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Cropping frequency and area response to climate variability can exceed yield response

Avery S. Cohn[1*], Leah K. VanWey[2,3], Stephanie A. Spera[2,4] and John F. Mustard[2,4]

The sensitivity of agricultural output to climate change has often been estimated by modelling crop yields under climate change scenarios or with statistical analysis of the impacts of year-to-year climatic variability on crop yields[1,2]. However, the area of cropland and the number of crops harvested per growing season (cropping frequency) both also affect agricultural output and both also show sensitivity to climate variability and change[3–9]. We model the change in agricultural output associated with the response of crop yield, crop frequency and crop area to year-to-year climate variability in Mato Grosso (MT), Brazil, a key agricultural region. Roughly 70% of the change in agricultural output caused by climate was determined by changes in frequency and/or changes in area. Hot and wet conditions were associated with the largest losses and cool and dry conditions with the largest gains. All frequency and area effects had the same sign as total effects, but this was not always the case for yield effects. A focus on yields alone may therefore bias assessments of the vulnerability of agriculture to climate change. Efforts to reduce climate impacts to agriculture should seek to limit production losses not only from crop yield, but also from changes in cropland area and cropping frequency.

Yearly agricultural crop production in a given region is equal to the sum over each of the region's harvested crops of that crop's yield multiplied by its area[10]. Although in theory each component of this production equation—crop yield, cropping area and crop frequency—could be sensitive to climate change and/or climate variability, this is the first empirical study, to our knowledge, to estimate the response of agricultural output to climate shocks as a function of each of these three components.

Research on impacts of climate on agriculture has focused on the impacts of climate change, decadal climate variability, and interannual climate variability on crop yields[11,12]. Hotter (and sometimes drier) conditions can cause abrupt and/or persistent declines in agricultural yields[2]; wet conditions can also reduce yields when they interrupt sowing, harvesting, or both[13]. Interannual climate variability is associated with a substantial share of yield variation, but the most damaging temperature and precipitation anomalies vary greatly across crops and regions[14,15]. Crop sensitivity to interannual climate variability depends strongly on the portion of the growing season during which the anomaly occurs. Anomalies occurring at different stages of crop development have varied impacts on agricultural output[16].

Research on the response of cropland area to climate has estimated the association of cross-sectional climatic variation with cropping area[17] or has identified the relationship between cropping area under region-wide climate shocks, such as El Niño, as compared with more typical production years[7,8]. The subset of this research that investigates the impacts from spatio-temporally variable climate shocks generally uses area data that are aggregate measures. These do not allow for the disentangling of year-to-year fluctuations in cropland utilization versus more persistent changes in agricultural land use associated with agricultural expansion or abandonment. One recent study proposed a useful metric for assessing yield potential—the utilization fraction[18]. However, this conflates two sources of utilization change that are likely to have different drivers and should ideally be studied separately—ephemeral changes versus persistent changes. Thanks to a spatially explicit, sub-annual, satellite remote-sensing-derived agricultural land-use data set, we can explicitly distinguish between frequency of cropland utilization (cropping frequency) and changes in cropland area that persist for two or more years (cropland area).

In production systems with more than one crop per growing season, one recent study showed that the first and second crops exhibit some common and some differential responses to interannual climate anomalies[4]. Another study used crop modelling to show that second-crop sensitivity to climate can be substantial relative to first-crop effects and can partially 'offset' modelled losses from first crops under warming[5]. However, neither study allows for analysis of the relative importance for agricultural output of changes in cropping yield versus cropping frequency versus cropland area associated with a given set of climate anomalies.

We focused our analysis on an emerging tropical agricultural production centre, the Brazilian State of Mato Grosso (MT). MT is a 90-million-hectare state where agricultural output increased threefold from 2000 to 2010[19]. In 2013, agriculture comprised roughly 40% of the state's land cover and 72% of the state's GDP (gross domestic product). In 2013, MT produced 10% of global soybeans on 10 million hectares of cropland. Ranging from 7.23°–17.87° S to 50.57°–61.52° W and with mean annual precipitation ranging from 1,000 mm in the southeast to over 2,500 mm in the northwest, in typical years, much of MT is suitable for the production of two rainfed crops per growing season (Supplementary Fig. 5). In 2010, roughly half of MT's cropland produced two commercial crops per growing season, usually a soy harvest followed by a corn harvest[20]. In net, the area of cropland and the frequency of cropping grew steadily from 2000–2010 but this masks substantial instability—over the period 3 million hectares of agricultural abandonment occurred and 3 million additional hectares of double-cropping abandonment occurred[20].

[1]Fletcher School at Tufts University, 160 Packard Avenue, Medford, Massachusetts 02155, USA. [2]Institute at Brown for Environment and Society, Brown University, Box 1951, 85 Waterman Street, Providence, Rhode Island 02912, USA. [3]Department of Sociology, Brown University, Box 1916, 112 George Street, Providence, Rhode Island 02912, USA. [4]Department of Earth, Environmental and Planetary Sciences, Brown University, Box 1846, 324 Brook Street, Providence, Rhode Island 02912, USA. *e-mail: avery.cohn@tufts.edu

We investigated whether interannual climate variability was associated with changes in cropland area, cropping frequency, and crop yields of soy and corn agriculture in MT (which in 2013 together constituted approximately 73% of agricultural area in the state)[19]. The analysis used mean monthly precipitation estimates from the Tropical Rainfall Measuring Mission[21], mean monthly temperature data from the University of Delaware[22], soy and corn yields from the Brazilian Institute of Geography and Statistics[19], and maps of agricultural frequency, agricultural expansion, and agricultural abandonment described in a recent paper[20]. We performed six separate regressions at the level of the county-growing year, each regressing a distinct agricultural production variable on the same set of climate variables. Agriculture production variables were soy yield, corn yield, cropland expansion, cropland abandonment, double-cropping expansion, and double-cropping abandonment. Each model included the linear and quadratic terms for mean temperature and mean precipitation by month of each growing year, and controlled for county and year fixed effects, over the period 2002/03–2009/10. We then predicted changes in production stemming from each agricultural variable under a range of precipitation anomaly scenarios crossed with a range of temperature anomaly scenarios. Scenarios investigated range from $\pm 1\,^{\circ}$C from local mean within sample temperature and $\pm 30\%$ from local mean within sample precipitation. Soy production was converted to corn-equivalent units using a ratio of 2.2 tons of corn to 1 ton of soybeans, in line with the long-run soy to corn price ratio. Further details of data employed, methods used, and robustness checks undertaken can be found in the Supplementary Information.

To enable comparison of the crop production impacts of the sensitivity to climate of each agricultural outcome variable investigated, all results are reported as a percentage of 2009/2010 total MT soy and corn production (in tons of corn equivalent).

Soybeans were cultivated on most of the cropland area (58%) and account for 72% of the total annual crop value in the state. On roughly half the area where soy was cultivated, a second crop was cultivated during the same growing season[19]. Over 90% of the time, this second crop was corn[20]. Our results (Fig. 1) show that despite soy's dominant contribution to MT's crop production, interannual climate variability had larger impacts on crop production through corn yields than through soy yields (Fig. 1a). Our predictions show that a temperature anomaly of $+1\,^{\circ}$C was associated with a rise in soy yield equivalent to a 1.7% of total 2010 soy and corn production in MT. This same $+1\,^{\circ}$C anomaly, however, reduced corn yields an amount equivalent to a 2.6% loss in the state's crop production (Fig. 1b). Thus, in sum, the combined corn+soy yield effect of an increase in temperature of $+1\,^{\circ}$C was a loss of 0.9% of production. Under the $-1\,^{\circ}$C anomaly, the results were roughly reversed—a loss of 2.5% from soy yield and a gain of 3.2% from corn yield were predicted. Conditions 30% wetter than the local mean slightly increased corn yields, but reduced soy yields substantially. Conditions 30% drier than normal were found to be associated with increased soy yields and reduced corn yields. One mechanism for this effect may be farmer decisions about planting a single long-cycle soybean or a short-cycle soybean together with a second crop. Shorter-cycle soybeans facilitate second-crop production, but reduce first-crop yields.

In MT, as in other low-latitude agricultural regions, agricultural productivity depends not only on yield, but also on the number of crops cultivated per growing season (frequency). We found that interannual climate variability was associated with more change in agricultural output through these cropping frequency changes than due to cropping yield changes. A temperature anomaly of $+1\,^{\circ}$C from local means was found to be associated with a decline in cropping frequency equivalent to a 3.2% loss in 2010 production in MT (Fig. 1c). Under $-1\,^{\circ}$C, the results were roughly reversed—a 4.6% gain was modelled. Wetter conditions slightly reduced cropping frequency, whereas drier conditions slightly increased cropping frequency.

		Precipitation scenario	Temperature scenario −1 °C	Local mean	+1 °C
a	Soy yield (%)	−30%	−1.4	1.2	2.9
		−20%	−1.6	1.0	2.7
		−10%	−2.0	0.6	2.3
		Local mean	−2.5	0.0	1.7
		10%	−3.3	−0.8	0.9
		20%	−4.3	−1.7	0.0
		30%	−5.4	−2.9	−1.1
b	Corn yield (%)	−30%	2.7	−0.5	−3.1
		−20%	2.9	−0.3	−2.9
		−10%	3.1	−0.2	−2.7
		Local mean	3.2	0.0	−2.6
		10%	3.3	0.1	−2.5
		20%	3.4	0.2	−2.4
		30%	3.5	0.3	−2.3
c	Frequency (%)	−30%	4.4	0.1	−2.9
		−20%	4.5	0.1	−3.0
		−10%	4.6	0.1	−3.1
		Local mean	4.6	0.0	−3.2
		10%	4.5	−0.1	−3.4
		20%	4.4	−0.3	−3.7
		30%	4.1	−0.5	−3.9
d	Area (%)	−30%	1.2	−3.2	−6.5
		−20%	3.3	−1.9	−5.5
		−10%	4.8	−0.7	−4.7
		Local mean	5.7	0.0	−4.2
		10%	6.0	0.3	−4.2
		20%	5.6	−0.1	−4.6
		30%	4.6	−1.0	−5.3
e	Total (%)	−30%	7.0	−2.4	−9.5
		−20%	9.1	−1.1	−8.6
		−10%	10.5	−0.2	−8.2
		Local mean	11.0	0.0	−8.3
		10%	10.5	−0.5	−9.1
		20%	9.1	−1.9	−10.6
		30%	6.8	−4.1	−12.7

Figure 1 | Changes in Mato Grosso agricultural output from response of crop yield, crop frequency and crop area to interannual climate variability. **a–e**, Coefficients obtained from six separate regressions investigating changes in agricultural dependent variables caused by climate anomalies were used to model, *ex post*, four mechanisms (corn yield, soy yield, cropping frequency and cropping area) through which interannual climate variability has impacted the agricultural output of Mato Grosso. All table values are percentages of total corn+soy production in Mato Grosso in the 2009/10 growing season. Table cell shading is proportional to the magnitude of cell values. Each value in **e** is the sum of values in **a–d** for a given climate scenario. Yield impacts, the most commonly studied channel of crop sensitivity to interannual climate variability, were similar in magnitude to crop frequency impacts or the impacts from crop area change. However, the combined frequency and area response far exceeded the yield response.

MT is a region undergoing large-scale changes in cropping area. Agriculture is expanding onto lands that were not previously cultivated and areas under cultivation are being left fallow or abandoned for two or more years. Our results reveal that the fraction of these changes caused by interannual climate variability has had a substantial effect on the region's crop production. An anomaly of $+1\,^{\circ}$C from local mean temperatures was found to be associated with a decline in cropping area equivalent to a 4.2% loss in 2010 production in MT. Under the $-1\,^{\circ}$C anomaly, the results

Table 1 | Sensitivity of output change to climate anomalies across the growing year.

	Cropland expansion (%)	Cropland abandonment (%)	Double-crop expansion (%)	Double-crop abandonment (%)	Soy yield (%)	Corn yield (%)
August–October	27.1	31.1	13.3	21.6	35.1	26.7
November–January	30.6	28.1	18.2	20.6	34.8	28.6
February–April	28.4	19.7	32.1	26.3	23.1	17.2
May–July	14.0	21.1	36.4	31.4	7.0	27.5
Total	100	100	100	100	100	100

Here we report the portion of the total variance in each agricultural output indicator variable explained by climate anomalies in each quarter of the growing season. Each column is a dependent variable investigated in our analysis. Each row represents the combined effect size of mean temperature for each month of the quarter and total precipitation for each month of the quarter. The columns sum to 100% of the variance in each agricultural variable explained by variance in interannual climate variability.

were roughly reversed—a 5.7% gain was found (Fig. 1d). Wetter conditions slightly reduced crop output, whereas drier conditions slightly increased output.

The sensitivity of each agricultural variable to interannual climate variability varied substantially across the quarters of the growing year (Table 1). We investigated the influence of climate from months August–October, November–January, February–April, and May–July under the uniform +1 °C and +30% precipitation scenario. We found that that variation in agricultural output was explained by climate shocks occurring throughout the year. The primary exception was that soy yield was only weakly affected by May to July climate variability. This is likely to be because soy is often harvested earlier in the growing season. Conversely, it is notable that frequency effects and corn yield effects are spread across the entire growing year, despite the fact that frequency is a measure of second-crop area and corn is primarily a second crop. This may be because deleterious conditions for soy production in the beginning of the growing year can spill over to affect the second crop by delaying its plant date or limiting available soil moisture.

This paper extends the study of the impacts of interannual climate variability on agriculture by comparing the impacts of interannual climate variability on cropping frequency versus cropland area versus crop yields. The magnitude and direction of our findings on corn yield are in line with numerous previous studies on the links between interannual climate variability and corn yield at many scales[11]. Our soy yield findings diverge from the literature, but this is likely due to the high prevalence of the cultivation of two crops per growing season in MT. There, higher soy yields may be associated with an adaptive measure—longer-cycle soybeans cultivated instead of the combination of shorter-cycle soybeans and an additional commercial crop. Overall, observations with higher than normal soybean yields had lower than normal overall yields, cropping frequency and cropping area. Further research should examine whether this pattern holds under exposure to heat waves, droughts, and dry spells in the wet season[2,15,23].

A ten-member ensemble of climate models predicts a 2.5 °C increase in mean temperature over MT by mid-century under the A2 scenario[24]. This is cause for concern given that the warming anomalies investigated caused crop production losses through yield, area and frequency. Crop yield sensitivity to interannual climate variability has been shown to be a reasonable proxy for crop yield sensitivity to longer, slower, expected climate variability or climate change—despite the fact that farmers and technologists were in theory able to adapt (M. Burke & K. Emerick, manuscript in preparation).

South American agricultural vulnerability to climate change has not been widely researched. Research has linked changes in corn yields[12,25] and soy yields[25] with climate variability, and reduced soy yields with heat waves[26], but no research has investigated year-to-year climate impacts on agriculture using a model of the type we employed for MT. The authors of one study that did investigate county-level climate impacts on soy and corn in Brazil restricted their sample to counties with constant borders over their study period—1980–2006. Mato Grosso was thus largely excluded from their analysis because many county borders in Mato Grosso have shifted recently[25].

Climate change may pose qualitatively different risks for MT and regions like it versus established agricultural regions. High population mobility, substantial land availability, a lack of insurance, murky land title, and weak governance characterize MT and a number of regions across the tropics that have recently become or are projected to become important new centres of agricultural production. It is possible that area and frequency effects are more responsive to climate shocks in MT and comparable regions than in more established agricultural regions, regions that can readily support two crops per growing season, or regions that support just one crop per growing season.

We have used evidence from Mato Grosso (MT) to show that changes in agricultural output stemming from the sensitivity of cropland area and cropping frequency to interannual climate variability are of similar magnitude to agricultural output changes associated with the sensitivity of crop yield to interannual climate variability. Area and frequency effects may either exacerbate or offset production losses through yield effects. Therefore, it may be inaccurate to use yield sensitivity to climate variability as a proxy for crop production sensitivity to climate variability. Area responses may contribute to agricultural production and socio-economic development[27], but by requiring land conversion they may also result in a host of negative environmental impacts. The trading of scarce or threatened environmental resources for crop output can be socially costly and could even compromise future crop production in MT[28]. Our findings suggest a research agenda to better understand the coupled biophysical and socio-economic dynamics of agriculture under climate variability. Such research should inform policies designed not only to enhance adaptation, but also to increase the social benefits of agricultural adaptation to climate change.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions
A.S.C., L.K.V. and J.F.M. designed the research; A.S.C. and L.K.V. performed the research; A.S.C., L.K.V. and S.A.S. analysed the data; A.S.C. and L.K.V. wrote the paper.

Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to A.S.C.

Competing financial interests
The authors declare no competing financial interests.

Methods

The variables mechanized-agriculture expansion, mechanized agricultural abandonment, double-cropping expansion and double-cropping abandonment were developed using ~250-m-resolution satellite remote-sensing agricultural land-use maps available for Mato Grosso over the period 2000/01–2011/12. New single or double cropping is all pixels that were single- or double-cropped in a given year and non-agriculture (for single cropping) or either non-agriculture or single cropping (for double cropping) in the two previous years. Abandoned single or double cropping in year t is all pixels that were single or double cropping in the year $t-1$, but were not that land use in both t and $t+1$ (that is, abandonment was classified if the land was taken out of a given use for two or more years). The underlying thematic classification of satellite remote-sensing data identified agriculture by detecting sharp peaks in greenness of maturing crops followed by troughs associated with chemical desiccation and mechanized harvest of crops. It distinguishes between non-agricultural areas, single cropping, and double cropping with 93% accuracy. Details of the approach are provided in ref. 20.

Soy and corn yields were obtained from administrative data collected by the Instituto Brasileiro de Geografia e Estatística through their Produção Agricola Municipal (PAM) data series[19]. These data were collected from annual polling of local officials and experts and were reported at the município (county) level. The PAM distinguishes between first-harvest corn yield and corn yield from the second harvest of the growing season. We use only the latter.

We represented climate with monthly mean temperature and monthly total precipitation in each month of the agricultural year (August–July). The growing season is generally considered to be September–July, but we start observations of climate variables in August to capture the impacts of climate on soil moisture in the lead up to the beginning of planting. We follow the convention of Brazilian statistics and refer to growing season beginning in, for example, September 2000 and ending in August 2001 as 2000/2001. Precipitation data were derived from satellite observations collected through the Tropical Rainfall Measuring Mission and were provided at the 0.25° level[21]. Monthly mean precipitation data from the Climate Research Unit are provided for comparison, and were used in sensitivity tests presented in the Supplementary Information[29]. Temperature data are a spatio-temporal interpolation of weather station data and were provided by the University of Delaware at the 0.5° grid level[22]. Temperature data from the National Centers for Environmental Prediction and Climate Research Unit were also used for sensitivity tests[29,30].

Each observation in our data set corresponds to the minimum comparable area unit (MCA)-year. MCAs are necessary because of changes over time in the boundaries of municípios. Over the study period, some municípios were subdivided, creating new municípios. Other new munícipios were created through the merging of multiple municípios. We developed an algorithm in ArcGIS to identify a set of 95 MCAs over the analysis period (eight years). We developed another algorithm to calculate values for these MCAs for the soy and corn yields from weighted (by area) averages of the values reported for municípios that existed in each year. We directly aggregated the land-use and climate measures to the MCAs by summing the area in each land use across all pixels in an MCA and averaging the climate values in pixels in each MCA.

Supplementary Tables 1 and 2 show the distribution of mean monthly temperature and precipitation in the region. A wetter, hotter rainy season with less temperature deviation than the dry season is evident.

We performed six separate regressions, each regressing a distinct agricultural production variable on the same set of climate variables. The dependent variables investigated were soy yield, second-crop corn yield, abandonment of mechanized agriculture, expansion of mechanized agriculture, abandonment of two-crop per growing season agriculture, and expansion of two-crop per growing season agriculture. The primary specifications reported in the paper differ by dependent variable. In all cases, we performed ordinary least-squares regression with fixed effects for each growing season and each MCA. These regressions controlled for all fixed characteristics of each MCA and also all time-variant factors affecting the entire state uniformly. We also controlled for several additional land-use variables that vary across both space and time. The climate variable categories included are the MCA mean temperature and the MCA mean precipitation for each of the 12 months in each growing year (August–July). We are therefore estimating the correlation between year-to-year deviation from local mean climate and year-to-year variation or change for each of the six agricultural production variables.

The regression specification for the agricultural land-use variables is:

$$(\text{land}_{\text{it}}) = \beta_0 + \boldsymbol{\beta}_1(\mathbf{wx}_{\text{it}}) + \boldsymbol{\beta}_2(\mathbf{wx}_{\text{it}}^2) + \boldsymbol{\beta}_3(\mathbf{protect}_{\text{it}}) + \beta_4(\text{res}_{\text{it}}) + c_i + d_t + \varepsilon_{\text{it}} \quad (1)$$

where land_{it} is a measure of agricultural expansion, agricultural abandonment, second-crop expansion, or second-crop abandonment investigated in MCA, i, for each growing year, t, over the period 2002/03–2009/10. On the right-hand side of each land-use regression, $\mathbf{wx}_{\text{it}}$ is the mean monthly total precipitation and the mean monthly temperature for each month in each growing year, $\mathbf{wx}_{\text{it}}^2$ is the quadratic term for each monthly climate variable, $\mathbf{protect}_{\text{it}}$ is two variables, the indigenous reserve area in each MCA-year and other protected area extent in each MCA-year, and res_{it} is the land reserve in each MCA-year. Land reserve is the area of each MCA at the start of each growing year that is comprised of single cropping or double cropping (in the case of land abandonment) or not comprised of the dependent variable in the case of land expansion. Land reserve is the area at risk of experiencing the land-use change indicated by the dependent variable. Land reserve is therefore different for each land use. The analysis also contains fixed effects to control for time-invariant characteristics of each MCA, c_i, and to control for space-invariant characteristics of each year, d_t. The MCA fixed effects control for variables such as mean local climate, elevation, access to major highways, and history of agriculture. The year fixed effects control for uniform, statewide effects such as fluctuations in the price of commodities and droughts.

The specification for the two yield regressions is:

$$\text{yield}_{\text{it}} = \beta_0 + \boldsymbol{\beta}_1(\mathbf{wx}_{\text{it}}) + \boldsymbol{\beta}_2(\mathbf{wx}_{\text{it}}^2) + \boldsymbol{\beta}_3(\mathbf{protect}_{\text{it}}) + c_i + d_t + \varepsilon_{\text{it}} \quad (2)$$

where yield_{it} is soy yield or second-crop corn yield. The right-hand side of equation (2) is identical to equation (1) except for the absence of the control for land reserve, res_{it}. Descriptions of the regressions performed are shown in Supplementary Table 3. The standardized effects of the climate variables, the four land-use variables, and two yield variables are shown in Supplementary Figs 1 and 2.

The regression results were used to generate predicted changes in each of the six agricultural production variables under a set of climate scenarios uniform in their deviation from local (MCA) monthly mean temperatures and local monthly mean precipitation totals over the eight years included in the analysis (2002/03–2009/10). For each prediction scenario, we began with the intercept and regression coefficients estimated from each regression, replaced the values of each climate variable in the data set with a uniform deviation from the local means (and 2009/10 values for non-climate variables) and then inserted these alternative values of the climate variables into the regression equations to obtain the predictions under the climate deviations. After calculating the predictions, we compared the total agricultural production under mean climate conditions and under each scenario and calculated the percentage of deviation from production under mean climate to investigate the impacts to agricultural production associated with the impacts of climate deviations on each agricultural variable. The aim of this approach was to be able to quantify the impact to agricultural production of a given deviation from mean temperature, precipitation, or both. This enables us to test our overarching hypothesis that losses to agricultural production from climate-caused changes in agricultural land use are of comparable scale to changes from yields. Note that these results should not be interpreted as prediction of the future climate and its impacts to agriculture. Our results could be combined with modelling of the future climate to predict the aggregate impacts to agricultural production from the predicted changes in the climate.

For each of the land-use-dependent variables, we created a new data set where, for every year, the climate variables for each MCA, $\mathbf{wx}_{\text{it}}$ and $\mathbf{wx}_{\text{it}}^2$, were replaced with $\overline{\mathbf{wx}_i}$ and $\overline{\mathbf{wx}_i^2}$, the local means of the climate variable over the range of the data set, 2002/03–2009/10. We next combine this new data set with the coefficients and intercepts obtained from the regressions in equation (1) to predict each land use at local mean climate:

$$\widehat{\text{land}}_{\text{it}\bar{c}} = \widehat{\beta}_0 + \widehat{\boldsymbol{\beta}}_1 \times (\overline{\mathbf{wx}_{\mathbf{i}}}) + \widehat{\boldsymbol{\beta}}_2 \times (\overline{\mathbf{wx}_{\mathbf{i}}}^2) + \widehat{\boldsymbol{\beta}}_3 \times (\mathbf{protect}_{\text{it}}) + \widehat{\beta}_4 \times (\text{res}_{\text{it}}) + \hat{c}_i + \hat{d}_t \quad (3)$$

Next we develop a set of climate scenarios, wx_{ic}, consisting of seven precipitation levels crossed with three temperature levels for a total of 21 climate scenarios. Precipitation levels are −30%, −20%, −10%, 0%, +10%, +20% and +30% different from $\overline{\text{wx}_i}$, the local mean precipitation from 2002/03 to 2009/10. Temperature levels are −1 °C, 0 °C, +1 °C different from $\overline{\text{wx}_i}$, the local mean temperature for years 2002/03 to 2009/10. We then repeat the calculation shown in equation (3) for each of the 21 climate combinations to obtain $\widehat{\text{land}}_{\text{itc}}$, 21 separate predicted quantities of each of the four dependent variable land uses in MCA, i, year t, under that MCA's temperature scenario, and precipitation scenario, c.

Next we calculate the predicted change in each of the four land uses—double-cropping expansion (DCM), double-cropping abandonment (DCA), mechanized-agricultural-area expansion (AGM) and mechanized-agriculture abandonment (AGA)—caused by each climate scenario. The equation is:

$$\Delta\widehat{\text{land}}_{\text{itc}} = \widehat{\text{land}}_{\text{itc}} - \widehat{\text{land}}_{\text{it}\bar{c}} \quad (4)$$

As year fixed effects, protected areas, and land reserve vary from year to year, the change in land use predicted also varies slightly from year to year. However, these changes are small and for this reason, we report only $\Delta\widehat{\text{land}}_{i2010c}$, the predicted change in land use under conditions comparable to the last year of the data set, 2009/10.

Next we calculate the statewide change in agricultural production in 2009/10 from the change in each land use from each climate change scenario:

$$\triangle\widehat{\text{Production}}_{i2010c} = \triangle\widehat{\text{land}}_{i2010c} \times \text{yield}_{i2010} \tag{5}$$

Agricultural production effects are obtained by multiplying the predicted climate-caused change in land use by the government-reported mean within MCA yield of the affected land in the year 2009/10. All agricultural production effects are reported in tons of corn equivalent. Every ton of soy is considered to be equivalent to 2.2 tons of corn, in line with the long-run average price ratio between soybeans and corn. For first-crop expansion and abandonment, we use the soybean yield (expressed in tons of corn equivalent). For second-crop expansion and abandonment, we use the second-crop corn yield.

Next we sum equation (5) over all MCAs to obtain a state-level estimate of cropland-area-change-driven changes in agricultural for each climate change scenario:

$$\triangle\text{Production}\widehat{\text{From}}\text{AreaVar}_{2010c} = \sum_i \triangle\widehat{\text{food}}_{i2010c} \tag{6}$$

Next we perform a similar sequence of post-estimation calculations for the two yield variables. We predict yields in essentially the same manner as we predict the land uses. To calculate the agricultural production impacts of the yields, we multiply the predicted yields by the appropriate areas of agricultural land use observed in our data set:

$$\triangle\text{Production}\widehat{\text{From}}\text{YieldVar}_{i2010c} = \triangle\widehat{\text{yield}}_{i2010c} \times \text{land}_{i2010} \tag{7}$$

Soy yield impact on agricultural production is obtained by multiplying predicted soy yield change by the government statistics on the area of soy in the region. Corn production impacts are obtained by multiplying predicted second-crop corn yield change by the government statistics on the area of all second-crop corn in the region.

Total agricultural production effects from each climate change scenario are thus:

$$\begin{aligned}\triangle\widehat{\text{Food}}_{2010c} = &\sum_i \triangle\text{Production}\widehat{\text{From}}\text{AllYield}_{i2010c}\\ &+\sum_i \triangle\text{Production}\widehat{\text{From}}\text{AllArea}_{2010c}\end{aligned} \tag{8}$$

In the paper, we also report a number of other metrics that are *ex post* sums of salient combinations of the predictions. Frequency is the sum of second-crop expansion (DCM) less second-crop abandonment (DCA) and is thus:

$$\triangle\widehat{\text{Frequency}}_{2010c} = \sum_i \triangle\widehat{\text{DCM}}_{i2010c} - \sum_i \triangle\widehat{\text{DCA}}_{2010c} \tag{9}$$

Cropland area change is the sum of mechanized-agriculture expansion (AGM) and mechanized-agriculture abandonment (AGA) and is thus:

$$\triangle\widehat{\text{Area}}_{2010c} = \sum_i \triangle\widehat{\text{AGM}}_{i2010c} - \sum_i \triangle\widehat{\text{AGA}}_{2010c} \tag{10}$$

We express all agricultural production as the percentage of difference in production predicted under a climate change scenario relative to agricultural production predicted under the data set mean climate. This estimate is obtained by dividing the outcomes of equations (6)–(11) by the sum of total government-reported soybean and second-crop corn production in Mato Grosso in 2009/10. Our estimates for area effects are slightly conservative because they ignore lost second crops from abandonment of the first crop of agriculture that was double cropping, and they count just one year of lost production from abandonment when, in reality, all land classified as abandoned had no agriculture for two more years subsequent to the climate shock. Our yield effects may be slightly distorted because they assume that all first-crop area lost was soybean and that all second-cropped area lost had corn. In reality just ∼60% of crop area in the state is soy and just ∼90% of the second crop is corn.

The effect size of climate variability occurring within each quarter of the growing season is obtained through four steps: estimating a regression for each dependent variable as detailed in equations (1) and (2); recording the model sum of squares for this base model (MSS_0) and the residual sum of squares for the base model (RSS_0); conducting additional regressions identical to the regressions in equations (1) and (2), except that in each additional regression, all climate variables from quarter q are omitted and the MSS and RSS from the additional regression with a climate quarter were omitted from equation (3); and then, we calculate the effect size of the omitted variables using the equation:

$$\text{Effect}_q = \frac{\text{MSS}_0 - \text{MSS}_q}{(\text{MSS}_0 + \text{RSS}_0)} \tag{11}$$

Following that, we perform the regressions as specified in equations (1) and (2) except that in each additional regression, all climate variables from all quarters are omitted. We then calculate the total climate effect:

$$\text{Effect}_{\text{clim}} = \sum q(\text{Effect}_q) \tag{12}$$

The percentages reported in Table 1 are obtained by the equation:

$$\text{Portion}_q = \frac{\text{Effect}_q}{\text{Effect}_{\text{clim}}} \tag{13}$$

Data and code for replication are available for download at: http://dx.doi.org/10.7910/DVN/H3UUSN[31].

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