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Impacts of ozone and climate change on yields of perennial crops in California

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Changes in temperature and air pollution affect agricultural productivity, but most relevant research has focused on major annual crops (for example, wheat, maize, soy and rice). In contrast, relatively little is known about the effects of climate change and air quality on perennial crops such as fruits and nuts, which are important to dietary diversity and nutrition, and represent ~38% of California's agriculture by economic value. Moreover, the adaptive capacity of perennial crops may be limited by their long lifespans and sometimes large establishment costs. Here, on the basis of statistical modelling of historical data and down-scaled climate model projections, we jointly assess the impacts of climate and ozone levels on historical and future yields of perennial crops in California. Although the effects of warming to date are not statistically significant for many perennial crops, the yields of most perennials show a significant negative response to ambient ozone, ranging from -2% for strawberries to -22% for table grapes, implying total losses of roughly US\$1 billion per year. This suggests that historical improvements in California's air quality that reduced ozone exposures may have had large, unaccounted co-benefits for the state's perennial crop yields, and further pollution reduction could create additional gains. Indeed, the co-location of regions with high production and high ozone damage indicates that opportunities to improve crop yields through pollution mitigation are large.

rop production is vulnerable to both climate change and air pollution¹⁻⁵. To date, efforts to understand the agricultural impacts of climate change and air pollution have focused on annual crops such as wheat, rice, maize and soybean⁶⁻⁸, which provide the majority of calories directly consumed by humans. In contrast, relatively few studies have assessed such impacts on longlived perennial crops such as fruits and nuts9-14, which are important for dietary diversity and nutrition, and are often grown in niche environments¹⁵⁻¹⁷. Indeed, the few studies that exist have focused on climate impacts9-12, and very little is known about how air pollution has affected perennial crops. Moreover, given their long lifespans (many trees grow for 30 yr) and large establishment costs (for example, ~US\$20,000 per hectare of almonds; 3-4 yr for grape vines or orange trees to begin bearing fruit)18, adaptive responses such as the adoption of new varieties will be slower than for annual crops¹⁹. Perennials may thus be especially vulnerable to both climate and ozone trends in the coming decades.

California produces over 400 agricultural commodities, supplies two-thirds of the nation's fruits and nuts, and over one-third of the nation's vegetables²⁰. In 2015, the state's agricultural output was valued at US\$59.4 billion, accounting for 13% of the national total, with more than one-third (US\$23.0 billion) derived from long-lived perennial crops such as almonds, grapes and strawberries²¹. The state also plays an important role in the world food economy, and global food and nutrition security: California exports approximately 28% of its agricultural production²², and as but one example, it is a major producer of tree nuts and grows over 80% of the world's almonds²².

Meanwhile, despite steady improvements (Supplementary Fig. 1) and efforts to raise environmental standards, cut carbon emissions and combat climate change, California's particulate and ozone pollution remains among the worst in the nation²³. Some of the productive agricultural areas in California are exposed to elevated ozone levels (Supplementary Fig. 2). The combined historical and future effects of ozone and climate trends on the yields of different perennial crops in California are not well understood. More in-depth research in this direction is essential to identify key vulnerabilities and to prioritize adaptation strategies.

Tropospheric ozone (O₃) is produced when nitrogen oxides (a large component of anthropogenic pollutant emissions) and volatile organic compounds react in the presence of sunlight. Ozone, a powerful oxidant, enters leaves via the stomata, damaging plant tissues and impairing photosynthesis^{3,8,24}. There are several approaches to estimate crop yield responses to climate and ozone at regional scales. Damage functions (also known as dose-response or exposure-response functions) derived from controlled experimental and field studies are one possibility, but extrapolating over larger regions on the basis of limited observations at a small number of field locations may be unreliable, particularly for perennial crops⁸. In contrast, long-term records of perennial crop yields, climate and air pollution in the state provide a new opportunity to determine their relationships by analysing the covariance among them with statistical models²⁵. Regression analysis of historical data is independent of experimental and field studies, and may be especially useful for perennial crops, where there are few experimental studies and limited reliable process-based models.

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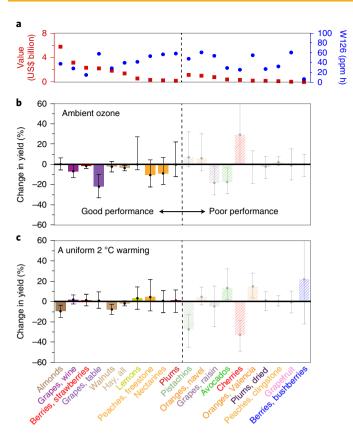


Fig. 1 | Yield response of the 20 most valuable perennial crops to ambient ozone and a uniform 2 °C warming. The average yield response over the period 1980 to 2015 is plotted as bars with points (median estimates), with error bars (95% CIs) calculated by bootstrapping the model 1,000 times. The darker-shaded bars on the left denote models of good performance (with high training and test determination coefficients), as opposed to models of poor performance (on the right, with significantly lower R² test values; see Methods). a, Left y axis: crop types in two groups (good and poor model performance) ranked by the mean economic value of production for 2011-2015. Right y axis: state-wide average ozone exposures (W126 index) for each crop, calculated similarly to the state-wide average yields, with the county weights proportional to the harvested areas in each county. b, The percentage reduction from ambient ozone, estimated as the difference between predictions using historical ozone levels (W126 index) and a hypothetical scenario with zero ozone (W126 index). c, The yield response to warming, shown as percentage changes in yields that would result from a uniform 2°C warming.

This study jointly assesses the impacts of climate and ozone levels on historical and future yields of multiple perennial crops. We use a panel regression analysis of historical crop yields and exposures from 1980 to 2015 to estimate the sensitivities of a suite of perennial crops to ozone and temperature. We then estimate future crop yields to 2050 by combining our estimated historical responses with downscaled climate model projections, including ozone concentrations, under two representative concentration pathways (RCPs) 4.5 and 8.5^{26,27}.

Yield response to ozone and temperature

Figure 1 represents the response of California's top 20 most valuable perennial crop yields to ambient ozone and a uniform 2 °C warming. The average yield response over the period 1980–2015 is plotted as bars with points (median estimates), with confidence intervals (CIs) calculated by bootstrapping the model 1,000 times using the least absolute selection and shrinkage operator (LASSO) regression.

Darker-shaded bars denote crop models with good performance, as determined by out-of-sample cross-validation. Crop models with both high training and test determination coefficients (R^2) are considered to have good performance, while models in which the test R^2 was significantly lower than the training R^2 indicate the risk of overfitting. Ten perennial crops (almonds, wine grapes, strawberries, table grapes, walnuts, hay, lemons, freestone peaches, nectarines and plums) exhibit good model performance, with the models explaining more than 50% of the variance in training data and 35% of the variance in test data (Supplementary Fig. 3), and accurately predicting historical yields (Supplementary Fig. 4). The remaining crops exhibit poor model performance, with a relatively low or even negative test R^2 that differs substantially from their training R^2 , although their training R^2 is generally higher than 0.4. Our results focus on the crops with good model performance. Interestingly, the crops with good model performance are high value and represent the majority of the economic value of California's perennial crops (Fig. 1a, left axis).

The yield response to ambient ozone was estimated from the percentage difference between predictions using historical ozone levels and a hypothetical scenario with zero ozone (Fig. 1b). We calculated three widely used ozone cumulative exposure indices (W126, AOT40 and SUM06) during the warm season to reflect ozone exposures on perennial crops. Only results for the W126 ozone index are reported here; responses for good-performance models were similar when using the AOT40 and SUM06 indices (Supplementary Fig. 5). For most of these crops, ozone has significant negative effects on yields. The yield changes from ambient ozone (that is, the change in yield given the estimated sensitivity of crops and the ozone exposure in growing areas) range from less than -2% (95% CI: 0% to -4%) for strawberries to -22% (95% CI: -10% to -33%) for table grapes (Fig. 1b). Seven of the ten crops with good model performance (wine grapes, strawberries, table grapes, walnuts, hay, freestone peaches and nectarines) appear to have significant reductions in yield in response to ambient ozone (-7%, -2%, -22%,-3%, -4%, -11% and -9%, respectively), and many of them are among the top ten most valuable perennial crops in California. The variations in yield response to ambient ozone between crops are not only attributed to their different ozone sensitivity, but also due to their different ozone exposures in differentiated growing regions. Grapes appear to be more sensitive to ozone than many other perennial crops (Supplementary Fig. 6); this finding is consistent with literature describing grapes as a moderately ozone-sensitive crop¹³ that can experience visible leaf damage from ozone exposure14. The high ozone damage to table grapes is also related to their high ozone exposure (W126—58 parts per million hours (ppmh); Fig. 1a, right axis) (most grapes are grown in the San Joaquin Valley; Supplementary Fig. 2), while the small ozone damage to strawberries is partly related to their low ozone exposure (15 ppm h; Fig. 1a, right axis) (many of them grow in the Central Coast; Supplementary Fig. 2). The total economic loss from ozone damage to these seven crops was estimated at roughly US\$1 billion (95% CI: US\$0.5-1.3 billion) per year, ignoring price feedback effects. This significant loss of yield and production value indicates that ozone has a considerably negative impact on California's agricultural economy, and thus provides an important motivation for further reduction of ozone levels.

Using the same LASSO-based approach, we also extract the yield response to warming, which is shown as percentage changes in yields that would result from a uniform 2°C warming (an approximation for the magnitude of warming by 2050) (Fig. 1c). In contrast to ozone, yield responses to warming are not significant for most crops, with CIs often spanning zero. Only two crops (almonds and walnuts) appear to have significant negative yield responses to warming (-9% and -8% from a uniform 2°C warming, respectively). Almonds are susceptible to winter warming, which may be

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associated with poor pollination and chilling hour accumulation¹¹. Walnut yields are sensitive to warming, which may be partly related to their substantial chilling requirements¹². We also assessed the sensitivity of the yield responses to different warming levels (1 °C, 2 °C and 3 °C) and found that greater warming has a greater impact on the yield for most crops (Supplementary Fig. 7). These results are generally consistent with those identified by Lobell and Field¹¹, indicating that an additional decade of agriculture and climate data have not altered previously observed relationships, and that the effects of warming, at least within the range observed in historical data, may not be as significant as ozone damage.

Historical trends from 1980 to 2015

Figure 2 shows historical relative yield changes for six important perennial crops over the period from 1980 to 2015 due to changes in ozone concentrations (Fig. 2a-d) and temperature (Fig. 2e,f) over that time period. Historical changes in ambient ozone levels and temperature are shown in Supplementary Fig. 1. As ozone concentrations have decreased in California over the past several decades (Supplementary Fig. 1), ozone damage to yields has declined (Fig. 2a-d), but damage in recent years is still large. For table grapes and nectarines, the ozone damage on yields remained relatively constant until the year 2000, when there was a trend towards less ozone damage, consistent with the ozone trend in the San Joaquin Valley (Supplementary Fig. 1) where most of them are grown. In the case of table grapes, yield losses were 28% (95% CI: 13% to 42%) in the 1980s and declined to 14% (95% CI: 6% to 22%) in the 2010s (Fig. 2c). For nectarines, the 67% CI of the ozone impact is negative, but the 95% CI extends to positive values, indicating that the impact may be less significant than for table grapes. Ozone damage to strawberries peaked in the 1980s, and has declined since, in part affected by the ozone trend in Southern California (Supplementary Fig. 1) where many of them were grown. Interannual variations in yield loss due to ozone damage (mainly attributable to meteorological differences) were as high as nearly 10% for table grapes in the 1990s, but have been decreasing in recent years probably due to reduced emissions of ozone precursors. In general, our results suggest that air quality regulations in California have been effective in reducing ozoneinduced crop production losses, and that there are opportunities for further improvements. Reductions in ozone levels between the 1980s and the early 2010s are modelled to have increased the agricultural output of the seven crops with ozone damage by US\$0.6 billion (95% CI: US\$0.1-1.1 billion) per year.

Figure 2e,f shows the impact of year-to-year temperature variability on yields of almonds and walnuts during the period 1980–2015. In contrast to ozone, there is not a significant historical temperature trend, although there are large interannual variations (up to 2 °C) and a recent upward trend. The variations in yield due to temperature are mostly within $\pm 10\%$ (Fig. 2). The yield responses to historical temperatures also do not exhibit a clear trend, with the possible exception of 2010–2015, during which a warming period reduced yields of both nuts (Fig. 2e,f and Supplementary Fig. 1).

Projections of impacts to 2050

Figure 3 shows the projected 2005–2050 changes in yields of four perennial crops by agricultural district (see Supplementary Fig. 2 for region definitions) due to warming and ozone changes from 2001–2010 to 2046–2055 in the RCP4.5 and RCP8.5 climate scenarios, with uncertainty ranges quantified using bootstrapping. Projected changes in ambient ozone levels and temperature under the two RCPs scenarios are shown in Supplementary Fig. 8. The large ozone precursor emission reductions ^{28–30} lead to greater warmseason daylight ozone reductions in RCP4.5 (Supplementary Fig. 8). Assuming no changes to agronomic technology or crop area, the greater ozone reductions in RCP4.5 (Supplementary Fig. 8) lead to

larger benefits to yields (+5%, +20% and +8% for wine grapes, table grapes and nectarines, respectively), compared to +3%, +13% and +5% for the same crops, respectively, in RCP8.5 (Fig. 3). Similarly, higher levels of warming under RCP8.5 (Supplementary Fig. 8) correspond to larger yield losses: for example, 16% for almonds compared to 11% under RCP4.5 (Fig. 3). Under RCP4.5, the benefits of ozone reductions are larger than the effects of warming for most crops in most districts, leading to a net gain in yield for some crops. In particular, the yield benefits of ozone reduction could be as high as 20% for table grapes. However, future warming may cause yield loss for particular crops such as almonds.

The impacts show regional differences across California. For example, the San Joaquin Valley, where many of the nation's fruits and nuts (such as grapes and nectarines) are grown, is the region most severely affected by ozone (Supplementary Fig. 2), and may thus witness substantial benefits from ozone reduction in the future (Fig. 3 and Supplementary Fig. 8). For example, yields of wine grapes in the San Joaquin Valley are projected to increase by 6% in the RCP4.5 scenario due to ozone reductions, substantially more than other regions (1-4%). Most table grapes are currently grown in counties with high ozone levels in the San Joaquin Valley and Southern California (Supplementary Fig. 2), and their yields are projected to increase by up to 20% in the RCP4.5 scenario due to ozone reductions. Our results reveal the co-location of regions with high agricultural production and high ozone damage, suggesting the potential benefits on future yields by reducing ozone levels or by relocating crop planting areas.

Discussion

Our results suggest that for most perennial crops, ozone damage to yields may be more substantial than warming effects. This is consistent with studies of major crops from other parts of the world. In California, our models suggest current production losses due to ozone damage can be as high as US\$1 billion (95% CI: US\$0.5-1.3 billion) per year. Reducing air pollution may provide immediate benefits for agricultural producers. Substantial warming from historical emissions will be difficult to avoid, although mitigation measures will help to limit the overall magnitude of future warming. The substantial decline in yield loss from ozone since 1980 indicates that pollution control has had widespread benefits on perennial crop production (increased agricultural output by US\$0.6 billion per year). Yield losses of 5-15% for some crops are still occurring currently. Our projections suggest that further pollution reduction would create further benefits. The co-location of regions with high production and high ozone damage indicates large opportunities to improve crop yields. For regions where yield loss due to ozone damage is large, the success in California suggests that air quality regulation in those regions could be an effective means of boosting crop yields. In contrast to ozone, the limited temperature trends (Supplementary Fig. 1) exhibit no clear pattern on yields (Fig. 2e,f), and may be related to the protective effect of irrigation against crop damage from high temperature^{31,32}.

Although we have used longer records of agricultural production and temperature than prior studies, our analyses of crop responses to warming are generally consistent with studies that evaluated the effects of climate and ozone in isolation on perennial crop yields. For example, Lobell and Field¹¹ used data spanning 1980–2005 and also found that few of California's perennial crops showed damage due to warming. Earlier, Olszyk et al.³³ summarized the yield loss equations for California crop ozone exposure based on experimental field studies and found that grapes and hay were estimated to have yield losses from ozone greater than 5% and strawberries less than 5%, similar to the statistical results of this study. Olszyk et al.³³ had no air pollution response data to assess walnuts and nectarines, but noted that those crops were potentially at risk from ozone, a suggestion that is supported by this study's results.

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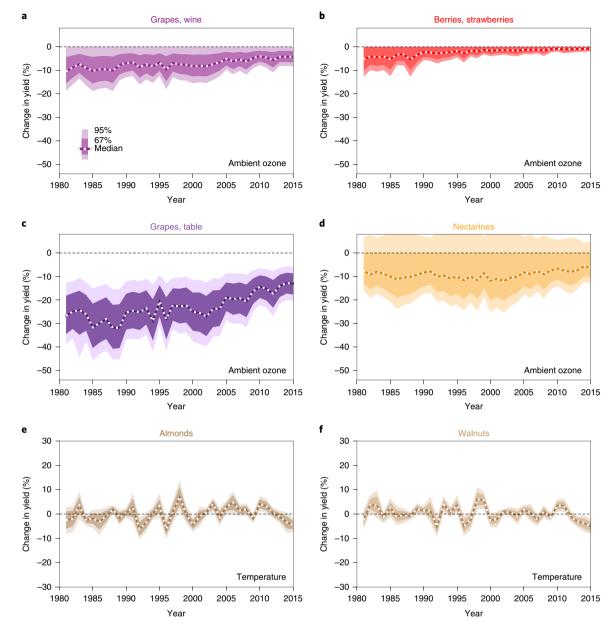


Fig. 2 | **Historical yield changes for selected perennial crops during 1980-2015. a-f**, Yield changes of six important perennial crops over the period from 1980 to 2015 due to changes in ambient ozone (**a-d**) and temperature (**e,f**). The dotted lines denote the median estimates, and the dark and light areas span the 67% and 95% CIs, respectively. The percentage reduction from ambient ozone was estimated from the difference between predictions using historical ozone levels (W126) and a hypothetical scenario with zero ozone (W126). The impact of historical climate trends on crop yields was estimated from the difference between predictions using historical temperature and a hypothetical scenario using the 1980-2015 average temperature, thus representing the impact of year-to-year temperature variability during 1980-2015. The 95% CIs of ozone damage for some crops extend to zero or positive values, indicating that ozone coefficients were shrunk to zero or positive values for some bootstrap replicates by the LASSO model.

Our findings are subject to several important caveats and limitations. First, we have reported large uncertainties associated with the modelled responses of crops to changes in temperature and ozone concentrations. To further evaluate uncertainties, we compare the results of our LASSO with those from stepwise regression. The stepwise results generally support the LASSO results. For most crops, the two models provided similar predictions, with overlapping CIs (Supplementary Fig. 9). The stepwise results showed that negative yield responses to ozone for wine grapes, strawberries, table grapes, hay and nectarines are all significant ($P \le 0.05$; Student's t-test). Although we find significant ozone damage for some crops (for example, table grapes), other crops show little response to ozone within the range of historical observations. We calculated ozone

cumulative indices over the warm season; additional regression using ozone cumulative indices over the whole year provided similar predictions (Supplementary Fig. 10). Second, like other statistical approaches, our results depend on the model specification. Our model includes time trends that control for technological changes and county fixed effects that control for cross-sectional differences in management and soil quality across the state. However, the model specification presented here ignores interactions between independent variables, such as the interactions between ozone and temperature, but supplementary analysis suggests that ozone–temperature interactions may not significantly alter the estimated yield responses (Supplementary Notes). We also assessed collinearity between independent variables such as ozone and temperature (Supplementary

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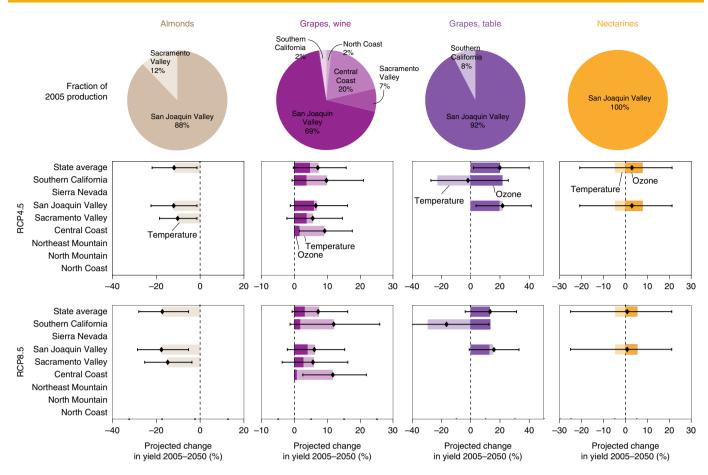


Fig. 3 | Projected percentage change in yields of selected crops by region 2005—2050. Future changes in yields in eight agricultural districts in California due to temperature and ozone concentration changes under RCP4.5 and RCP8.5. The top panels show the contributions to current production from eight agricultural districts (see Supplementary Fig. 2 for region definitions). The middle and bottom panels show the projected 2005—2050 percentage change in yield. The dark and light bars denote ozone and temperature effects (median estimates), respectively. The total yield change is plotted as points (median estimates), with error bars (95% CIs) calculated by bootstrapping the crop model 1,000 times.

Notes). Correlations between some of the variables indicate that our estimates of effects are not ideal, but the relationships are not strong enough to undermine our conclusions. We also focus our analysis of climate change on the temperature effects; other factors related to climate change, including the fertilization effect of future elevated atmospheric CO₂, are not investigated (past studies have highlighted the potential effects of warming on perennial crops in California¹¹). We also assessed uncertainties in model simulations, and found that our future projections are generally consistent with multi-model ensembles, and the warming we project is near the upper bounds (Supplementary Notes).

Agricultural adaptation efforts such as heat-tolerant and ozone-resistant crop varieties²⁴ may bring future gains in perennial crop production and warrant further investigation, although implementation may be challenging given the normally slow turnover of long-lived perennial crops. Even with these limitations, our results suggest that clean air policies have been an unheralded but particularly effective and practical option to secure perennial crop production, and that collaboration among agricultural policymakers, air quality managers and climate policymakers can thus help to ensure the future productivity of perennial crops in California in a changing climate.

Methods

County-level data in California. We use annual crop yields, harvested area, production and economic value data for 58 counties in California for the years 1980–2015 from the California County Agricultural Commissioners' reports²¹.

We analyse the 20 most valuable perennial crops in California: almonds, wine grapes, strawberries, table grapes, walnuts, hay, pistachios, navel oranges, raisin grapes, lemons, avocados, cherries, freestone peaches, nectarines, Valencia oranges, plums, dried plums, clingstone peaches, grapefruit and bushberries11. These crops represent an average total production value of US\$23.0 billion per year over the period of 2011-2015, accounting for more than 70% of the production value of all perennial crops in California²¹. The relationships of agricultural production, climate and ozone are analysed using historical climate and ozone data. The monthly average of the daily maximum temperature (T_{MAX}) and the monthly total precipitation (PRCP) at 379 stations in California are obtained from the National Weather Service Cooperative Network, Hourly ozone data at 190 sites in California from the Environmental Protection Agency's Air Quality System34 are used to calculate three widely used ozone cumulative indices designed to reflect ozone exposures on plants (that is, W126, AOT40 and SUM06)8,24. W126 is a cumulative indicator of hourly ozone concentrations weighted by a sigmoidal scale. AOT40 and SUM06 are cumulative indicators of hourly ozone concentrations exceeding 0.04 ppm and 0.06 ppm thresholds, respectively. They are calculated as:

$$W126 = \sum_{h=1}^{n} \left(O_h \times \frac{1}{1 + 4,403 \times e^{-126 \times O_h}} \right)$$

$$AOT40 = \sum_{h=1}^{n} C_h \text{ where } C_h = \begin{cases} O_h - 0.04, & O_h > 0.04 \\ 0, & O_h \le 0.04 \end{cases}$$

$$SUM06 = \sum_{h=1}^{n} C_h \text{ where } C_h = \begin{cases} O_h, & O_h > 0.06 \\ 0, & O_h \le 0.06 \end{cases}$$

where O_n is the hourly ozone concentration in ppm for hour h during daylight hours (8:00–19:59), and n is the total number of hours within a period. The ozone cumulative indices are cumulated over the warm season (March to August) when ozone levels are the highest and plant growth is more likely to be affected. To adjust for missing hourly observations, similar to the correction approach suggested by the US Environmental Protection Agency³⁵, we sum the cumulative indices over the reporting hours, divide by the number of reported hours and then multiply by the

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total number of daylight hours within the period. To be comparable with crop data at the county level, data for sites adjacent to cropland areas within each county were averaged to produce county-wide averages. The cropland map obtained from the US Department of Agriculture National Agricultural Statistics Service³⁶ was used to limit the observations to relevant agriculture areas. Counties with less than 20 yr of data are excluded from the analysis.

Statistical yield models. On the basis of the historical data, we develop statistical yield models for each crop using the following linear regression model:

$$\begin{aligned} \text{yield}_{yi} &= \beta_o \times \text{OI}_{yi} + \sum_{s=1}^{4} \left(\beta_{T,s} \times T_{\text{MAX},syi} + \beta_{T2,s} \times T_{\text{MAX},syi}^2 \right. \\ &+ \beta_{P,s} \times \text{PRCP}_{syi} + \beta_{P2,s} \times \text{PRCP}_{syi}^2 \right) + \beta_{CY,i} \times \text{year}_y + \beta_{C,i} \end{aligned}$$

where OI is one of the three warm-season ozone cumulative indices (in units of ppm h); $T_{\text{MAX svi}}$ and PRCP svi here are seasonal mean of daily maximum temperature (°C) and seasonal total precipitation (mm), respectively; the subscripts y, i and s are indices for year, county and season, respectively, such that $T_{\text{MAX},\text{syi}}$ is T_{MAX} in season sof year y in county i; β_o , β_T , β_{T2} , β_{P2} , β_{P2} , β_{CY} and β_C are regression coefficients. Similar to a previous study of the temperature sensitivity of California perennials¹¹, for each harvest year we consider weather variables from the September prior to the harvest year to the August of the harvest year to account for different seasonal influences. We use seasonal average weather variables instead of monthly variables in the model to avoid too many predictor variables and thus overfitting. The four seasons are defined as autumn (September-November), winter (December-February), spring (March-May) and summer (June-August). The county-specific time trend (represented by the year term) accounts for changes in agronomic practices over time that influence yields. County fixed effects account for time-invariant factors that vary across counties, such as differences in soil quality. Similar crop models have been used in previous studies of ozone and climate^{8,11}

We use the LASSO³⁷ regression method to fit the regression model, in which predictors are chosen in an automatic manner (using the 'lars' package in R) that is thus independent from researcher choice. The LASSO method selects a subset of predictors that explain most of the variation in outcomes by shrinking the regression coefficient towards zero, avoiding the statistical penalties of including irrelevant predictors, and is thought to improve prediction accuracy. We then perform an out-of-sample cross-validation as a robustness check, using two-thirds of the data for training (that is, model calibration), and the other one-third for testing. We compute determination coefficients (R^2) between actual and predicted yields for both the training and test data. Models in which the test R^2 was significantly lower than the training R^2 indicate the risk of overfitting. CIs of R^2 are derived from 1,000 repeated tests with a random one-third of observations omitted.

On the basis of temperature and ozone sensitivities given by the statistical yield model, we then determine the crop yield responses as percentage changes in yields. We first estimate the overall yield response to warming as the percentage difference between predictions using historical temperature and a scenario with a uniform 2°C warming (an approximation for the magnitude of warming by 2050). Next, the impact of historical climate trends on crop yields is estimated from the difference between predictions using historical temperature and a hypothetical scenario using the 1980-2015 average temperature, to evaluate the impact of year-to-year temperature variability during 1980-2015. Similarly to Lobell and Field11, we also found small sensitivities to precipitation for many crops, presumably because most crops are irrigated¹². Given the small sensitivities and large uncertainties in precipitation projections^{9,12}, we focus our analysis of climate change on the temperature effects. The yield effect of ambient ozone is estimated from the percentage differences between predictions using historical ozone levels and a hypothetical scenario with zero ozone (which has been used in other studies)³ To get state-wide average yields, yields are weighted by the harvested area of each crop in each county. To analyse regional differences, we also gathered counties into eight agricultural districts. The definition of agricultural districts is consistent with the California County Agricultural Commissioners' reports (Supplementary Fig. 2).

Finally, to determine the CIs related to these estimates, we use the bootstrapping method. It is produce distributions by using a set of crop models generated from resampling (with replacement) the observations 1,000 times, and the 2.5th and 97.5th percentiles from the 1,000 bootstrap replicates are selected as 95% CIs. By selecting new predictors for each replicate, the bootstrapping method accounts for uncertainties in model formulation.

Future projections. On the basis of the crop models we developed, we combine historical sensitivities with future projections of ozone and climate to assess their potential impacts on yields to 2050. The future projections assume no new adaptation between now and then, or holding technology equivalent to current levels (2001–2010), so that the effects of changes in ozone levels and climate on future yields can be isolated. Two RCP scenarios (RCP4.5 and RCP8.5) are used to represent a range of policy options regarding ozone regulation and climate adaptation. RCP8.5 represents a business-as-usual scenario in which mean global temperatures increase by >4 °C (ref. 26), while RCP4.5 represents a mitigation scenario with moderate ozone regulation that is likely to limit the increase of mean global temperature to ~3 °C (ref. 27).

We use decadal projections of regional air quality and climate over the US for current (2001-2010) and future (2046-2055) decades at a 36-km resolution simulated by the Weather Research and Forecasting Model with Chemistry (WRF/ Chem)30,39, downscaled from the North Carolina State University's version of the Community Earth System Model (CESM_NCSU)40-42. Future predicted air quality takes changes in both emissions and climate into account. The gridded data are aggregated to the county level by calculating the average of all the grids classified as cropland areas within each county. Climate and air quality data are bias-corrected to ensure that they are consistent with the observations used in model calibration. For the climate data, following Bruyère et al.43, seasonal mean biases between simulations and observations by county are calculated and then subtracted from the original simulations for both current and future years to generate the biascorrected data. We corrected the simulated ozone exposures in each county by multiplying the ratio of observed/simulated ozone levels in current years as has been done in previous similar studies4. The simulated data at county level are combined with statistical yield models to predict yields of each county, assuming the current technology. State-average yields are calculated by assuming the current crop area distribution. To obtain CIs related to crop model uncertainty, the yield projections are repeated 1,000 times by using a set of crop models generated from bootstrap samples of historical observation data.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All historical data used are publicly available and open access, with the data sources listed in the Methods. The other data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability

The LASSO regression was conducted by using the lars 1.2 package in R, which is available at https://CRAN.R-project.org/package=lars.

Received: 23 May 2019; Accepted: 31 January 2020;

Published online: 16 March 2020

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Acknowledgements

C.H., Y.Q., A.A., J.A.B., F.C.M. and S.J.D. were supported by the US National Science Foundation (NSF) and the US Department of Agriculture (INFEWS grant EAR 1639318); D.T. was supported by NASA's IDS programme (80NSSC17K0416). We acknowledge helpful discussions with D. B. Lobell. WRF/Chem outputs were generated under the US NSF EASM Program (AGS-1049200). WRF/Chem simulations were performed and processed under high-performance computing support from Yellowstone (ark:/85065/d7wd3xhc; https://www2.cisl.ucar.edu/supercomputer/yellowstone) provided by NCAR's Computational and Information Systems Laboratory, sponsored by the NSF, and the national supercomputer TACC/NSF STAMPEDE2, provided as an Extreme Science and Engineering Discovery Environment digital service by the Texas Advanced Computing Center (http://www.tacc.utexas.edu), which is supported by NSF grant number aci-1053575.

Author contributions

S.J.D., N.D.M. and C.H. designed the study. C.H. performed the analyses, with support from Y.Z. on datasets and S.J.D., N.D.M., J.A.B., A.A., F.C.M., Y.Q. and D.T. on analytical approaches. C.H. and S.J.D. led the writing with input from all co-authors.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s43016-020-0043-8.

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Last updated by author(s):	Dec 17, 2019

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The manuscript contains the following data availability statement - "All historical data used are publicly available and open access, with the data sources listed in Methods. The other data that support the findings of this study are available from the corresponding author upon reasonable request."

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- 1. Crop yield, harvested area, production and economic value data were obtained from the California County Agricultural Commissioners' reports (https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php).
- 2. Historical climate data at 379 stations in California were obtained from the National Weather Service Cooperative Network (https://www.ncei.noaa.gov/data/).
- 3. Historical ozone data at 190 sites in California were obtained from the EPA's Air Quality System (https://aqs.epa.gov/aqsweb/airdata/download_files.html).
- 4. Cropland map was obtained from the USDA-NASS Cropland Data Layer (https://www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php).
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Study description	We use a panel regression analysis of historical crop yields and exposures from 1980 to 2015 to estimate the sensitivities of a suite of perennial crops to ozone and temperature. County-level ozone exposure (i.e., W126, AOT40 and SUM06), seasonal average of maximum temperature and precipitation from 1980 to 2015 were used in a regression model to determine their effects on yields of perennial crops.				
Research sample	The research sample is historical yield, ozone and weather observations in each county in California in each year. The main advantage of using county data is that it provides more data points and a wider range of ozone and temperature than looking at the statewide average.				
Sampling strategy	To include as many samples as possible, all the valid county-year observations in 58 counties in California during 1980-2015 were used for the regression. We also performed an out-of-sample cross validation as a robustness check, and used bootstrap resampling to determine the confidence intervals related to our estimates.				
Data collection	Annual crop yields data for each county in California for the years 1980-2015 were obtained from the California County Agricultural Commissioners' reports. Monthly average of daily maximum temperature and monthly total precipitation at 379 stations in California were obtained from the NWS (National Weather Service) Cooperative Network. Hourly ozone data at 190 sites in California were obtained from the EPA's Air Quality System.				
Timing and spatial scale	Timing scale: each year from 1980 to 2015, the same as the reporting years of county statistics. Spatial scale: county level in California. To be comparable with crop yield data at the county level, ozone and weather data for sites adjacent to cropland areas within each county were averaged to produce countywide averages.				
Data exclusions	To include a sufficiently long period, counties with less than 20 years of observations are excluded from the analysis. Extreme outliers and large jumps were identified and removed from the time series of yield, ozone and climate data by county, which may reflect aberrations in data quality or abnormal factors that the model cannot explain.				
Reproducibility	We rerun the regression model with bootstrapping methods, and got very similar estimates and confidence intervals. All attempts to repeat the experiment were successful.				
Randomization	To determine the confidence intervals related to our estimates, we use the bootstrapping method to produce distributions by using a set of crop models generated from resampling (with replacement) the observations 1000 times, and the 2.5th and 97.5th percentiles from the 1000 bootstrap replicates are selected as 95% CIs. By selecting new predictors for each replicate, the bootstrapping method accounts for uncertainties in model formulation.				
Blinding	We used historical records, so blinding was not relevant to this study.				
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