke's impact on yields becomes more negative, as suggested by linear extrapolation of current trends, then this pattern of spatial changes in production—where more smoke-exposed counties increase their production faster than less exposed counties—will result in greater losses due to smoke relative to a counterfactual in which counties maintain today's share of production.

Our future projections are highly uncertain and highlight a number of areas for continued research. Climate change may lead to an acceleration in burned area relative to existing trends. On the other hand, better management of forest fuel loads in the future may reduce the intensity of fires and their subsequent smoke production, although recent evidence suggests that reductions in fuel loads by fires themselves will not act as a meaningful constraint on fire behavior until at least 2050.[29] How future changes in burned area will translate into additional smoke days of varying densities is therefore an important unanswered question. Understanding the interaction between smoke plumes and clouds may also be particularly important for understanding the impact of future increases in smoke plumes. Implicitly, our projections assume the number of cloudy days will remain similar in the future. A greater number of cloudy days may reduce the beneficial impacts of low-density smoke plume days, while fewer cloudy days could conceivably increase it.

In addition, understanding the interaction between future smoke exposure and future changes in temperature and precipitation is an important area of research. To the extent that the largest changes in smoke exposure are predicted to occur in more northern growing regions (e.g. Wisconsin and the eastern Dakotas) where crop production might naturally migrate to take advantage of milder temperatures, farmers may face a trade-off between avoiding future increases in temperature and future increases in smoke exposure. The magnitude and extent of this trade-off is an important open question, although our estimated impacts of smoke exposure are relatively small compared to estimates of the damage from higher temperatures.[27]

Our results underline the wide-ranging impacts of climate change-driven increases in wildfire activity. Large fires have clear implications for local and non-local air pollution, but can also influence crop yields hundreds of miles away. As wildfire activity changes over time, so may the impacts of smoke on these distant yields. Our results also suggest an additional pathway, less direct than the well-researched impacts of changes in temperature and precipitation, through which climate change may impact crop yields and food security.

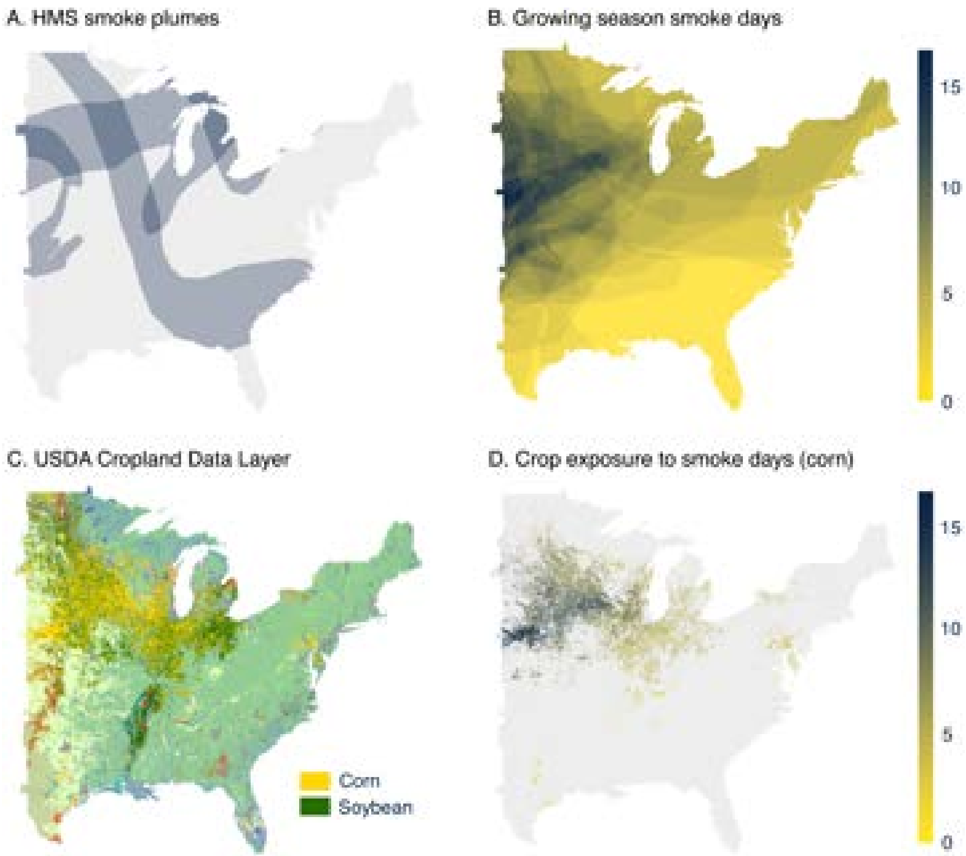

Figure 5: Combining smoke plume data and crop type data to obtain crop exposure to smoke. Smoke plumes from NOAA's HMS dataset (panel **A**) were aggregated across the growing season to create maps of low- and high-density smoke days in our study region (panel **B**). Smoke day maps were then intersected with information on the location of corn and soybean fields from the USDA's Cropland Data Layer (panel **C**) to obtain smoke exposure for corn or soybeans (panel **D**).

4 Data and Methods

4.1 Data

4.1.1 Daily low- and high-density smoke plumes over North America

Our smoke plume data comes from the Hazard Mapping System (HMS) Fire and Smoke Product, which is produced by the National Oceanic and Atmospheric Administration (NOAA) for identifying fires and smoke emissions[30] (Figure 5 panel **A**). The dataset spans North America from January 1, 2006 to December 31, 2020. The plumes are georeferenced polygons hand-drawn by HMS analysts and are stratified into "low", "medium", and "high" densities based on visual inspection of Geostationary Operational Environmental Satellite (GOES) imagery. According to HMS, these density categories correspond roughly to surface smoke concentrations of 5, 16, and 27 $\mu g/m^3$, respectively. Smoke plumes during the year 2009 did not contain density information and were removed from analysis. Since crop type data starts in 2008 (Section 4.1.2), our final smoke plume dataset spans 2008–2020, excluding 2009, and includes 332,547 plumes total. Of these, 250,406 are low density, 58,847 medium density, and 23,294 high density. Due to the small number of high-density smoke plumes, we grouped medium- and high-density smoke plumes together and refer to this group as high-density smoke in this paper.

From these raw plumes, we created daily smoke exposure polygons over the growing season. We first took the union of all low-density smoke plumes at daily resolution from May 1 to September 30. We did the same for all high-density smoke plumes. We then subtracted the footprint of high-density smoke from low-density smoke daily, because low-density smoke plumes are often drawn in ways that include high-density smoke (i.e. they may represent *at least* low density smoke). Since smoke plumes were aggregated to daily temporal frequency, if a given area is under a low-density smoke plume early in the day and then under a high-density smoke plume later, we classified it as being exposed to a high-density, and not a low-density, plume for that day. These steps were performed in `Python` using the `geopandas` package.

Lastly, we rasterized the daily plume polygons into images at 30m resolution, using the same projection as our crop type maps (Section 4.1.2). Every day has two rasters, one for low smoke and one for high smoke. Each pixel of a raster has value 1 if a smoke plume covered that pixel that day, and value 0 otherwise. We summed the daily images to obtain one final raster for low and high smoke, where each pixel represents the total number of days during the growing season that the pixel was exposed to a low- or high-density plume (Figure 5 panel **B**).

4.1.2 Corn and soybean exposure to smoke

We use Google Earth Engine[31] to access the USDA's Cropland Data Layer (CDL),[32] which maps crop types across the coterminous US at 30m spatial resolution (Figure 5 panel **C**). CDL is available from 2008 to 2020 and allows us to precisely map corn and soybean exposure to smoke plumes. We overlaid CDL with our growing season low- and high-density smoke rasters (Figure 5 panel **D**), and, for each county and year between 2008 and 2020 (excluding 2009), we computed the average number of days that crops in a given county were under low- and high-density smoke for corn and soybeans from May 1 to September 30. These values are the treatment variables on the right-hand side of Equation (1).

4.1.3 Meteorological variables

To measure temperature and precipitation in each county-year, we collected an updated version of the modified PRISM dataset used in ref.[33] We modified this data to pixel-weight it by crop and aggregated to the county level.[1] To do so, we start with the daily measures of minimum and maximum temperature and total precipitation at each 2.5×2.5 mile grid point. We then weight each grid point by the number of crop pixels of each type of crop (corn or soybeans) that are in each grid point's unique catchment area. We then calculate the weighted average of each weather measure at the county level for each day.

We calculated the total growing degree days and extreme degree days for each crop in each county during the growing season (May 1 to September 30). We used bins from 10°C to 29°C and above 29°C for corn and 10°C to 30°C and above 30°C for soybeans. We calculated the total precipitation prior to the growing season and during the growing season for each county-year.

We measured cloud cover using data from the ERA5 re-analysis product that records the fraction of cloud cover each hour.[2] We calculated the daily average fraction of cloud cover from 6am to 8pm for each day during the growing season and the number of days the average total fraction of cloud cover falls into bins from 0–25, 25–50, 50–75, and 75–100 percent during the growing season.

4.1.4 Yield data

For both corn and soybean, we downloaded annual data on yield in bushels per acre at a county level from the USDA's National Agricultural Statistics Service (NASS) database. We also collected total bushels produced for each crop in each county and year in the sample.

4.2 Empirical approach

4.2.1 Estimation of smoke's present day marginal impact

In order to identify the marginal impact of smoke plumes on yields, we rely on the assumption that the incidence of smoke days across counties in a given year is plausibly random conditional on county and year fixed effects. In other words, we assume the amount of a given county's exposure to smoke after removing the portion of a county's exposure in a given year that would be considered average for that county and the portion that is experienced by all other counties in the same year, or the portion that is due to a universal increase in smoke, is quasi-random. Some counties may be consistently more exposed to smoke than others; we show that counties in the upper Midwest generally experience more smoke days in a given year than the rest of our sample (Figure 1), but we expect differences in year-to-year exposure within a county is quasi-random. These differences are driven by weather conditions in the location of fires, generally the

[1] The original data is available here: `http://www.columbia.edu/~ws2162/links.html`

[2] Data available here: `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview`

American and Canadian Rockies and coastal mountain ranges, and weather and wind patterns that vary from year to year and dictate where smoke is transported. As a result, year-to-year exposure is expected to be driven by weather conditions in locations far from our counties of interest and hence uncorrelated with weather in our county of interest. We find that burned area in California is not correlated with meteorological variables in the primary corn and soybean producing states (Table SI3). Correlations between burned area and extreme degree days for corn, soybeans, and total precipitation are all between -0.5 and 0.5 with the majority between -0.3 and 0.0.

We control for county-specific determinants of yields that are unchanging over our sample period (e.g. soil quality or elevation) with a county fixed effect. We account for time-varying determinants of yield that are common across counties (e.g. general improvements in agricultural technology) with year-specific fixed effects. We also include a range of annual county-specific meteorological controls to account for correlation between smoke exposure and weather-related determinants of yield. For example, denser smoke plumes may reduce surface-level temperatures in ways that enhance yields.[16]

We also include county-specific controls for the fraction of cloud cover to account for the possibly confounding effect that clouds may have on the ability of analysts to accurately draw smoke plumes and the direct impact that clouds can have on yields themselves.[22,5] Summary statistics for all measures included in our regressions are presented in Table SI4. The full estimating equation is:

$$\begin{aligned} Ln(y_{it}) = {} & \beta_1 \text{Low-density smoke}_{it} + \beta_2 \text{High-density smoke}_{it} + \delta \text{GDD}_{it} + \Delta \text{EDD}_{it} \\ & + \psi \text{Pre precip}_{it} + \omega \text{Pre precip}_{it}^2 + \theta \text{Growing precip}_{it} + \Theta \text{Growing precip}_{it}^2 \\ & + \gamma \text{Low cloud}_{it} + \Gamma \text{High cloud}_{it} + \alpha_i + \chi_t + \epsilon_{it} \end{aligned} \tag{1}$$

where $Ln(y_{it})$ represents the natural log transformation of the yield of either corn or soybeans in county i in year t. “Low-density smoke” and “high-density smoke” are the number of days during the growing season that each county was under a low-density or high-density smoke plume in the HMS data, averaged across corn or soy pixels. We control for the total growing degree days and extreme degree days in each county-year where the thresholds for extreme degree days varies by crop (29°C for corn and 30°C for soybeans). We also include quadratic controls for pre-season and growing season precipitation in each county-year. “Low cloud” and “high cloud” control for the number of days during the growing season in each county-year that have a cloud fraction between 50-75% (low) and 75-100% (high). Binning days by cloud cover allows for a non-linear response to cloud cover.[22] α_i and χ_t are county and year fixed effects that account for county specific determinants of yield that do not vary over time (i.e. soil quality) and shocks that may impact yield in all counties in a given year (i.e. a drought that covers a large part of the country). In our primary specifications, we cluster errors at the county level. However, we also calculate Conley standard errors allowing for spatial auto-correlation.[24] We use the method described in ref.[25] This alternative clustering does not change our results.

Our estimates of interest are β_1 and β_2. β_1 represents the percentage change in yield due to one more day under a low-density smoke plume and β_2 represents the change due to one more day under a high-density smoke plume. In both cases, the counterfactual is a day not under a smoke plume of any density. We define exposure to smoke plumes so that it is exclusive; a day under a high plume is counted only as a day under a high plume, not as a day under both a low and high plume.

4.2.2 Calculating the total impact of smoke on yields

To calculate the total change in yields that our marginal estimates imply, we start by calculating the average number of days each county experiences under plumes of low and high density from 2008–2020. We omit 2009 because data on the density of plumes is not available for 2009. For each county, we then calculate the total impact of low plumes as

$$\text{Low plume impact} = \beta_1 \overline{\text{Low density}} \tag{2}$$

and high density plumes as

$$\text{High plume impact} = \beta_1 \overline{\text{High density}} \tag{3}$$

with the total impact that we plot in panels **B** and **C** of Figure 2 calculated as

$$\text{Total impact} = \text{Low plume impact} + \text{High plume impact} \tag{4}$$

4.2.3 Predicting future smoke days

Predicting future smoke days is highly uncertain. We are aware of only one widely-cited study that seeks to project increases in smoke days out to mid-century across a large part of the United States.[34] The area examined in that study is restricted to the Western United States. None of the counties that we include in our study are included in those projections. The object that they project—smoke waves, defined as at least two consecutive days where levels of $PM_{2.5}$ due to wildfire smoke at ground level are above the 98^{th} percentile of the distribution of $PM_{2.5}$ due to wildfire smoke across the whole study area today—is a significantly more restrictive measure of whether a location is under a smoke plume than we use in our study. Our analysis is not limited to consecutive smoke days, and smoke can interfere with solar radiation even if it does not substantially increase ground-level pollution.

Despite these differences, it is worth noting their estimates. For areas of the United States west of roughly Kansas, they predict an increase of 57% in the number of days under a smoke wave and a 60% increase in the number of smoke waves by 2050 relative to 2004-2009. They also predict that these smoke waves will be 30% more intense. For comparison, ref.[1] show that the raw number of smoke days averaged across all counties in the United States has increased 127% from 2006 to 2020.

Because of the lack of projections of future smoke days over the relevant study area, we consider two alternative methods of extrapolate how smoke exposure will change in the future. As described in the main text, our first extrapolation extends the linear trend of smoke days from 2008–2020. Our second projection considers how other measures of wildfires (for which there exist future projections) relate to smoke days and what projected changes in those measures imply about the change in future smoke days.

In the first extrapolation, we fit a linear trend to the number of days counties growing corn or soybeans experience each plume density during 2008–2020. For corn, low-density smoke days are increasing at the rate of 0.41 per year and high-density smoke days are increasing at the rate of 0.5 per year. For soybeans, these rates are 0.46 and 0.48, respectively. We extend these trends to 2050 and calculate the percentage increase relative to the 2008–2020 average. We assume all counties will experience this uniform percentage increase from their sample average to project the number of days each county will experience under plumes of each density by 2050 (Figure SI3).

Our projections suggest substantial increases in both low- and high-density smoke plumes by 2050. Low-density smoke plume days are projected to increase by 63% for corn and 65% for soybeans. High-density smoke plumes are projected to increase by 245% for corn and 266% for soybeans. As we show in Table SI1, these projections translate to low-density smoke days increasing from roughly 15% of the growing season to 25% and high-density smoke days from 4% of the growing season to 15% by 2050.

These linear estimates are below what extrapolating the trends in ref.[1] would suggest. Across the whole country, they find that smoke days of any kind increase at a rate of 1.89 per year from 2006 to 2019. Extending this trend to 2050 suggests an increase of 400% relative to 2006. Extrapolating a non-linear trend (quadratic & fractional polynomial) fit to the observed data from 2006-2020 predicts that smoke days will peak in 2022 and decline to 0 by the mid-2030s. We believe these predictions are implausible and so use the linear trend.

We construct bounds on these linear projections using the confidence interval of the forecast, which includes both the uncertainty of the mean prediction and the residual. This interval ranges from a decline of ≈15% to an increase of ≈570% for high-density days. For low-density days, it ranges from a decline of 100% (bounded at zero days) and an increase of ≈320%. To examine how our projected impacts change over this large uncertainty range, we estimate average impacts for every combination of changes within the bounds of our linear extrapolation – for high density days from a 15% decline to a 570% increase and for low density days a 100% decline to a 320% increase.

In contrast to the lack of research projecting the number of smoke days under climate change, there is a substantial literature that predicts changes in burned area, biomass consumed by wildfire, and increases in particulate pollution due to wildfires. Ref.[14] reviews several of the pre-2009 estimates of changes in burned area for the Western U.S. and Canada. On average, the reviewed studies predict a 65% increase in the continental U.S. and western Canada by mid-century relative to the 2010s. This is much less than the observed increase (roughly 200%) in the United States from 1985 to 2020.[1]

In general, the newer papers reviewed predict larger increases by 2050. Ref[14] suggests an increase in burned area of 160% across the whole Western U.S. Other recent work suggests increases of up to 1000% in the Rockies, increases of 78-175% in the Pacific Northwest and the Rockies, and increases of burned area of between 75-310% and biomass consumed of 127-410% in the Pacific Northwest.[15,11,35] Ref.[1] reports annual area burned in the United States from 1985 to 2020. Extrapolating the linear trend from that data results in a 235% increase by mid-century relative to the average from 1985 to 2020.

Increases in burned area may be constrained in the future by the availability of fuel as more consistent, and larger fires, result in landscapes that carry lower fuel loads.[15] However, this does not appear to meaningfully reduce burned area estimates until after mid-century.[36,29]

In order to use projections of burned area in our specification, we need to determine the relationship between burned area and smoke exposure. We also need to determine whether low- and high-density smoke days increase uniformly or if changes in biomass burned or fire intensity will lead to changes in the relative number of low- and high-density smoke days. For the first conversion, we can rely on ref.,[1] who document the increase in burned area as well as the increase in smoke days. They observe that, from 2006 to 2020, burned area increased by 32% while smoke days increased by 127%, implying smoke days may increase 4× faster than burned area. Unfortunately, they do not separately measure the change in low- and high-density smoke days.

Combining the central estimate of increases in burned area from ref.[14] of 160% with this 4× relationship implies that smoke days will increase by 460% by mid-century. This is substantially higher than the increase suggested by our linear extrapolation.

There is little evidence that indicates how the increase in smoke days will be apportioned between low- and high-density days. Projections suggest the number of hazy days, total particulate pollution from wildfires, biomass burned, and intensity of fires will all increase relative to today.[14,1,34,35,37] Estimates suggest haze will increase, reducing visibility by 30-40%.[14,34,37] Particulate matter produced by wildfire smoke is projected to increase by between 90% and 400%.[34,37] Finally, total biomass burned in wildfires is projected to increase, driven by increases in intensity, by between 127% and 500%.[35,14] In all cases, the percentage change is for levels at mid-century relative to levels observed between 2000 and recent years.

There is no straightforward way to convert these projections into relative changes in low- and high-density smoke days. However, they all suggest that the number of high-density days will increase relatively more than low-density days. As a crude bounding exercise, we can compare the change in the share of total smoke days that are high-density today to the number we predict in the future under our linear extrapolation. Table SI1 indicates that roughly 22% of smoke days are high-density today. The linear extrapolation predicts that 39% will be high-density by 2050—an increase of 77%. This is at the low end of the range of predicted increases in wildfire-generated particulate matter and biomass burned. Our results indicate that high density smoke days are correlated with higher levels of particulate matter. It may be the case that burning more biomass during the fire season also increases high density smoke days. If the number of high-density days increases linearly with increases in particulate matter and/or biomass burned, our estimates for the increase in high-density smoke days appear to be conservative.

5 Acknowledgments

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Supplementary Information

SI1 Additional Methods

SI1.1 Estimating the impact of smoke on weather

To estimate the direct impact of smoke plumes on our weather outcomes we randomly draw 1,000 gridpoints from the PRISM grid that we use to measure weather. We then calculate the daily smoke exposure for each of those gridpoints during every day of each of the growing seasons in our sample. That allows us to estimate the following equation:

$$y_{idy} = \beta \mathbb{1}\left[\text{Smoke density}_{idy}\right] + \delta \text{Cloud fraction}_{idy} + \omega \text{Cloud fraction}^2_{idy} + \alpha_{id} + \chi_y + \epsilon_{idy} \quad (5)$$

where α_{id} is a gridpoint $\times$ day-of-year fixed effect and χ_y is a year fixed effect. y_{idy} is the weather outcome of interest (e.g. growing degree days) at gridpoint i on day d in year y. When we estimate the impact on cloud fraction we omit the cloud fraction control.

In this specification β provides an estimate of the impact on the daily value of the weather measure of interest of being under a plume of either low or high density on a given day. When we examine the impact on precipitation and cloud fraction we include seven daily lags of smoke exposure to account for any potential delays in the impact of smoke exposure on cloud formation.

SI1.2 Estimating the change in AOD

To estimate the impact of smoke plumes on AOD we collect data on AOD on a 1km grid for our sample area using NASA's MAIAC product.[1] We then calculate the average AOD by county-day in our sample for all days our measurements of AOD are not missing. To control for weather on each day we have an AOD measurement we use the same grid of 1,000 PRISM points and run two sets of analysis. One were we assign the county average AOD to each gridpoint-day and one where we calculate the county-day average meteorological variables using all the gridpoints within a given county. We estimate regressions of the following form:

$$IHS[y_{idy}] = \beta \mathbb{1}\left[\text{Smoke density}_{idy}\right] + \omega \text{Cloud fraction}^2_{idy} + \alpha_{id} + \chi_y + \epsilon_{idy} \quad (6)$$

where α_{id} is a gridpoint or county $\times$ day-of-year fixed effect and χ_y is a year fixed effect. $IHS[y_{idy}]$ is the inverse hyperbolic sine transformation of AOD taken so that our coefficients measure percent changes at gridpoint or county i on day d in year y.

SI1.3 Measuring the impact of ground level pollution

Ground level pollutants can interfere with plant growth and crop yields.[2,3] Wildfire smoke has been shown to increase ground level pollution, especially $PM_{2.5}$.[4] As a result, the negative yield impacts we measure may be a result of increasing ground level pollution, due to wildfire smoke, rather than changes in solar radiation due to the wildfire smoke. In that case the positive yield impacts we estimate would be net of these effects and, which implies that the positive impacts of diffuse radiation are greater than the point estimates we present here would indicate.

In an ideal case we would be able to test this hypothesis by including controls for contemporaneous levels of pollution in all of our regressions. Data at the correct spatial and temporal scales to do this does not exist to our knowledge. In order to control for pollution we face a trade-off between high spatial resolution and incomplete temporal coverage and complete temporal coverage and incomplete spatial coverage.

We deal with this in two ways. First, we use incomplete spatial data from EPA monitoring stations to include controls for ozone and $PM_{2.5}$ for a subset of counties in our sample. We re-estimate our primary specification for both corn and soybeans using these controls. We follow the existing literature and measure ozone exposure as the number of hours between 10am-5pm during the growing season that the county average ozone exceeds 40ppb.[3] We measure $PM_{2.5}$ as the average of the daily maximum across the county during the growing season.[2] We present results of these regressions in Table SI10. While the estimated impacts of smoke plumes are much less precise, due to substantially smaller sample sizes, the point estimates are qualitatively similar. This suggests that our effect is not driven by changes in ground level pollutants. However, more work is necessary to cleanly identify the individual contribution of changes in solar radiation from exposure to wildfire smoke and changes in ground level pollution due to exposure to wildfire smoke.

The second way we deal with this is by using highly spatially resolved measures of $PM_{2.5}$ for a subset of years in our sample to estimate the impact of wildfire smoke on ground level $PM_{2.5}$ in our sample area.[5] We then take these estimated changes in $PM_{2.5}$ levels and use the changes in yields measured in ref.[2] to calculate implied changes in yield in our setting. When we do so we find that smoke-driven changes in ground level $PM_{2.5}$ suggest a reduction in yields of 0.02% on a low density smoke day and 0.06% on a high density smoke day. These effects are about 20% and 50% respectively of the effects that we measure for low and high density smoke days (though opposite signed for low density smoke days). That suggests that our estimated impact of low density smoke days might be 20% larger if not for the impact of ground level pollutants while only 50% of the impact we estimate for high density smoke days is operating through the solar radiation pathway. However, we point out that these estimates are very uncertain and our data linking smoke plumes to ground level pollution levels does not cover our entire time period.

Estimation with a more complete pollution data set may lead to different results.

Taken together these two approaches suggest that change in ground level pollutants due to wildfire smoke may explain some — between 0% and 50% — of our results but do not indicate that the solar radiation pathway is not operating. More research is needed to understand which of these two pathways is more important in determining the overall impact of wildfire smoke on crop yields.

SI1.4 Estimating the change impact on insolation

A direct test of the hypothesis that smoke plumes reduce the amount of direct radiation that reaches crops and increase the amount of diffuse radiation would be to examine the impact of smoke plumes on radiation reaching the surface as measured by the World Radiation Data Center (WRDC). The WRDC operates a network of stations around the world that monitor the amount of direct, diffuse, and total radiation reaching the surface that has been used in past work to examine how aerosols and cloud cover influence the amount of radiation available for plants on a global scale.[6,7] This work takes advantage of the nearly 900 global stations to assess changes in radiation levels. Unfortunately, only 9 of those stations report data in the continental United States during the period for which we have data on smoke plumes. We have attempted to measure how smoke plumes impact radiation by constructing a daily panel of radiation measures at these stations and implementing a similar fixed effects approach to estimating the impact of being under a plume of a given density on these outcomes. Because of the relatively small number of stations for which we have data, and in some cases short panel, those estimates are very imprecise and we do not believe they can provide a meaningful direct estimate of how radiation changes based on the presence of smoke plumes overhead.

SI1.5 Assessing the changing location of production

Both corn and soybean production has trended up during the period of our sample so to assess whether production is moving towards areas that have been more impacted by smoke we examine how counties' production has changed relative to national trends. To do so we calculate the linear trend in the area in production in each county as

$$p_{idy} = \beta Year + \alpha_i + \epsilon_i \tag{7}$$

where α_i is a county fixed effect and $Year$ is a continuous measure of the year of production. p_{iy} is the area in production measured in millions of pixels in county i in year y.

We then calculate what the area in production would have been from 2018-2020 in every county if the area in production increased by β every year from 2008 to 2020, starting from the base level in 2008. The “change in the area produced relative to the trend” measure that we report in Figure SI4 is the actual average area in production of each crop in each county from 2018-2020 minus this predicted average area in production.

SI2 Supplementary Tables

Table SI1: Smoke days as a share of the growing season

	Historic days	*Share of growing season*	Future days	*Share of growing season*
Smoke Coverage, Corn				
Low smoke days	23.77	0.15	38.68	0.25
High smoke days	6.67	0.04	23.13	0.15
Smoke Coverage, Soybeans				
Low smoke days	24.14	0.16	39.74	0.26
High smoke days	6.85	0.04	25.08	0.16

NOTES: Smoke coverage measured as the number of days each type of crop is under a smoke plume of the described density during the growing season. We define the growing season as May to September.

Table SI2: Impact of smoke plumes on AOD

	Gridpoints	Counties
Low plume	0.16***	0.16***
	(0.02)	(0.02)
High plume	0.55***	0.53***
	(0.05)	(0.05)
Outcome mean	276.94	279.35
Controls:		
Cloud cover^2	Y	Y
Fixed effects:		
Geography × DOY	Y	Y
Year	Y	Y

NOTES: The outcome in all columns is the IHS transformation of daily AOD over the county. In column one observations are at the PRISM gridpoint level and all gridpoints in a county are assigned the county AOD level. In column two we assigned counties the densest smoke plume that any gridpoint in the county experiences on that day and aggregate all other measures to the county level. In all cases the coefficient×100 can be interpreted as the percentage change in AOD if the geographic unit is under a plume of the specified density on a given day. All regressions include quadratic controls for cloud cover. All regressions are at the daily level. Heteroskedasticity robust standard errors clustered by county and year are in parentheses (* p<.10 ** p<.05 *** p<.01). Compiled 29 Apr 2021

Table SI3: Correlation between EDD and CA burned area

	EDD, corn	EDD, soybean	Precipitation
Iowa	-.26	-.23	-.01
Illinois	-.37	-.32	.34
Indiana	-.36	-.3	.31
Minnesota	-.3	-.26	-.34
Missouri	-.42	-.38	.21
North Dakota	-.23	-.18	-.34
Nebraska	-.36	-.32	-.36
Ohio	-.38	-.31	.26
South Dakota	-.31	-.28	-.48
Wisconsin	-.2	-.17	.03

NOTES: We report the correlation between the average annual number of extreme degree days for corn in soybean for selected states in our sample and the total burned area in California, which we use as a proxy for burned area in the western United States and Canada, from ref..[4]

Table SI4: Summary statistics

	Corn				Soybean			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Outcome								
Yield (bu/ac)	144.52	38.55	0.00	246.70	43.58	10.69	3.60	80.40
Smoke days								
Low smoke days	24.08	13.99	0.00	77.10	24.68	14.10	0.00	77.13
Non-low smoke days	6.82	6.53	0.00	37.15	7.08	6.66	0.00	37.28
Weather measures								
Growing degree days	1,711.17	977.21	0.00	5,052.82	1,740.53	948.83	0.00	5,045.60
Extreme degree days	75.69	121.47	0.00	1,220.11	38.26	61.63	0.00	740.98
Growing season precipitation (mm)	528.84	142.37	81.50	1,206.90	532.85	144.30	89.85	1,457.60
Pre-growing precipitation (mm)	311.68	145.65	31.29	1,046.78	312.94	149.19	31.46	1,044.56

NOTES: Summary statistics are calculated across all the counties in our sample for the years from 2008-2019, omitting 2009 due to lack of information about the type of smoke plumes in the original smoke plume data.

Table SI5: Impact of smoke days on corn and soy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Corn							
Low smoke days	-0.0059***	0.0005	-0.0060***	-0.0037***	-0.0040***	0.0005	-0.0056***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
High smoke days	-0.0088***	-0.0010**	-0.0088***	-0.0063***	-0.0063***	-0.0011**	-0.0082***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
N	14,026	14,026	14,026	14,026	14,026	14,026	14,026
(B) Soybeans							
Low smoke days	-0.0054***	0.0008***	-0.0054***	-0.0033***	-0.0033***	0.0010***	-0.0052***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
High smoke days	-0.0094***	-0.0018***	-0.0093***	-0.0068***	-0.0068***	-0.0015***	-0.0086***
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
N	13,232	13,232	13,232	13,232	13,232	13,232	13,232
Controls:							
Growing season temperature		Y				Y	
Growing season precipitation				Y	Y	Y	
Pre-growing season precipitation			Y		Y	Y	
Growing season cloud cover							Y
Fixed effects:							
County	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y

NOTES: The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01). Compiled 19 May 2021

Table SI6: Impact of smoke days on corn and soy

	Corn	Soybeans
Low smoke days	0.0003	0.0013***
	(0.0004)	(0.0003)
High smoke days	-0.0010*	-0.0015***
	(0.0006)	(0.0005)
N	12,767	12,070
Controls:		
Growing season temperature	Y	Y
Growing season precipitation	Y	Y
Pre-growing season precipitation	Y	Y
Growing season cloud cover	Y	Y
Annual avg. $PM_{2.5}$	Y	Y
Annual avg. NH_4	Y	Y
Annual avg. SO_4	Y	Y
Annual avg. NO_X	Y	Y
Fixed effects:		
County	Y	Y
Year	Y	Y

NOTES: The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01). Compiled 4 May 2021

Table SI7: Impact of smoke days on corn and soy

	Corn	Soybeans
Low smoke days	0.0005	0.0010***
	(0.0004)	(0.0002)
High smoke days	-0.0010**	-0.0014***
	(0.0005)	(0.0004)
N	14,026	13,232
HAC p-values:		
Low smoke days		
High smoke days		
Controls:		
Growing season temperature	Y	Y
Growing season precipitation	Y	Y
Pre-growing season precipitation	Y	Y
Growing season cloud cover	Y	Y
Fixed effects:		
County	Y	Y
Year	Y	Y

Notes: The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01). We report p-values calculated using Conley (HAC) standard errors calculated as in ref.[8] in the row labeled HAC p-values.

Table SI8: Impact of smoke days on corn and soy excluding 2012

	Corn	Soybeans
Low smoke days	-0.0008**	0.0013***
	(0.0004)	(0.0003)
High smoke days	-0.0033***	-0.0012***
	(0.0004)	(0.0004)
N	12,493	11,832
Controls:		
Growing season temperature	Y	Y
Growing season precipitation	Y	Y
Pre-growing season precipitation	Y	Y
Growing season cloud cover	Y	Y
Fixed effects:		
County	Y	Y
Year	Y	Y

NOTES: This table is the same as Table SI7 except that we drop 2012 from the analysis because it was an unusually severe drought year across the entire United States. The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table SI9: Impact of smoke days on corn and soy by tercile of average cloud cover

	Tercile 1	Tercile 2	Tercile 3
(A) Corn			
Low smoke days	0.0026***	0.0035***	0.0013*
	(0.0006)	(0.0007)	(0.0007)
High smoke days	0.0043***	-0.0003	-0.0035***
	(0.0009)	(0.0007)	(0.0011)
N	4,586	4,565	4,545
(B) Soybeans			
Low smoke days	0.0016***	0.0019***	0.0023***
	(0.0005)	(0.0005)	(0.0005)
High smoke days	0.0010	-0.0014**	-0.0045***
	(0.0007)	(0.0007)	(0.0009)
N	4,340	4,313	4,266
Controls:			
Growing season temperature	Y	Y	Y
Growing season precipitation	Y	Y	Y
Pre-growing season precipitation	Y	Y	Y
Growing season cloud cover	Y	Y	Y
Fixed effects:			
County	Y	Y	Y
Year	Y	Y	Y

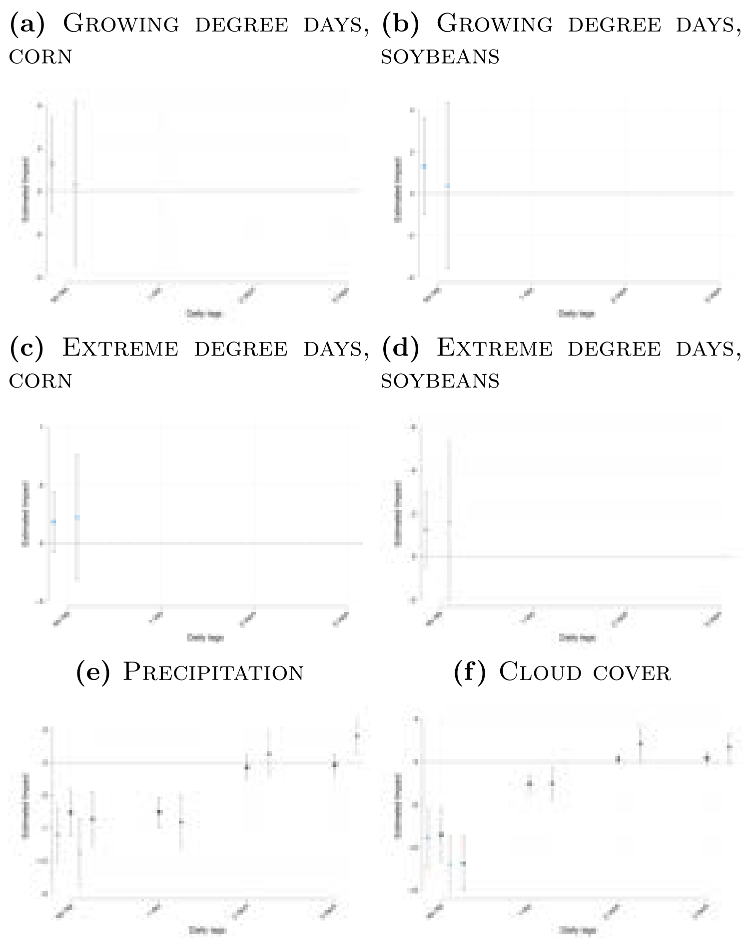
NOTES: The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Terciles are defined based on the average cloud cover during the growing season over our full sample period. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01). Compiled 24 May 2021

Table SI10: Impact of smoke days on corn and soy with ozone controls

	Base specification		Ozone		$PM_{2.5}$	
	Corn	Soybeans	Corn	Soybeans	Corn	Soybeans
Low smoke days	0.0005	0.0010***	-0.0009	0.0002	0.0002	-0.0003
	(0.0004)	(0.0002)	(0.0008)	(0.0005)	(0.0014)	(0.0012)
High smoke days	-0.0010**	-0.0014***	-0.0021	-0.0035***	-0.0014	-0.0026
	(0.0005)	(0.0004)	(0.0013)	(0.0011)	(0.0022)	(0.0020)
N	14,026	13,232	3,260	3,075	852	789
Controls:						
Growing season temp.	Y	Y	Y	Y	Y	Y
Growing season precip.	Y	Y	Y	Y	Y	Y
Pre-growing season precip.	Y	Y	Y	Y	Y	Y
Growing season cloud cover	Y	Y	Y	Y	Y	Y
Ozone hours			Y	Y		
Avg. $PM_{2.5}$					Y	Y
Fixed effects:						
County	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y

NOTES: The outcome in all columns is the natural log of crop yields in a given year. Independent variable is the count of the annual average days under smoke plumes of the described density. Ozone hours measures the number of hours during the growing season where county average ozone exceeded 40 ppb. Avg. $PM_{2.5}$ is the average of the daily maximum level of $PM_{2.5}$ during the growing season. Heteroskedasticity robust standard errors clustered by county are in parentheses (* p<.10 ** p<.05 *** p<.01). Compiled 20 Jul 2021

SI3 Supplementary Figures



(a) Growing degree days, corn

(b) Growing degree days, soybeans

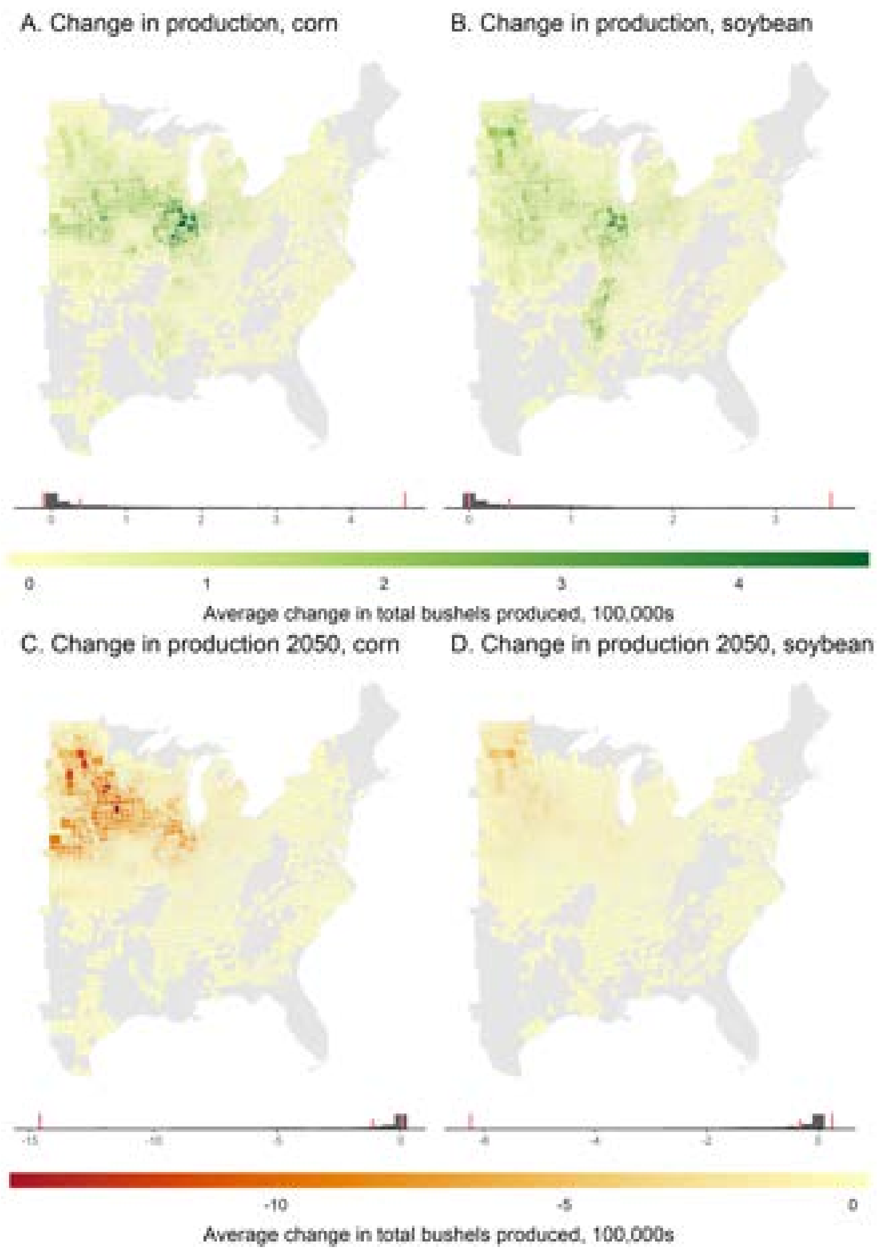
(c) Extreme degree days, corn

(d) Extreme degree days, soybeans

(e) Precipitation

(f) Cloud cover

Figure SI1: Impact of smoke plumes on weather outcomes. Each figure reports the coefficients from a panel fixed effects regression with the named weather variable as the outcome. Squares indicate the coefficent on an indicator for low density smoke plumes, triangles are for high density plumes. Light blue indicators show the coefficients in a regression without lags. All regressions are run at the PRISM gridpoint × day level. We select 1,000 PRISM gridpoints from our sample area, east of the 100^{th} meridian, at random and collect each weather outcome at the daily level over all the growing seasons in our sample. The coefficients reported are those on an indicator for whether the gridpoint was under a low density or high density plume on a given day. Regressions reported in panels **A-C** include include a quadratic control for cloud cover. All regressions include gridpoint × day-of-year and year fixed effects. We cluster errors at the county and year level. In panels **E-F** we include seven days of lags but only report the first three lags for parsimony because the subsequent lags do not differ from the estimated impacts of lags 2 or 3.

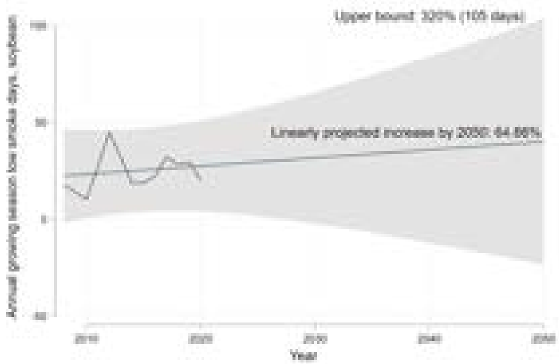


NOTES: **A-B** show the estimated impact of smoke on total production in 100,000s of bushels by county for corn and soybeans based on the number of days that each county experiences under each type of plume in an average year in our sample. If we assume these days increase in line with our baseline expectations **C-D** show the impact on total production in 2050. In both cases the change in production is relative to a counterfactual in which there were no smoke days.

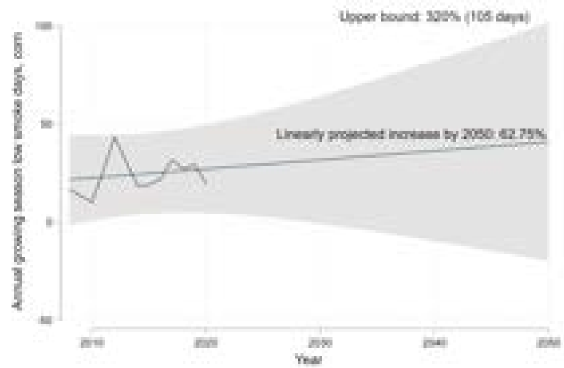
Figure SI2: Impact of smoke on production. We calculate the linear trend of low- and high-density smoke days for the counties in our sample by crop type. We show in the solid line the average number of each type of smoke days across all the counties in our sample by crop from 2008–2020. The dashed blue line shows the linear trend in these days projected out to 2050. Percentage increases are calculated relative to the average level in our sample period. The shaded gray area indicates the 95% confidence interval calculated using the standard error of the forecast.

Figure SI3: Trend in growing season smoke days, 2008–2050

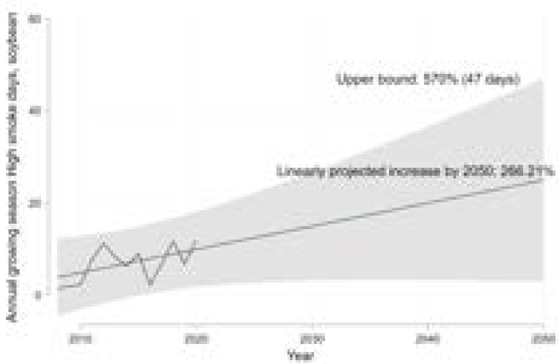
(a) Low-density smoke days, soybeans



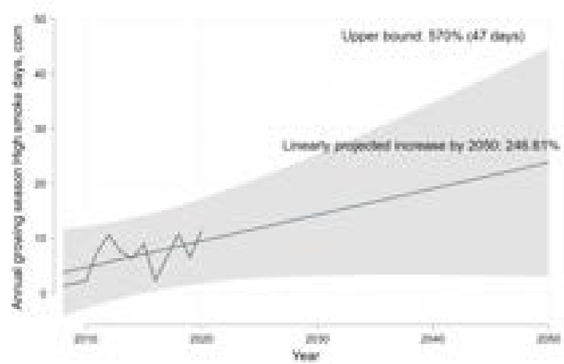
(b) Low-density smoke days, corn



(c) High-density smoke days, soybeans



(d) High-density smoke days, corn



(a) Corn **(b)** Soybeans

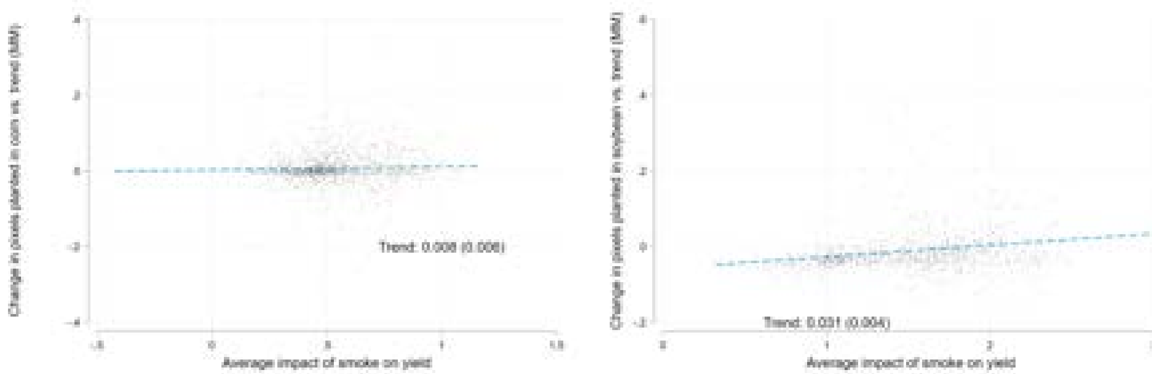


Figure SI4: Relationship between changes in planted area and smoke impacts. Each figure shows the scatter of counties by average the percent impact of smoke on yields during our sample period against the number of pixels, measured in millions, that were planted in each crop on average from 2018-2020 relative to how many pixels would have been planted over that time period if the area planted in each county had grown from its level in 2008 at the national trend. Positive numbers on the y-axis indicate that the area planted in a given crop in a given county increased faster over our sample period than the national average growth rate. Higher x-axis values indicate that smoke had a larger beneficial impact on yields in that county on average over our sample period.

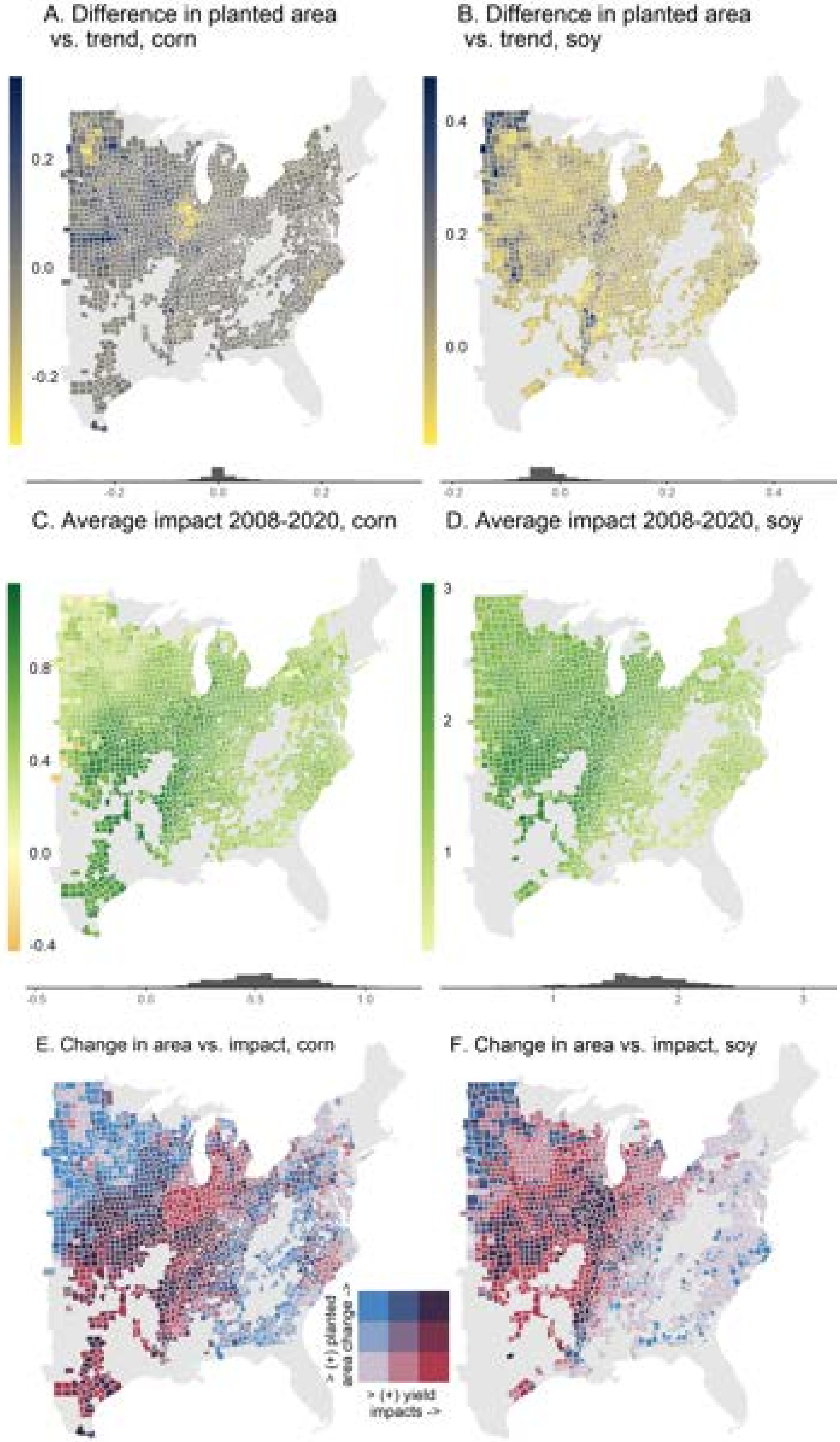
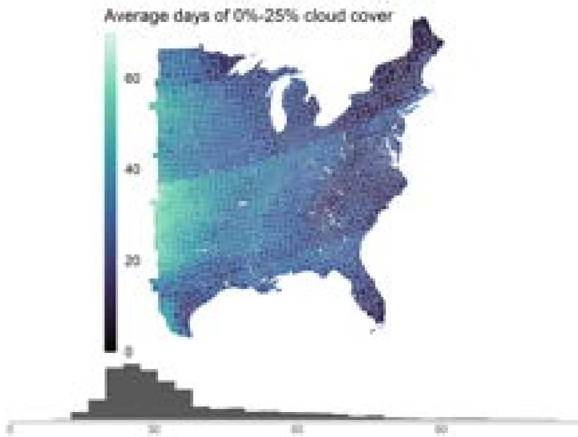
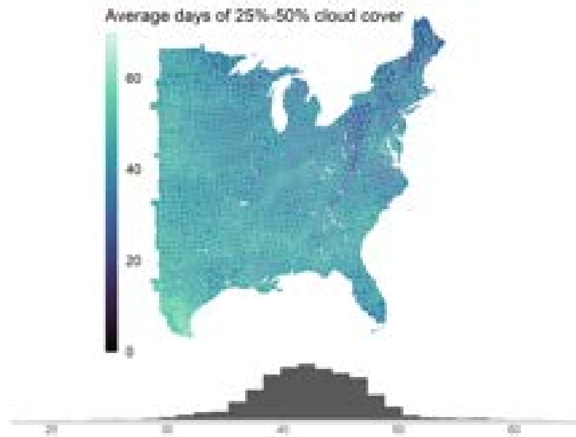


Figure SI5: Change in planted area and impact of smoke. Panel **A-B** report the county by county difference between the number of pixels planted in each crop from 2018-2020 compared to the level predicted in those years if each county had increased their area planted by the national average trend over the intervening time period. Lighter colors indicate counties have increased their planted area faster than average while darker colors indicate slower increases or reductions. We measure planted area in millions of pixels. Panels **C-D** repeat panels C and D from figure 2 and show the average impact that smoke has had on yields over our time period. Panels **E & F** show the co-location of changes in planted areas and the impact of smoke. Dark purple areas indicate that the impact of smoke has been large and positive and the change in planted area has exceeded the national average trend. Dark red areas indicate a large and positive increase in yields due to smoke but a below trend increase in planted area. Dark blue areas indicate a small yield effect (in the case of corn possibly negative) but increases in planted area above trend.

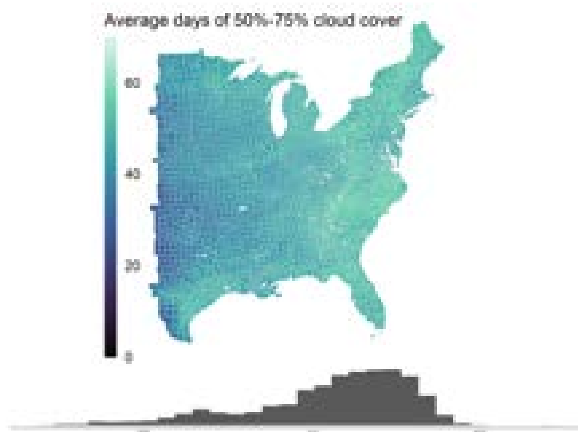
(a) 0%-25% COVERAGE



(b) 25%-50% COVERAGE



(c) 50%-75% COVERAGE



(d) 75%-100% COVERAGE

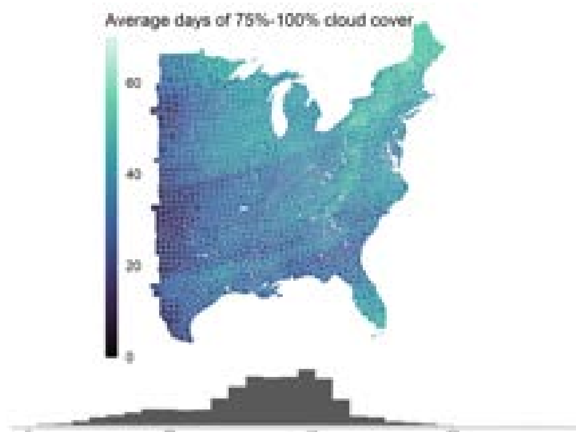


Figure SI6: Average cloud cover We report here the average number of days during the growing season that counties are under cloud coverage of 0%-25%, 25%-50%, 50%-75%, and 75%-100% for the years 2008–2020, omitting 2009. Data comes from ERA5.

SI4 Supplementary References

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[8] Solomon M Hsiang. “Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America”. In: *Proceedings of the National Academy of sciences* 107.35 (2010), pp. 15367–15372.