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Estimating global agricultural effects of geoengineering using volcanic eruptions

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I. SUPPLEMENTARY INFORMATION

Our analysis has three goals: to estimate the impact of SSAs on the quantity and quality of insolation, to estimate the impact of these changes in insolation on yields, and to estimate the total effect of changes in SSAs on yields in an SRM scenario. We discuss the estimation of these three responses, as well as the data used in the analysis, in the four supplementary information sections below.

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I. Data

This section describes and discusses the datasets used in this analysis.

I.1 Insolation

The World Radiation Data Centre (WRDC) provides daily insolation data from 1953 to 2013 [9]. Beginning with the entirety of their records ($N = 8,394,737$), we removed all data that either had missing total radiation values, was flagged as poor quality by the WRDC, or had higher reported diffuse radiation than total radiation ($N = 7,334,570$). In our main sample from 1983-2009 there are 3,311,553 observations from 859 stations of total insolation; of these, 889,327 observations from 324 stations split the total insolation measurements into direct and diffuse light.

I.2 Yield

The Food and Agricultural Organization of the United Nations Statistics Division provides annual country-level yields of corn, soybeans, rice and wheat [22]. These four crops make up roughly half of global caloric consumption. We included only countries that have no missing observations from 1983-2009 to balance the panel; notably, this drops countries created or dismantled by the break up of the Soviet Union in 1991. The cleaned panel contains data for maize, soy, rice and wheat in 100, 50, 61 and 80 countries, respectively (Extended Data Fig. 1).

I.3 Growing season and cropped fraction

We obtained global crop planting and harvesting dates from Sacks et. al. 2010 [32]. We obtained cropped area fraction (all agricultural land and crop-specific) data from Ramankutty et. al. 2008 [31] and Monfreda et. al. 2008 [39].

I.4 Stratospheric aerosol optical depth

We measure SSA concentrations using optical depth. Optical depth is a measure of opacity, defined as the natural logarithm of the ratio of incoming to transmitted direct light at a given wavelength:

$$\text{optical depth} = \ln \left(\frac{\text{incident direct light}}{\text{transmitted direct light}} \right) \quad (1)$$

We use three SAOD datasets in this analysis that share many similarities, but differ in the observations included in the analysis, the way they were processed, and the wavelength at which optical depth is measured.

For our main analysis we use the Goddard Institute for Space Studies (GISS) dataset, which is an updated version of the data presented in ref [10].¹ This dataset provides global SAOD (550nm) from 1850-2012 at 5 degree latitudinal resolution. We use the GISS dataset as our preferred specification because it measures SAOD at 550 nm, which is at the center of the photosynthetically active range (400-700nm) and is the same wavelength as the SAOD applied in the G3 SRM scenario

¹Data available at <http://data.giss.nasa.gov/modelforce/strataer/>; accessed 8/8/16.

that we use to calculate the total effect of SSAs on yields. For the time period of our study (1979-2009), the GISS dataset incorporates observations from satellites (Stratospheric Aerosol and Gas Experiment (SAGE) I, SAGE II, Stratospheric Aerosol Measurement II) as well as aircraft, ground-based observations and balloon measurements.

We corroborate our main findings by using two additional SAOD datasets that measure optical depth at 1000 nm. These datasets are interpolated using similar methods and from similar data as the GISS dataset, but measure SAOD at a different wavelength and have different spatial resolutions and temporal extents. The first, produced by the Stratospheric Processes and their Role in Climate (SPARC) report [24], spans both the El Chichón and Pinatubo eruptions (available 1979-2003) but has only latitudinal resolution (5 degree, the same as GISS). The second, produced using a similar methodology to the SPARC dataset and which we call SPARC2² spans only Pinatubo (Oct 1984 - July 2005) but is interpolated to give both latitudinal and longitudinal spatial resolution (5 x 15 degrees).

All three SAOD datasets used in our analysis combine observations from many sources because of important gaps in the satellite record. The primary gaps in the SAGE record are between November 1981 and October 1984, when there were no satellite observations of stratospheric aerosols and during the Mount Pinatubo eruption (June 1991 to 1993) when the instruments on SAGE II were saturated by the unanticipated density of particulate matter in the stratosphere. Though these gaps in the satellite record were filled and re-calibrated using non-satellite observations, they present an unavoidable source of measurement error. Measurement of SAOD before the satellite era is very coarse. Further, because there were no low-latitude observing satellites during the Chichón eruption, measurement following the Chichón eruption was much less precise and accurate than after the Pinatubo eruption. The poor observation of the Chichón eruption is why we focus our analysis on the Pinatubo eruption.

1.5 Climate variables

Our analysis uses historical temperature, precipitation, and cloud data as controls in our empirical estimation of the insolation effect. The Berkeley Earth Daily Land gridded dataset provides daily average surface temperature values from 1880 to present at 1-degree resolution [35]. The University of Delaware Air Temperature and Precipitation dataset provides monthly total precipitation over land (mm/month) from 1900 to 2010 at 0.5-degree resolution [36]. The International Satellite Cloud Climatology Project (ISCCP) gridded cloud product (D1) dataset contains 202 remotely sensed cloud parameters every 3 hours on a global 280 km equal area grid from July 1983 to December 2009 [34]. We use two versions of this dataset in our statistical estimation. Our analysis of SSA impacts on yields uses a *monthly* cloud fraction dataset that was corrected for artefacts in the data [37]. Our analysis of SSA impacts on insolation uses the *3-hourly* cloud fraction records directly, which we average to daily temporal resolution (excluding nighttime observations). For our analysis of yields we use the corrected monthly observations because the outcome is annual, so having daily cloud resolution does not provide benefits relative to monthly averages.

²Acquired through personal communication with the author of the SPARC Assessment of Stratospheric Aerosol Properties (Chapter 4) report, Larry Thomason (07/10/2015).

II. Insolation response

A central contribution of this study is to document the impact of SSAs on insolation at a global scale and to test how these changes in insolation impact yields. In this section we describe how we empirically estimate the effect of SSAs on insolation.

II.1 Estimating the impact of SSAs on insolation

To identify the impact of SSAs on insolation (Extended Data Table [1](#)) at station i on day τ we estimate:

$$\ln(I_{i\tau}^X) = \psi S_{im} + \eta C_{i\tau} + \theta_1 E_y + \theta_2 E_{y-1} + \phi_{id} + \epsilon_{i\tau} \quad (2)$$

Where I^X is either direct (I^D), diffuse (I^F) or total (I^T) insolation, m is month of sample, y is year of sample, and d is day of year. S_{im} are monthly SAOD measurements, $C_{i\tau}$ are daily observations of cloud fraction, and E_y and E_{y-1} are current and lagged values of the average monthly Niño 3.4 index (E) from May-December [\[38\]](#). The parameter of interest is ψ , which describes the effect of SAOD on insolation. The low temporal resolution of our SAOD measurements is a source of measurement error which could attenuate our estimated coefficients towards zero. We include station-by-day-of-year fixed effects (ϕ_{id}) to non-parametrically control for all time-invariant differences between stations, such as average tropospheric aerosol optical depth, and for location-specific seasonal patterns within each location, such as dust storms in the summer or smog from heating in the winter. Any remaining variation in surface insolation that is affected by tropospheric aerosols is assumed to be orthogonal to overhead SAOD variations (measured predominately by the SAGE II satellites) and thus captured by the disturbance term ($\epsilon_{i\tau}$), which is averaged out of the conditional expectation function. Such idiosyncratic changes in insolation might be caused by, for example, the one-time closure (or opening) of a coal power plant near an insolation station. As long as these types of human-caused events are not systematically correlated with SAOD throughout our sample, both over time and coherently around the world, then our estimated effect of SAOD on insolation, ψ , will be unbiased. In this model ψ is identified by comparing SAOD and insolation measurements across years within a station-day-of-year (e.g. insolation and SAOD on March 1, 1990 in Berkeley, CA, USA is compared to insolation and SAOD on March 1 1991 in Berkeley, CA, USA), after accounting for local cloud cover and the global ENSO state. We compute standard errors allowing for arbitrary patterns of serial correlation over time between all stations in the same country and for arbitrary patterns of autocorrelation across all station observations within the same year [\[23\]](#). In cases where the estimated variance-covariance matrix is non-positive semi-definite, we apply the adjustment from Cameron, Gelbach & Miller [\[40\]](#).

To compare the response of insolation to SSAs from the eruptions of El Chichón and Pinatubo (Extended Data Table [1](#) Cols. 3,6,9) we make two changes to the model. We replace $\psi S_{i\tau}$ with $\psi_{Chichon} S_{i\tau} \mathbb{1}(\tau \in [1979, 1989]) + \psi_{Pinatubo} S_{i\tau} \mathbb{1}(t \in [1990, 2009])$, which allows the effect of SSAs on insolation, ψ , to be different for the El Chichón and Pinatubo eruptions. $\mathbb{1}(\cdot)$ is an indicator function which equals 1 if the day-of-sample is within the specified years and 0 otherwise. We drop cloud controls because the cloud data are available beginning in 1983, which is after the El

Chichón eruption.

This analysis captures the average effect of SAOD on all-sky surface insolation across 859 stations (Fig. 1d). Using a global sample of stations enables us to average over local heterogeneity in the effect of SAOD due to interactions of SAOD scattering with further scattering and absorption by clouds or tropospheric aerosols. Though the higher density of insolation stations in northern latitudes and near urban centers means that our estimates are most representative of these areas, this global analysis is substantially more representative than previous studies, which have been limited to a few individual stations [41, 11].

This large sample of insolation stations also allows us to tease out the relatively small SAOD signal from substantial background noise due to clouds and tropospheric aerosols. This enables us to calculate the effect during all days—the crop-relevant effect—rather than limiting our analysis to clear-sky and minimally cloudy days, as previous analyses of individual stations have done [41, 11].

II.2 Estimating the impact of SSAs on atmospheric forward scattering

We define w as the proportion of light that makes it to the surface after being scattered:

$$w = Pr(\text{photon reaches the surface} | \text{photon interacts with any particle}) = \frac{I^F}{I^F + I^R} = \frac{I^F}{I^0 - I^D} \quad (3)$$

Where the third equality uses the identity that top of atmosphere insolation (I^0) is the sum of direct, diffuse, and reflected or absorbed light (I^R):

$$I^0 = I^D + I^F + I^R$$

Thus, w can be calculated using data on I^F (measured), I^D (measured), and I^0 (calculated as a function of latitude, longitude, and date). Rearranging Eqn. 3 shows that w measures how much diffuse light is gained from the loss of one unit of direct light:

$$I_{i\tau}^F = w \underbrace{\left[I_{i\tau}^0 - I_{i\tau}^D \right]}_{\text{blocked insolation}} \quad (4)$$

In our sample, w is on average 0.32 meaning that about one third of insolation that does not make it to the surface as direct radiation ends up making it to the surface as diffuse radiation.

To estimate the effect of SSAs on w (Extended Data Table 3) we estimate:

$$w_{i\tau} = \alpha S_{im} + \eta C_{i\tau} + \theta_1 E_y + \theta_2 E_{y-1} + \phi_{id} + \epsilon_{i\tau} \quad (5)$$

The coefficient α describes the impact of a one unit increase in SAOD on the forward scattering probability (w) of the entire atmospheric column. The other parameters in Eqn. 5 are defined in the same way as in Eqn. 2. We model heterogeneous effects of SSAs on w across volcanic eruptions (Extended Data Table 3 Col. 3) in the same way that we model heterogeneous effects of SSAs on

insolation across eruptions, which is described in the previous section.

III. Agricultural response

In this section we present a framework for empirically estimating the insolation effect and the total effect of SSAs on yields.

III.1 Empirical framework

We consider a situation where yield (Y) is a function of inputs: insolation (I), temperature (T), precipitation (P), cloud fraction (C), and other unobservable variables (U) such as labor supply, or surface ozone concentration. Indexing observations by country i and year t we have:

$$Y_{it} = Y(T_{it}, P_{it}, C_{it}, I_{it}, U_{it}) \quad (6)$$

A challenge in this context is that these inputs are themselves functions of SSAs (S), ENSO (E), and other factors (Z):

$$T_{it} = T(E_t, S_{it}, Z_{it}) \quad (7)$$

$$P_{it} = P(E_t, S_{it}, Z_{it}) \quad (8)$$

$$C_{it} = C(E_t, S_{it}, Z_{it}) \quad (9)$$

$$I_{it} = I(E_t, S_{it}, Z_{it}) \quad (10)$$

$$U_{it} = U(E_t, S_{it}, Z_{it}) \quad (11)$$

We discuss ENSO explicitly because the eruptions of both El Chichón and Pinatubo coincided to some degree with strong El Niño events, which could confound our estimation of the SSA insolation effect, and thus total effect, if not appropriately controlled for. ENSO is a global phenomenon so E_t itself does not vary by location; though its impacts on T , P , C , I and U , and in turn on Y , may vary across space (Supplementary Information [III.2](#), [III.3](#)).

To consider the impacts of SSAs on yield, we differentiate Y (Eqn. [6](#)) with respect to S , which decomposes the effect of SSAs into an insolation term, a temperature term, a precipitation term, a cloud term, and a term capturing any residual effects of SSAs:

$$\frac{dY}{dS} = \underbrace{\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S}}_{\text{insolation effect}} + \underbrace{\frac{\partial Y}{\partial T} \frac{\partial T}{\partial S}}_{\text{temperature effect}} + \underbrace{\frac{\partial Y}{\partial P} \frac{\partial P}{\partial S}}_{\text{precipitation effect}} + \underbrace{\frac{\partial Y}{\partial C} \frac{\partial C}{\partial S}}_{\text{cloud effect}} + \underbrace{\frac{\partial Y}{\partial U} \frac{\partial U}{\partial S}}_{\text{residual effect}} \quad (12)$$

Ideally, to empirically recover the insolation effect ($\frac{\partial Y}{\partial I}$) and the total effect ($\frac{dY}{dS}$) we would observe the changes in these climatic, insolation, and residual variables due to SSAs (i.e. $\frac{\partial I}{\partial S}$, $\frac{\partial T}{\partial S}$, $\frac{\partial P}{\partial S}$, $\frac{\partial C}{\partial S}$, $\frac{\partial U}{\partial S}$), but we cannot measure these directly. What we are able to observe instead is how some of these variables and SSAs change over time (i.e. $\frac{\partial S}{\partial t}$, $\frac{\partial T}{\partial t}$, $\frac{\partial P}{\partial t}$, $\frac{\partial C}{\partial t}$). To see how these observations are

useful, we differentiate our original yield equation (Eqn. 6) with respect to time to get:

$$\frac{dY}{dt} = \frac{\partial Y}{\partial T} \frac{dT}{dt} + \frac{\partial Y}{\partial P} \frac{dP}{dt} + \frac{\partial Y}{\partial C} \frac{dC}{dt} + \frac{\partial Y}{\partial I} \frac{dI}{dt} + \frac{\partial Y}{\partial U} \frac{dU}{dt} \quad (13)$$

Changes in yield over time are the combined effect of changes over time due to each input. Differentiating the climate, insolation, and residual equations (Eqns. 7-11) with respect to time and then substituting into Eqn. 13 gives the change in yield over time due to changes over time in the factors that determine each input.

$$\begin{aligned} \frac{dY}{dt} = & \frac{\partial Y}{\partial T} \underbrace{\left[\frac{\partial T}{\partial E} \frac{dE}{dt} + \frac{\partial T}{\partial S} \frac{dS}{dt} + \frac{\partial T}{\partial Z} \frac{dZ}{dt} \right]}_{\frac{dT}{dt}} + \frac{\partial Y}{\partial P} \underbrace{\left[\frac{\partial P}{\partial E} \frac{dE}{dt} + \frac{\partial P}{\partial S} \frac{dS}{dt} + \frac{\partial P}{\partial Z} \frac{dZ}{dt} \right]}_{\frac{dP}{dt}} \\ & + \frac{\partial Y}{\partial C} \underbrace{\left[\frac{\partial C}{\partial E} \frac{dE}{dt} + \frac{\partial C}{\partial S} \frac{dS}{dt} + \frac{\partial C}{\partial Z} \frac{dZ}{dt} \right]}_{\frac{dC}{dt}} + \frac{\partial Y}{\partial I} \underbrace{\left[\frac{\partial I}{\partial E} \frac{dE}{dt} + \frac{\partial I}{\partial S} \frac{dS}{dt} + \frac{\partial I}{\partial Z} \frac{dZ}{dt} \right]}_{\frac{dI}{dt}} \\ & + \frac{\partial Y}{\partial U} \underbrace{\left[\frac{\partial U}{\partial E} \frac{dE}{dt} + \frac{\partial U}{\partial S} \frac{dS}{dt} + \frac{\partial U}{\partial Z} \frac{dZ}{dt} \right]}_{\frac{dU}{dt}} \end{aligned} \quad (14)$$

Because we observe and are able to control for them directly, we condense the $\frac{dT}{dt}$, $\frac{dP}{dt}$, and $\frac{dC}{dt}$ terms:

$$\frac{dY}{dt} = \frac{\partial Y}{\partial T} \frac{dT}{dt} + \frac{\partial Y}{\partial P} \frac{dP}{dt} + \frac{\partial Y}{\partial C} \frac{dC}{dt} + \frac{\partial Y}{\partial I} \left[\frac{\partial I}{\partial E} \frac{dE}{dt} + \frac{\partial I}{\partial S} \frac{dS}{dt} + \frac{\partial I}{\partial Z} \frac{dZ}{dt} \right] + \frac{\partial Y}{\partial U} \left[\frac{\partial U}{\partial E} \frac{dE}{dt} + \frac{\partial U}{\partial S} \frac{dS}{dt} + \frac{\partial U}{\partial Z} \frac{dZ}{dt} \right]$$

Re-arranging further shows the terms that will be represented directly in our empirical model:

$$\begin{aligned} \frac{dY}{dt} = & \underbrace{\frac{\partial Y}{\partial T} \frac{dT}{dt}}_{\frac{\partial}{\partial T} f_T(\cdot)} + \underbrace{\frac{\partial Y}{\partial P} \frac{dP}{dt}}_{\frac{\partial}{\partial P} f_P(\cdot)} + \underbrace{\frac{\partial Y}{\partial C} \frac{dC}{dt}}_{\frac{\partial}{\partial C} f_C(\cdot)} \\ & + \underbrace{\left[\frac{\partial Y}{\partial I} \frac{\partial I}{\partial E} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial E} \right] \frac{dE}{dt}}_{\frac{\partial}{\partial E} g(E)} + \underbrace{\left[\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial S} \right] \frac{dS}{dt}}_{\beta} + \underbrace{\left[\frac{\partial Y}{\partial I} \frac{\partial I}{\partial Z} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial Z} \right] \frac{dZ}{dt}}_{\epsilon} \end{aligned} \quad (15)$$

Observed quantities are in bold. Quantities estimated in our empirical model, discussed in the following section, are shown in underbraces.

III.2 Empirical model

We estimate the structure of Eqn. 15 to recover the insolation-mediated impact of SSAs on yields ($\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S}$) (Fig. 3 Model 1, Extended Data Table 1) in country i year t by fitting the model:

$$\ln(Y_{it}) = f_T(T_{it}) + f_P(P_{it}) + f_C(C_{it}) + g(E_t, E_{t-1}, i) + \beta S_{it} + \lambda_i + \phi_{i1}t + \phi_{i2}t^2 + \epsilon_{it}. \quad (16)$$

β is the insolation-mediated effect of SSAs on yields and is the coefficient of interest in our study. It captures both the impact of decreasing total radiation and increasing the diffuse fraction, as well as any residual impacts of SSAs not mediated through T, P , or C (i.e. $\frac{\partial Y}{\partial U} \frac{\partial U}{\partial S}$), if they exist. Y_{it} are yields of either maize, wheat, soy, or rice. $f_T(\cdot), f_P(\cdot)$, and $f_C(\cdot)$ are restricted cubic splines which allow for estimation of a flexible response [42]. λ_i are country fixed effects which account for all time invariant differences between countries, such as topography or cultural history. $\phi_{i1}t + \phi_{i2}t^2$ are country-specific quadratic time-trends which control for gradual country-specific developments, such as smooth changes in technology or income.³[23].

$g(\cdot)$, defined as

$$g = (\theta_1 E_t + \theta_2 E_{t-1})\mathbb{1}(i \in \text{tele}) + (\theta_3 E_t + \theta_4 E_{t-1})\mathbb{1}(i \notin \text{tele}), \quad (17)$$

controls for current and lagged values of the average monthly Niño 3.4 index (E) from May-December, and allows the responses of teleconnected regions to differ from those of non-teleconnected regions [38]. $\mathbb{1}$ is an indicator function, so $\mathbb{1}(i \in \text{tele}) = 1$ if country i is teleconnected and 0 otherwise. ϵ_{it} captures factors that impact yield, and vary over time within a country but are not captured by the quadratic country-specific time trend or the climate controls, and are uncorrelated with SAOD, such as the price of oil. In all yield regressions we compute our standard errors allowing for arbitrary patterns of serial correlation within countries over time and for arbitrary patterns of autocorrelation within years across countries [23]. In cases where the estimated variance-covariance matrix is non-positive semi-definite, we apply the adjustment from Cameron, Gelbach & Miller [40]. We model the impact of SAOD on yields linearly because flexible estimation of the response suggests that a linear fit is appropriate over the support of SAOD values observed during the eruptions of El Chichón and Pinatubo as well as those used in the SRM projections (Extended Data Fig. 3).

III.2.1 Pooled C3 response Soy, rice and wheat share the same metabolic pathway for carbon fixation and thus their yields may respond similarly to changes in sunlight induced by SSAs. To estimate a pooled insolation effect for these C3 crops (Fig. 3| Extended Data Table 2) we fit the model:

$$\ln(Y_{itj}) = \beta_{C3} S_{itj} + f_{Tj}(T_{itj}) + f_{Pj}(P_{itj}) + f_{Cj}(C_{itj}) + g_j(E_t, E_{t-1}, i) + \lambda_{ij} + \phi_{i1j}t + \phi_{i2j}t^2 + \epsilon_{itj} \quad (18)$$

where j indexes crop (soy, rice, wheat). This is the same model as for individual crops except that here, changes in SSAs, and in turn insolation, are assumed to have a common effect (β_{C3})

³Controlling for spatial-unit-specific polynomial time trends is a commonly used approach to account for gradual changes in yields, such as those driven by adoption of new technology. Though aggregation up to the national level will likely smooth out changes that are discontinuous at the local level, some abrupt or discontinuous changes in national crop production technologies will not be accounted for by these polynomial trends. Directly measuring and accounting for each change in agricultural technology is not possible. Thus, instead, to address these unobserved variables we leverage the notion that SSA concentrations were as good as randomly assigned by the unanticipated eruptions of El Chichón and Pinatubo to obtain an unbiased estimate of the impact of SSAs on yields, despite the potential presence of these omitted variables. With this strategy, in order for a discontinuous change in technology to bias our estimated effects of SSAs, it would need to be the case that technology all around the world changed abruptly, discontinuously, and coherently at the time of these eruptions. Given the gradual nature of agricultural technological diffusion, we do not find this plausible. See Supplementary Information III.3 for an in-depth discussion of identification.

across all C3 crops. Temperature effects, precipitation effects, cloud effects, ENSO effects and time trends are still allowed to be crop-specific. $g_j(\cdot)$ shares the same form as Eqn. 17 for each crop j . Thus, all parameters other than β_{C3} are estimated ‘as if’ individual versions of Eqn. 16 were estimated for each crop.

III.2.2 Heterogeneous effects across eruptions To compare the response of crops to the eruptions of El Chichón and Pinatubo (Fig 3a Models 7-8) we make two changes to Eqn. 16. We replace βS_{it} with $\beta_{Chichon} S_{it} \mathbb{1}(t \in [1979, 1989]) + \beta_{Pinatubo} S_{it} \mathbb{1}(t \in [1990, 2003])$, which allows the estimated insolation effect to differ across the two eruptions. We also drop cloud controls because the cloud data are only available beginning in 1983 (after the El Chichón eruption). We similarly alter Eqn. 18 to allow the C3 insolation effect to vary across the two eruptions.

III.2.3 Leads and lags To estimate the effect of SSAs in years prior to and after the current growing season on the current growing season’s yield (Fig 3d) we use the same form as Eqn. 16 and include two years of lags and leads for SAOD, temperature, precipitation, cloud fraction and ENSO into the model.⁴ Coefficients for leads, lags and the contemporaneous effects are estimated simultaneously.

III.3 Identification strategy

Our experimental design and model specification address three main challenges to empirically estimating the insolation effect of SSAs on yields. First, the countries most heavily treated with SSAs (e.g. those in the tropics) may have different average yields than those that were less heavily treated. Second, there may be time-varying factors that are correlated with SSA exposure and affect yield. Third, in addition to affecting yields by changing sunlight, SSAs may affect yields by altering a variety of other yield inputs including temperature, precipitation, and cloud cover (as expressed in Eqn. 14).

Our fixed-effects panel estimation strategy estimates the impact of SSAs on yields by comparing countries to themselves over time with varying exposure to SSAs. This is achieved by including an indicator variable for each country in the model, which accounts for all time-invariant differences between countries. We identify the insolation effect using the remaining variation in yields and SSAs within individual countries over time. We also account for time-trending differences between countries using country-specific quadratic time trends.

We address potential confounding from unobserved time-varying determinants of yield by leveraging the quasi-random variation in SSAs induced by unanticipated volcanic eruptions and subsequent stratospheric aerosol transport. These natural experiments cause SSA concentrations over countries and over time to vary in a way that is arguably as good as randomly assigned. This quasi-random assignment of SSAs, like random assignment in a randomized control trial, balances unobserved covariates within countries before and after volcanic treatment.

A further complication specific to this study is that the SSA distribution engendered by the eruptions of El Chichón and Pinatubo happened, by chance, to coincide temporally and spatially

⁴Because ENSO is already lagged, the creation of two leads and lags for each variable creates duplicated ENSO controls in the model; we drop these before estimation.

with strong El Niño events, which are global climatic phenomena that affect yields through similar pathways to SSAs (Eqn. 14). We address this by both conditioning on the pathways through which ENSO is likely to affect yields (temperature, precipitation, and cloud cover) and by conditioning directly on the current and lagged ENSO index to account for any remaining pathways through which ENSO variation might impact yields (i.e. $\frac{\partial U}{\partial E} \frac{dE}{dt}$ or $\frac{\partial I}{\partial E} \frac{dE}{dt}$).

In addition to accounting for these time-varying factors, we address potential confounding due to the impacts of SSAs on other determinants of yield by directly controlling for observable determinants of yield that SSAs affect, such as temperature, precipitation, and clouds (Section III.1).

III.3.1 Identifying assumptions This identification strategy rests on two assumptions. First, we assume that the aerosol treatment is independent of other variables that impact yield, conditional on the model's controls. Put another way, we assume that a country before and after an eruption is a good "control" for the same country during overhead SSA "treatment," after conditioning on climate controls, ENSO, fixed effects, and time trends⁵. Second, we assume that SSAs affect yields through changing only insolation, temperature, precipitation, and clouds:

$$\frac{\partial Y}{\partial U} \frac{\partial U}{\partial S} = 0 \quad (20)$$

If both of these assumptions hold, then our estimate of the insolation effect will not be confounded. If Eqn. 19 (in footnote) holds but 20 does not, then instead of capturing only the insolation effect, β will additionally capture any residual effects of SSAs on yields that are localized to a country and that are not mediated through changes in temperature, precipitation, or clouds (i.e. $\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial S}$). Such potential channels include increases in ultraviolet radiation (UV), 43 and decreases in tropospheric ozone 44. It is unlikely that changes in tropospheric ozone are the mechanism that explain the estimated negative effect of SAOD on yields. Because tropospheric ozone reduces crop yields 45, concentrations of tropospheric ozone would have to be positively correlated with SAOD to explain the negative impacts of SSAs on yields. To the contrary, there is evidence that Pinatubo did 30 and SRM would 44 decrease tropospheric and surface ozone concentrations. Though it is unknown whether this had a measurable effect on yields during the Pinatubo eruption, if anything these changes in ozone would cause us to under-estimate insolation-mediated SAOD damages, rather than over-estimate them. It is possible that changes in UV radiation may explain part of our estimated "insolation effect" because UV radiation damages crop yields and there is some evidence that the decrease in ozone following the eruption let in more UV light than the sulfate aerosols directly blocked 43. Future research should further explore the mechanisms responsible for these empirically estimated effects of SSAs on yields.

⁵More formally, we assume that:

$$S_{it} \perp\!\!\!\perp \epsilon_{it} | f_T(T_{it}), f_P(P_{it}), f_C(C_{it}), g(E_t, E_{t-1}, i), \lambda_i, \phi_{i1}t, \phi_{i2}t^2 \quad (19)$$

where notation in the above equation is borrowed from our empirical model (Eqn. 16).

III.4 Robustness of the SSA insolation effect on yields

Here we examine the sensitivity of our estimation of the insolation effect of SSAs on yields to different model specifications, data samples, and data sources (Fig. 3, Extended Data Table 2).

To test the sensitivity of our results to the temperature, precipitation, cloud and ENSO controls we run the analysis without these climate controls (Extended Data Table 2 Column 1) and then add in temperature, precipitation, clouds and ENSO one at a time (Columns 2-5). Column 5 is our preferred specification. We see that the effect of SSAs is robust to removing these climate controls; all coefficients across all 5 specifications and all 5 crops and crop groups are negative, and tend to have similar magnitudes and precisions to our preferred specification.

To test the sensitivity of our results to different measures of SSA exposure, we divide SAOD by the cosine of the solar zenith angle (SZA) (Column 6). Motivation for this model stems from the insolation mechanism: if a ray of light passes through an aerosol layer at an angle, it interacts with more of the aerosol layer than if it passes through perpendicularly. Accounting for the angle of incident sunlight mechanically increases the treatment values (i.e. $SAOD < \frac{SAOD}{\cos(SZA)}$) and thus decreases the size of the estimated coefficient. The predicted average treatment effect between the CSZA and preferred specifications, however, is essentially unchanged.⁶ We avoid using the CSZA transformation as our preferred specification because it gives similar predictions and increases the conceptual and computational complexity of our model.

To test whether local, direct volcanic damages (e.g mudflows or avalanches of ash) are driving the global result, we drop the countries where these major eruptions occurred (Mexico and the Philippines) from our analysis; we find little difference in the results from our preferred specification (Column 10).

To test whether interannual fluctuations in carbon dioxide (CO₂) concentrations are driving the main result, we measure and control for surface CO₂ concentrations in our empirical model. We calculate the CO₂ concentration (ppm) for each year, country and crop by averaging monthly average CO₂ concentrations over the growing season. We use data from Mauna Loa [46] and Cape Grim [47] to measure CO₂ concentrations in the Northern and Southern Hemispheres, respectively. ⁷ We find that controlling for surface CO₂ concentrations has little impact on the main results (Column 11).

We test the robustness of the results across different SAOD datasets, by re-estimating the model with the SPARC and SPARC2 datasets, described in Supplementary Information IV (Columns 7,8,12). Though the coefficients are larger—because for a given concentration of SSAs, SAOD measured at 1000nm is smaller than SAOD measured at 550nm due to the fact that SSA particles block light at 550nm more efficiently than they do at 1000nm—we calculate predicted effects using these datasets that are similar to predicted effects using the preferred GISS dataset.⁸

⁶In 1992, the average SAOD at 550nm across countries is 0.13 and the SAOD coefficient is -.649, which gives a predicted effect on yields of -8.2%. Similarly, the average $\frac{SAOD}{\cos(SZA)}$ across countries is 0.21 and the coefficient for maize is -.392, which gives a predicted effect on yields of -8.3%.

⁷We assume that CO₂ concentrations are homogeneous within each hemisphere since within-hemisphere variation in CO₂ is relatively small (<3ppm) [48] and finer-scale measurements, such as those from remote sensing, are not available during our study period.

⁸In 1992, the average SPARC SAOD at 1020nm across countries is 0.076 and the SAOD coefficient is -.901, which gives a predicted effect on yields of -6.9%. Similarly, the average SPARC2 SAOD at 1020nm across countries is 0.099 and the coefficient for maize is -.776, which gives a predicted effect on yields of -7.8%. Tests for difference between these predicted

III.5 Interpretation of the insolation effect

Here we analyze what our estimation of the insolation effect ($\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S} = \beta$) suggests about the strength of the diffuse fertilization effect for the production of crop yield. From our most general yield model in the previous section we have:

$$Y = Y(T, P, C, I, U)$$

Allowing the effects of direct and diffuse light to differ, and taking a first order Taylor approximation gives:

$$Y = \gamma_1 I^D + \gamma_2 I^F + f(T, P, C)$$

Differentiating with respect to S to get the marginal impacts of SSAs gives:

$$\frac{\partial Y}{\partial S} = \underbrace{\gamma_1 \frac{\partial I^D}{\partial S} + \gamma_2 \frac{\partial I^F}{\partial S}}_{\text{insolation effect}} + \frac{\partial}{\partial S} f(T, P, C) \quad (21)$$

Here, the insolation effect ($\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S}$) is represented by the sum $\gamma_1 \frac{\partial I^D}{\partial S} + \gamma_2 \frac{\partial I^F}{\partial S}$. Equation 4 showed how w for the entire atmospheric column determines how much diffuse light is gained from the scattering of a unit of direct light. Differentiating Eqn. 4 with respect to S gives:

$$\frac{\partial I^F}{\partial S} = \frac{\partial w}{\partial S} [I^0 - I^D] + w \frac{\partial}{\partial S} [I^0 - I^D] \quad (22)$$

which describes how the optical behavior of the entire atmospheric column changes with respect to the concentration of SSAs. To limit the focus of this equation to the effects of scattering due to only SSAs, we define a new variable:

$$w_{ss} = Pr(\text{photon reaches the surface} | \text{photon hits a SSA particle}) \quad (23)$$

and substitute it in for w in Eqn. 22 to get:

$$\frac{\partial I^F}{\partial S} = \frac{\partial w_{ss}}{\partial S} [I^0 - I^D] + w_{ss} \frac{\partial}{\partial S} [I^0 - I^D] \quad (24)$$

Note that the definition of w_{ss} is identical to that of w except that w_{ss} is specific to SSA particles and w describes the scattering properties of the entire atmospheric column. Because $\frac{\partial w_{ss}}{\partial S}$ and $\frac{\partial I^0}{\partial S}$

effects and the predicted effect using the GISS dataset (-8.2%, see previous footnote) fail to reject the null hypothesis that the effects are the same ($p > 0.1$).

equal zero⁹ we can simplify this to:

$$w_{ss} = -\frac{\frac{\partial I^F}{\partial S}}{\frac{\partial I^D}{\partial S}} \quad (25)$$

Thus, similar to w , w_{ss} is both the probability that a ray of light makes it to the surface conditional on hitting a particle of SSA and the amount of diffuse light that is gained from the loss of one unit of direct light *due to SSA scattering*. Now, solving for $\frac{\partial I^F}{\partial S}$ in Eqn. 25 and substituting into Eqn. 21 we get:

$$\frac{\partial Y}{\partial S} = \underbrace{(\gamma_1 - \gamma_2 w_{ss}) \frac{\partial I^D}{\partial S}}_{\text{insolation effect}} + \frac{\partial}{\partial S} f(T, P, C) \quad (26)$$

This formulation of the yield model allows us analyze the relative contribution of direct and diffuse light to yield using our estimations of the insolation effect and the optical properties of SSA. Here, the insolation effect is $(\gamma_1 - \gamma_2 w_{ss}) \frac{\partial I^D}{\partial S}$, where w_{ss} describes the optical properties of the SSAs and γ_1 and γ_2 describe how direct and diffuse light impact yields. Because scattering blocks the transmission of direct light, $\frac{\partial I^D}{\partial S}$ is negative. Thus, the insolation effect is positive if $\gamma_1 - \gamma_2 w_{ss} < 0$ and negative if $\gamma_1 - \gamma_2 w_{ss} > 0$. The diffuse light fertilization effect suggests that diffuse light is used more efficiently in the production of yield than direct light, which means that $\gamma_2 > \gamma_1$. However, a unit of diffuse light comes at the cost of $\frac{1}{w_{ss}}$ units of direct light. If the benefit of diffuse light (γ_2) after accounting for the loss of direct light (w_{ss}) exceeds the benefit of direct light (γ_1), then $\gamma_1 < \gamma_2 w_{ss}$ and scattering will increase yields. If w_{ss} is too small, or the relative benefit of diffuse to direct light is too small, then $\gamma_1 > \gamma_2 w$ and scattering decreases yields.

Our finding that the insolation effect is negative suggests that $\gamma_1 > \gamma_2 w$. Calculation of w_{ss} using our insolation data, suggests that $w_{ss} \approx 0.85$.¹⁰ This means that $\gamma_2 < 1.2\gamma_1$, meaning that diffuse light is less than 1.2 times more efficiently used for the production of yield than direct light. This finding is in contrast to previous studies, which have found that scattering light tends to substantially increase plant growth [19, 15], though there are exceptions [50]. Our results suggest that either increasing the diffuse fraction increases photosynthesis less for crops than for other ecosystems,¹¹ or that scattering light reduces the harvest index,¹² or that past estimates have confounded the impacts of diffuse light with the effects of cooling. Though this calculation gives a rough upper bound for the strength of the diffuse fertilization effect in the production of crop yield, further research should more rigorously estimate the magnitude of this effect as well as how it depends on environmental conditions.

⁹Stating that $\frac{\partial w_{ss}}{\partial S} = 0$ rests on the assumption that adding more SSAs to the atmosphere does not impact the optical behavior of the SSAs already there (i.e. no multiple scattering). This assumption is likely to hold reasonably well over the range of optical depths observed during the Pinatubo and El Chichon eruptions as well as the SRM simulations [49].

¹⁰To estimate w_{ss} , we re-estimate Eqn. 2 using I^D and I^F , rather than $\ln(I^D)$ and $\ln(I^F)$ as outcome variables. We get $\frac{\partial I^F}{\partial S} = 1,909 \frac{Wh}{m^2 day}$ per unit SAOD ($p < .01$) and $\frac{\partial I^D}{\partial S} = -2,238 \frac{Wh}{m^2 day}$ per unit SAOD ($p < .01$), which gives a w_{ss} of 0.85 using Eqn. 23

¹¹Selective breeding for upright architectures and high photosynthetic capacity may be one reason for the relatively weaker diffuse fertilization effect in crops.

¹²The harvest index is the mass of edible yield divided by the total plant mass.

III.6 Discussion of potential mechanisms causing the differences in the estimated insolation effect between eruptions

Here, we expand our discussion in the main text of whether the differences in the insolation effect between the El Chichón and Pinatubo eruptions should be interpreted as a product of either attenuation bias or of differences in SSA radiative properties. We add two points to those made in the main text. First, if attenuation bias were the only mechanism at work, we might expect the estimated impact of SSAs on insolation (e.g. Extended Data Tables 1,3) to be attenuated towards zero as well. Rather, we estimate larger marginal effects of SSAs on diffuse radiation and on forward scattering during the El Chichón eruption than the Pinatubo eruption, which supports the argument that differences in SSA radiative properties may have played a role. The distribution of insolation stations, however, is concentrated in areas, such as Europe, where non-satellite measurements of SSAs would also be most available and accurate. Thus, it is possible that the measurement error of SSA concentrations is smaller over the insolation stations than over the countries included in the yield regressions, which include many tropical and subtropical countries with limited insolation and SSA monitoring. If that is the case, then the observed differences in the insolation effect could still be due to attenuation bias.

Second, as mentioned in the paper, we find that including data from the El Chichón and Agung eruptions, consecutively, makes the estimated insolation effect progressively closer to zero, though still negative. If SSA radiative properties are driving this, we would expect the radiative properties of the SSAs from the El Chichón and Agung eruptions to be more similar to each other than to the radiative properties of the SSAs from the Pinatubo eruption. Though we are unable to directly estimate the insolation impacts of the SSAs erupted by Agung using data from insolation stations, other measurements suggest that the SSAs from Agung were roughly similar in size to those of Chichón [10], and particle size is a key determinant of SSA radiative characteristics. This is consistent with SSA radiative properties contributing to the differences in the insolation effect between eruptions, though it should be noted that measurements of the particle size of Agung's SSAs were likely imprecise. Future research will hopefully clarify the degree to which attenuation bias or differences in SSA radiative properties explain the differences in the insolation effect across eruptions.

IV. Total effect estimation in SRM simulations

The last step of our analysis is to estimate the total effect of SSAs on yields in a SRM scenario. The SRM scenario we examine is the G3 experiment from the Geoengineering Model Intercomparison Project [51]. In the G3 scenario, SO_2 is injected into the stratosphere to keep the top of atmosphere radiation flux at 2020 levels by offsetting anthropogenic forcing from RCP4.5 [52]. The climate data we use in our analysis comes from the Max Planck Institute Earth System Model (MPI-ESM) [27]. We use stratospheric aerosol optical depth, surface air temperature, precipitation and cloud fraction fields generated by the experiment. We chose the MPI-ESM model because it participated in the GeoMIP G3 experiment and specifically modeled SRM with sulfur injection rather than

direct dimming of the solar constant.¹³ To calculate the total effect of SSAs on yields we compare a scenario with climate change – following RCP 4.5 – and SRM to a scenario with climate change only (CC) from 2050-2069:

$$\text{Total effect} = \text{Yields with SRM and climate change} - \text{Yields with climate change only} \quad (27)$$

IV.1 Model

The total effect of SRM on agriculture is the sum of SRM's effects through each determinant of yield that SRM affects. Our agricultural model from the previous section (Eqn. 12) breaks the total effect of SSAs down into an insolation effect, a temperature effect, a precipitation effect, a cloud effect and a residual effect:

$$\frac{dY}{dS} = \underbrace{\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S}}_{\text{insolation effect}} + \underbrace{\frac{\partial Y}{\partial T} \frac{\partial T}{\partial S}}_{\text{temperature effect}} + \underbrace{\frac{\partial Y}{\partial P} \frac{\partial P}{\partial S}}_{\text{precipitation effect}} + \underbrace{\frac{\partial Y}{\partial C} \frac{\partial C}{\partial S}}_{\text{cloud effect}} + \underbrace{\frac{\partial Y}{\partial U} \frac{\partial U}{\partial S}}_{\text{residual effect}}$$

To get the change in yields due to SRM we multiply through by the change in SAOD due to a given SRM scenario (G, for geoengineering):

$$\frac{dY}{dG} = \frac{dY}{dS} \frac{dS}{dG} = \underbrace{\frac{dS}{dG}}_{\text{ESM}} \underbrace{\left[\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial S} \right]}_{\beta_{SAOD}} + \underbrace{\frac{dS}{dG} \frac{\partial T}{\partial S}}_{\text{ESM}} \underbrace{\frac{\partial Y}{\partial T}}_{\frac{\partial}{\partial T} f_T(\cdot)} + \underbrace{\frac{dS}{dG} \frac{\partial P}{\partial S}}_{\text{ESM}} \underbrace{\frac{\partial Y}{\partial P}}_{\frac{\partial}{\partial P} f_P(\cdot)} + \underbrace{\frac{dS}{dG} \frac{\partial C}{\partial S}}_{\text{ESM}} \underbrace{\frac{\partial Y}{\partial C}}_{\frac{\partial}{\partial C} f_C(\cdot)} \quad (28)$$

Here, the change in yields due to SRM is expressed in terms that we can calculate using an ESM and our fitted empirical yield model. We model the SRM-induced changes in SAOD ($\frac{dS}{dG}$), temperature ($\frac{dS}{dG} \frac{\partial T}{\partial S}$), precipitation ($\frac{dS}{dG} \frac{\partial P}{\partial S}$) and cloud fraction ($\frac{dS}{dG} \frac{\partial C}{\partial S}$) induced by SRM using the MPI-ESM, and we estimate the impacts of these changes (β , $f_T(\cdot)$, $f_P(\cdot)$, $f_C(\cdot)$) using our statistical yield model (Eqn. 16).

IV.2 Calculation of the total effect of SRM on crop yield

To calculate the total effect of SRM on crop yield we first use bilinear interpolation to regrid all of the historical climate observations to the same resolution as the climate model output. We then mean-debias the climate model data by month [53], average the climate model data over the growing season for each crop for each year and then evaluate our statistical crop model at these growing season values to get an estimate of the yield for each year. We apply the statistical crop model fitted to data from 1983-2009 (Fig. 3a Model 1) because the SSAs from Pinatubo were substantially more accurately measured than those of any other major eruption [24], and the cloud data does not reach back to the Chichón eruption. We do the steps above for each crop (maize, soy, rice, wheat), each scenario (SRM, CC), each ensemble member (each scenario is run three times with slightly different initial conditions), and each year. We then average across years and ensembles to get an estimate of the future expected yield for each crop under each scenario. To

¹³The MPI model does not internally calculate the evolution of SO₂ in the stratosphere; rather it intakes aerosol radiative properties calculated from an aerosol microphysical model that simulates equatorial injection of SO₂ at 60hPa.

compare scenarios, we subtract their average yields.

Specifically, we calculate the effect of SRM on yields for each crop j in each year t and pixel p as the difference in yields in the SRM and CC scenarios:

$$\begin{aligned}\frac{\Delta Y}{\Delta G_{tpj}} &= Y_{tpj}^{SRM} - Y_{tpj}^{CC} \\ &= \beta_j S_{tpj}^{SRM} - \beta_j S_{tpj}^{CC} + f_{Tj}(T_{tpj}^{SRM}) - f_{Tj}(T_{tpj}^{CC}) + f_{Pj}(P_{tpj}^{SRM}) - f_{Pj}(P_{tpj}^{CC}) + f_{Cj}(C_{tpj}^{SRM}) - f_{Cj}(C_{tpj}^{CC}),\end{aligned}\quad (29)$$

where superscripts denote the scenario¹⁴. We then calculate the expected change in yields due to SRM for each pixel (Extended Data Fig. 5) by averaging over 2050-2069:

$$\frac{\Delta Y}{\Delta G_{pj}} = \sum_{t \in 2050-2069} \frac{1}{20} \frac{\Delta Y}{\Delta G_{tpj}} \quad (30)$$

And finally we calculate the global average total effect of SRM on yields (Fig. 4e) by averaging expected yield changes over pixels:

$$\frac{\Delta Y}{\Delta G_{world,j}} = \sum_{p \in world} v_{pj} \frac{\Delta Y}{\Delta G_{pj}} \quad (31)$$

Here, v_{pj} is a cropped-fraction and pixel-area weight such that $\sum_{p \in world} v_{pj} = 1$. We calculate the total effect separately for each ensemble member, as shown in Eqns. 29-31 and then average the effects. We do not include ENSO in our analysis of the total effect because its long term average effect is mean zero by construction. CO₂ fertilization effects will be equal in the SRM and climate change only scenarios, and thus do not affect our calculation of the total effect of SRM.

We note that calculation of the total effect will be accurate even if the assumption in Eqn. 19 is not satisfied. This is because β captures all effects of SSAs on yields not mediated by temperature, precipitation or clouds and thus captures both the insolation and residual effects ($\frac{\partial Y}{\partial I} \frac{\partial I}{\partial S} + \frac{\partial Y}{\partial U} \frac{\partial U}{\partial S}$) in Eqn. 28, if any residual effects exist.

IV.3 Comparisons to historical scenarios

To corroborate our methodology, we compare the CC scenario to a historical scenario (1940-1959). Using a similar methodology to estimation of the total effect of SRM on yields, we estimate that changes in temperature (2.6 °C), precipitation (1.0 mm/month) and cloud fraction (-0.03) from 1940-1959 to 2050-2069 under RCP4.5 decrease yields by 18%, 6%, 16%, and 6% for maize, rice, soy, and wheat, respectively (Extended Data Fig. 7a). These estimates are within the range of estimates reported by the IPCC [54].

Similarly, we compare the SRM scenario to the historical scenario. We find that SRM and climate change together decrease yields by 17%, 6%, 14%, and 7% for maize, rice, soy, and wheat, respectively (Extended Data Fig. 7b). Comparing the SRM - historical impacts to the CC -

¹⁴Thus, $f_{Tj}(T_{tpj}^{SRM}) - f_{Tj}(T_{tpj}^{CC})$ calculates the temperature-mediated impact of SRM on the yield of crop j in year t and pixel p .

historical impacts, we see that SRM mitigates yield losses from rising temperatures, but imposes equally-sized sunlight-mediated damages. Thus, we see again that, on net, SRM mitigates little to none of the damages from climate change to global agricultural production.

We note that we have not considered the effects of carbon fertilization when comparing SRM and climate change only scenarios to the historical scenario. Thus, we interpret these calculations as the impacts of changes in temperature, precipitation, clouds and sunlight only.

IV.4 Uncertainty of the total effect

We analyze uncertainty in the total effect of SSAs on yield from two sources. Statistical uncertainty comes from the fact that our crop model was estimated using historical data and thus its coefficients are not perfectly known due to sampling variability (this uncertainty is shown Extended Data Table 2 Column 5 and Extended Data Fig. 2). Variances depicted in maps of the total effect are of $\frac{\Delta Y}{\Delta G_{pj}}$ and variances depicted in the bar graphs are of $\frac{\Delta Y}{\Delta G_{world,j}}$. The error bars and hatchings in all figures that display analyses of the total SSA effect represent statistical uncertainty only. Model uncertainty comes from the fact that climate models do not perfectly predict the future climate. We estimate model uncertainty by calculating the effects separately for each of the three ensemble members rather than for their average (Extended Data Fig. 6) and find that our result that SRM mitigates little of the damages of climate change is stable across the three ensemble runs.

REFERENCES

- [39] Monfreda, C., Ramankutty, N. & Foley, J. A. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles* **22**, 1–19 (2008).
- [40] Colin Cameron, A., Gelbach, Jonah B. & Miller, Douglas L. Robust Inference With Multiway Clustering. *Journal of Business & Economic Statistics* **29**, 238–249 (2011).
- [41] Hayasaka, T., Iwasaka, N., Hashida, G., Takizawa, I. & Tanaka, M. Changes in stratospheric aerosols and solar insolation due to Mt. Pinatubo eruption as observed over the western Pacific. *Geophysical Research Letters* **21**, 1137–1140 (1994).
- [42] Harrell, F. *Regression Modeling Strategies* (Springer-Verlag, New York, 2001), 1st edn.
- [43] Vogelmann, A., Ackerman, T. & Turco, R. Enhancements in biologically effective ultraviolet radiation following volcanic eruptions. *Nature* **359**, 47–49 (1992).
- [44] Xia, L., Nowack, J. P., Tilmes, S. & Robock, A. Impacts of stratospheric sulfate geoengineering on tropospheric ozone. *Atmospheric Chemistry and Physics* **17**, 11913–11928 (2017).
- [45] McGrath, J. M. *et al.* An analysis of ozone damage to historical maize and soybean yields in the United States. *Proceedings of the National Academy of Sciences of the United States of America* **112**, 14390–5 (2015).

- [46] Mauna Loa CO2 monthly mean data. Accessed 03/16/2018. URL <ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2{ }mm{ }mlo.txt>.
- [47] Cape Grim Greenhouse Gas data. Accessed 03/16/2018. URL <http://capegrim.csiro.au/GreenhouseGas/data/CapeGrim{ }CO2{ }data{ }download.csv>.
- [48] Lobell, D. B. & Field, C. B. Estimation of the carbon dioxide (CO₂) fertilization effect using growth rate anomalies of CO₂ and crop yields since 1961. *Global Change Biology* **14**, 39–45 (2008).
- [49] Ge, J., Su, J., Fu, Q., Ackerman, T. & Huang, J. Dust aerosol forward scattering effects on ground-based aerosol optical depth retrievals. *Journal of Quantitative Spectroscopy and Radiative Transfer* **112**, 310–319 (2011).
- [50] Stine, A., Huybers, P. Arctic tree rings as recorders of variations in light availability. *Nature Communications* **5**, 3836 (2014).
- [51] Kravitz, B. *et al.* The Geoengineering Model Intercomparison Project (GeoMIP). *Atmospheric Science Letters* **12**, 162–167 (2011).
- [52] Taylor, K. E., Stouffer, R. J. & Meehl, G. A. An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society* **93**, 485–498 (2012).
- [53] Déqué, M. Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: Model results and statistical correction according to observed values. *Global and Planetary Change* **57**, 16–26 (2007).
- [54] Porter, J. R. *et al.* Food security and food production systems. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* 485–533 (2014).