Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41893-023-01152-2

Title: Key role of planted and harvested area fluctuations in US crop production shocks

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Accepted Manuscript version of:
Wei, D., Gephart, J.A., Iizumi, T. et al. Key role of planted and harvested area fluctuations in US crop production shocks. Nat Sustain (2023). https://doi.org/10.1038/s41893-023-01152-2

Abstract

Food production stability against climate variability and extremes is crucial for food security and is influenced by variations in planted area, harvested area, and yield. Yet research has focused on yield responses to climate fluctuations, ignoring how planted area and harvestable fraction (i.e., the ratio of planted area to harvested area) affect production stability. Here we apply a time-series shock detection approach to county-level data (1978-2020) on seven crops in the US, finding that shocks (i.e., sudden, statistically significant declines) in planted area and harvestable fraction co-occur with 51%-81% of production shocks, depending on the crop. Decomposing production shock magnitudes, we find yield fluctuations contribute more for corn (59%), cotton (49%), soybeans (64%), and winter wheat (40%), whereas planted area and harvestable fraction play a greater role for others. Additionally, climatic variables explain considerable portions of the variance in planted area (22%-30%), harvestable fraction (15%-28%), and yield (32%-50%). These findings demonstrate that crop production shocks are often associated with fluctuations in planted area and harvestable fraction. This highlights the (largely ignored) importance of producer decision-making about cropping patterns in stabilizing food production against climate variability and emphasizes the need to consider all three production components to improve food system stability.

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Main Text

Many countries are facing growing levels of food insecurity, with 193 million people acutely food insecure worldwide [1]. To achieve the United Nations' Sustainable Development Goal of Zero Hunger (SDG2) by 2030, urgent action is needed to ensure food security in all aspects. Least studied among the four food security pillars (availability, access, utilization, and stability) is food stability which refers to the ability of an individual, household, or population to have reliable access to adequate, safe, and nutritious food [2-4]. While stability can be affected at any step in the food supply chain, the largest number of disruption entry points are found at the production stage [5]. Food production shocks (i.e., sudden and unexpected losses in production) can be caused by a wide variety of factors including climate variability, extreme weather events, and economic and political disruptions [6-8]. With increasing climate variability [9] and climate extremes expected to become more frequent, intense, and prolonged [10-12], it is critical to understand the pathways through which environmental shocks impact production in order to develop more effective strategies for stabilizing crop production.

Food production instability (i.e., the occurrence and magnitude of year-to-year variability for a certain period) is determined by variability and shocks in planted area, harvestable fraction (i.e., the ratio between planted and harvested area), and yield (Box 1), each of which involves varying degrees of human decision making. Changes in planted area are determined mainly by farmer decisions before the growing season based on economic, policy, and climatic conditions [13,14]. Conversely, harvestable fraction (i.e., the portion of the planted area that is harvestable rather than lost within-season) is influenced by exogenous natural forces – such as climate extremes – and to some extent farmer decisions. Flooding, for example, can cause a portion of a field to be washed away, thereby reducing the harvested area but leaving yield unaffected [15]. Farmers may

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also decide not to harvest their crops – perhaps due to low yields, inferior quality, or low market prices – because the expected low revenue would not justify their time and effort [16,17]. For yield, changes are jointly dictated by within-season management decisions (e.g., irrigation, varietal choice) and environmental conditions (e.g., heatwave, drought, pests). Yet while all three of these components (planted area, harvestable fraction, and yield) can influence production outcomes, the vast majority of research on production instability to date has focused on the role of yield variations [7,18-23]. However, there are emerging efforts to understand how the different components of production contribute to its stability. For instance, some studies showed that production losses were associated with both harvested area and yield [24,25]. Other work in Brazil showed that harvested area and cropping frequency were more sensitive to climate variability than yield [26]. While these few studies suggest the importance of other non-yield components for determining production outcomes, the extent to which all three components of production (planted area, harvestable fraction, and yield) influence stability across different crops and regions is unknown [14]. Improving our understanding beyond yield variations can provide a more complete picture of the vulnerabilities of current crop production practices and can better inform strategies for adapting crop production to increasingly variable and extreme climate and other natural and human-made disruptions.

Here we focus on crop production shocks in the United States, the world's largest producer and exporter of cereal grains [27]. Because of its important role in the global food system, understanding the components that most contribute to US production shocks can improve strategies to ensure stable and reliable crop production and better protect national and global food supplies. To this end, we investigate how variations in planted area, harvestable fraction, and yield contribute to US crop production shocks and the extent to which these three components are affected by climate variability and extremes. We first assemble 43 years (1978-2020) of county-level agricultural data for 7 major crops (barley, corn, cotton, sorghum, soybeans, spring wheat, and winter wheat), which account for 70% of US cropland [28]. We then detect shocks (i.e., sudden and statistically significant decreases) in production and its components – planted area, harvestable fraction, and yield – using an automated quantitative statistical method that captures sudden changes in time series while ignoring long-term gradual fluctuations [29]. Through this approach, we quantify the number of years with production shocks (frequency) and estimate their co-occurrence with shocks in each of the three components. We then use a decomposition approach to investigate to what extent each of the three components contributes to the magnitude of production shocks [30]. Finally, we build random forest regression models to determine to what extent inter-annual variations in production and its three components are explained by climate variability and extremes. Together, these lines of investigation can provide valuable insights beyond the role of yield in influencing production stability and can serve as a basis for expanding the option space for interventions to address climate-related crop production losses.

Production Shock Frequency

Using an automated quantitative statistical shock detection method [29], we detected instances of negative deviations of production (hereafter, production shocks) ranging from 449 total negative shocks (for spring wheat) to 2532 shocks (for corn) in all counties between 1978 to 2020 (shock can only be detected from the second year)– the years for which data were available for all study crops. Production shocks varied both spatially and temporally between crops (Fig. 1). Production shock frequency has increased significantly for corn, cotton and soybeans ($P<0.05$, two-tailed Mann-Kendall test), with no significant trends in shock frequency being observed for all other study crops. In terms of geographic heterogeneity, we observed higher shock frequencies in Iowa, Illinois, and Missouri for corn, soybeans, and winter wheat, and in North Dakota for barley and spring wheat (Fig. 1).

We then compared the co-occurrence of production shocks with shocks in each of the three components of production. We found that more than half of the production shocks for 6 of the 7 study crops (barley, corn, cotton, sorghum, winter wheat, and spring wheat) co-occurred with shocks of area-related components (Fig. 2, Fig. S1). Conversely, for soybeans, the association with yield shocks dominates, co-occurring with 65% of production shocks. Across all seven crops, shocks related to planted area co-occurred with between 33% and 53% of production shocks, whereas shocks associated with harvestable fraction co-occurred with between 19% and 43% of production shocks. We found that between 17% and 31% of production shocks were associated with a combination of yield and area-related shocks, highlighting the fact that these components of production are not entirely independent of one another, depending on the nature of the disruption. We also compared shock outcomes between rain-fed and irrigated conditions across three crops – corn, winter wheat, and soybeans – for which there was sufficient data from 1978 to 2018 (Fig. S2). Not surprisingly, we found that shocks of area-related components co-occur more often with production shocks under irrigated conditions (potentially due to the buffering effects of irrigation on yield), whereas in rain-fed conditions, shocks related to yield comprise the majority of production shock co-occurrences. Looking across all component shocks (i.e., not limited to those co-occurring with production shocks), we found that shocks in any individual component are unlikely to result in production shocks (Table S1). Further, we find that the presence of co-occurring shocks in harvestable fraction and yield is still unlikely (except for corn) to result in a

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production shock in the same year, suggesting that in many cases planted area may have played an important compensatory role in mitigating production shocks (Table S1).

Production Shock Magnitude

We next quantified the magnitude of each of the detected production shocks and decomposed the contributions of each of the three components. On average, yield accounted for the largest portion of the production shock magnitude (31%-64%) across the study crops, followed closely by planted area (22%-53%), and then harvestable fraction (5%-29%) (Fig. 3, Fig. S3-S4). Yield was dominant in explaining the magnitude of production shocks for corn (average of 59% across available years), cotton (49%), soybeans (64%), and winter wheat (40%). Planted area was more important for barley (50% on average), sorghum (48%), and spring wheat (53%). As expected, the contribution of harvestable fraction shocks appears to be larger for crops with longer growing periods (GPs), while it is smaller for crops with shorter GPs. Over time, we also observed changing influences of the three components on production shock magnitude. For instance, while harvestable fraction represents a relatively small contribution to production shock magnitude for most crops, we saw an overall statistically significant increasing trend ($P<0.01$) of its contribution in corn (Table S2), and a fluctuating large proportion in cotton and winter wheat (Fig. 3). We also found a significant decreasing trend ($P<0.01$) of the contribution of yield in cotton (Table S2).

Links Between Climate Indicators and Agricultural Factors

Lastly, we employed random forest models to examine associations between climate variables (i.e., climate variability and extremes) (Table S3) and anomalies in planted area, harvestable fraction,

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and yield. While we expect that anomalies in these components will largely be affected by climate variables in the same GP, we also considered a 1-GP lag between climate variables and the planted area, as farmers may base their planting decisions partially on the (un)favorability of climate conditions in the previous GP (Fig. S5). We found that climate variability and extremes explain between 32% and 50% of yield anomalies, with yields for soybean (50%), corn (38%), and barley (37%) having the highest associations (Fig. 4). For planted area anomalies, we found that climate variables explained between 22% (for barley) and 31% (for cotton) of their variance. We obtained similar results when using climate variables from the previous GP (Fig. S5). Finally for harvestable fraction, we found that climate variables explained between 15% (spring wheat) and 24% (soybeans) of anomalies. The explanatory power of climate variables was highest for yield anomalies, then planted area, and lastly harvestable fraction. The relatively low associations with harvestable fraction may be because indicators for climate extremes considered in this study could not (due to data limitations) include variables of natural disasters (e.g., flooding, landslides, etc.), which are presumably the most influential factors on harvestable fraction [25], and re-planting in the same growing season after disaster. Across all three components and all crops, we found that temperature-related variables rank highest in importance (Table S4). These findings thus suggest that all components of production merit consideration as avenues for climate adaptation, particularly with regard to temperature. We note that our approach – which focuses on sudden, short-term reductions – likely does not capture the effects of longer-term, persistent climate extremes (e.g., multi-year droughts) which can also exercise influence on levels of crop production.

Discussion

The rise in climate variability, climate extremes, and other disruptions poses a growing threat to the stability of food supply chains. This is especially true for production which has numerous entry points for environmental, economic, and political disruptions [5,31], now and in the future [32-34]. Responding to these growing disruptions requires a comprehensive view of production and the components that dictate its outcomes. To this end, this study provides new insights into the extent to which the three factors (planted area, harvestable fraction, and yield) affect production stability and the degree to which they are affected by climate variability and extremes. We found that planted area, harvestable fraction, and yield all substantially influence both the frequency and magnitude of production shocks to varying degrees across crops. Considering shock frequency, shocks of area-related components co-occur with at least 50% of production shocks across all crops while yield-related shocks account for more than 31%. Although the effect of area-related components on production shock magnitude is generally lower than yield, we found large effects for certain crops (e.g., spring wheat) which deserve particular attention. Further, we found that climate variability and extremes can explain substantial fractions of the observed variations in each of the three components, indicating that there is a combination of complex factors (both climate-related and otherwise) that can contribute to instability in production. Together our results underline the importance of considering all three components to develop holistic approaches to improve production stability and the ability to withstand and recover from disruptions under ongoing climate change. Understanding the reasons behind the crop-to-crop differences in the relative importance of the three components will be an important next step of inquiry towards the development of adaptation strategies.

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Addressing food production shocks has direct implications for the entire food supply chain, negatively affecting food supply stability and posing a threat to food security. Limited availability of food can be a direct consequence of a production shock. At the same time, food production instability can dramatically increase food prices when stock is limited, lowering consumer purchasing power and potentially compromising human nutritional status, particularly among lower-income groups [35,36]. Sudden declines in production may also result in a decrease in food stocks; for instance, global grain reserves in 2008 fell to 18% of annual demand [37], which aggravated food system vulnerability. Because countries are becoming more reliant on global food trade, production shocks are affecting not only local markets and consumers but also global and distant markets when shocks cascade through the food trade network [5,38]. Despite international trade increasing the availability and diversity of food [39,40], it also exposes people to external disruptions in food production, particularly in regions that rely heavily on imports [41,42]. For instance, drought and extreme heat in 2012 caused a decline in US agricultural production that subsequently led to increases in global grain prices and compromised food access worldwide, especially for the world's poorest people [43]. This growing interconnectivity of nations means that increasing the stability of major grain producing nations' food production is a promising strategy for protecting global food security.

Our findings demonstrate that efforts are required in all components to stabilize production (with an exclusive focus on yield stability severely constraining the solution space) and that the stability of production is influenced by a variety of factors, including climate variability and extremes to a considerable degree. As such, holistic approaches that account for a variety of potential economic, political, and environmental disruptions – and their collective influences on all three components of production – are necessary to truly enhance the stability of crop production.

Yield has received the bulk of research and policy attention over the past few decades, with governments, international organizations, and other agencies developing cultivars with climate-resilient traits (e.g., heat tolerance) as well as practices to reduce the effects of environmental fluctuations on crop yields (e.g., agricultural inputs such as irrigation and soil organic matter) [23,44]. But such interventions provide little opportunity for improving the stability of planted areas and harvestable fractions, which are influenced through entirely different mechanisms. For instance, planted area is determined by farmer decisions which are influenced by a host of factors including environmental policies (e.g., the US's Conservation Reserve Program), market demand and food prices (which enable farmers to select the most profitable crops year after year), and farmer experience in accordance with weather forecasts over time. Economic incentives that account for these various influences can help to avoid sudden shifts in planted areas from year to year. In addition, harvestable fraction is influenced by both extreme events and farmer decisions. While extreme events remain difficult to predict, a suite of proactive actions can ameliorate their effects on harvestable fraction, including shifting cropping patterns, adjusting planting times to prevent loss of harvested area caused by environmental disruptions, and zoning within cropland to avoid utilizing land with a high probability of experiencing localized extreme events (e.g., floods). Meanwhile, strategies that improve crop quality, price and market access could encourage harvesting and thus reduce harvestable fraction losses at the harvest stage.

Stabilizing food production is a growing challenge for agricultural development. Although governments and researchers have worked to increase yield stability [19,45,46], focusing only on yield may miss a variety of important opportunities to stabilize production in the face of disruptions. This is well aligned with recent calls in the sustainability science community to actively design and manage response diversity to a growing suite of disruptions [47]. Our findings reveal that the

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relative importance of the different components of production varies by crop. Some crops are grown in a variety of locations throughout the United States (e.g., corn, winter wheat), allowing our approach to be applied at regional scales to tailor strategies to local circumstances. As such, developing strategies that employ a suite of interventions targeted at planted area, harvestable fraction, and yield offers the greatest flexibility for responding to local vulnerabilities and a variety of potential climatic and non-climatic disruptions.

Materials and Methods

Data

We rely on USDA Survey (USDA) data for US county-level harvestable fraction, planted area, yield, and production for 7 field crops), covering 70 % of planted area in the US [28]. Harvested area is the product of harvestable fraction and planted area. We separate the two components in order to better disentangle the influence of human and environmental influences on area-related shocks to production, with harvestable fraction more affected by within-season environmental factors, and planted area largely influenced by farmer decisions. Our analysis is limited to crops with available county data that represent 60% or more of national production for 20 consecutive years. The study covers the years 1978 to 2020, which are the years for which data were available across all study crops. It should be noted that the data for barley does not fully meet our criteria for inclusion after 2014, but we have examined them in the interest of completeness. Data for climatic variables were derived from the PRISM database [48], which provides high resolution (4km) daily and monthly mean, maximum and minimum temperature, and precipitation data for the whole US from 1981 to 2020. All the spatial data were re-gridded to county level by taking an area-weighted average of the grid cells within each county. Growing period data was derived from the latest USDA Usual Planting and Harvesting Dates in 2010 [49]. Although climate change has altered sowing dates and crop phenology, we used fixed crop calendars for calculating growing-season climate indices [50], as recent observed shifts in planting and harvesting dates have been less than 5 days per 1°C warming [51]. Using the example of corn, we find that our results are not sensitive to this choice of crop calendar (Table S5). Growing periods were then converted from dates to months to calculate climate variables over all months of each crop's growing period. Following Vogel et al [20], climate variables calculated in our study include mean monthly temperature (tmp), mean monthly precipitation (pre), maximum temperature (TXx), minimum temperature (TNn), warm day frequency (TX90p), cold night frequency (TN10p), maximum 5-day rainfall (Rx5day), diurnal temperature range (dtr), frost day frequency (frs), mean SPI-6, and mean SPEI-6 (Table S3). Climate variability is represented by the first two variables (tmp and pre), and climate extremes are represented by the others. All county-level agricultural and climate variables were detrended using the Singular Spectrum Analysis (SSA) method in R, to remove temporal trends due to technological progress, management changes, and long-term climatic changes. Because climate variables in particular can exhibit distinct temporal trends, detrending prevents the explained variance from being inflated as a result of the regression of two strongly trending variables. Except for SPEI-6 and SPI-6 (which are already standardized), all variables were then standardized by dividing by their standard deviation to enable the comparison of values across different locations.

Shock Detection

To identify and match the shock occurrence among planted area, harvestable fraction, yield, and production in all counties all crops, we adopted an automated quantitative statistical shock detection method following Gephart et al [29]. It is a method to capture sudden drops in a time series, with less sensitivity to high variable data and long-term, gradual fluctuations. The process of shock detection is mainly divided into four steps (Fig. S6): (a) fit the time series data by LOWESS regression (i.e., locally weighted smoothing, red line in the Fig. S6(a)) with a span of 2/3; (b) calculate residuals (i.e., the difference between the fitted and actual values, Fig. S6(b)); (c) plot residuals against the time-lagged residuals (i.e., residuals of its previous year, Fig. S6(c)); and (d) use Cook's Distance to identify extreme points in the regression of residuals versus time-lagged residuals (Fig. S6(d)). Counties with fewer than 20 data points were excluded due to their poor performance in shock detection. Points with Cook's D greater than the 4/N (N is the number of data points in a time series) were identified as shocks. While this shock detection method can identify both positive and negative deviations, we only considered production losses (i.e., negative production anomalies). Shocks for which the corresponding production data either did not have a value in the previous year or had a value identical to the previous year were not considered, due to data irregularities. Using this method, we identified shocks in all counties and all crops for each of the four agricultural variables (e.g., planted area, harvestable fraction, yield, and production).

To compare the frequency of production shocks to those in its three component factors, we examined whether each of the three components also experienced shocks when a production shock occurred. For example, corn production in Iowa County in Wisconsin had 5 production shocks over 43 years, and 3 of them happened in the same year as harvestable fraction shocks. Then we specified that 3 harvestable fraction shocks coincide with production shocks (Fig. S7). The same approach is used for shocks in yield and planted area. Thus, we determined the number of production shocks that co-occur with planted area, harvestable fraction, and yield shocks. It is worth noting that a production shock can occur in conjunction with shocks in several components, or it may not co-occur at all. As the shock detection method only captures relatively large drops and ignores gradual fluctuations and deals with each component of production independently, the two main reasons for no co-occurrences are 1) because the changes in the three components are minor but amplify one another; or 2) there is high variability in the time series of one or more of the components and a shock is not statistically detectable. Note that the shock frequency evaluation of our study does not account for differences in the area of each county. Because shocks were counted by county, this may potentially mute the average effect of the component shocks in the counties with larger areas and higher production.

Shock Decomposition

Based on the detected production shocks, we used a decomposition method [30] to measure the contribution of each component to the magnitude of production shocks. Decomposition follows the index decomposition analysis (IDA) [52] to express the overall change in an aggregate quantity as a sum of contributions from each of its components. The production of each county *i* is the product of planted area (*A*), harvestable fraction (*F*), and yield (*Y*). We used additive decompositions in IDA that converts the difference of national production between two consecutive years (Eq. 1, difference of all counties between year *t* and *t-1*) into the sum of contributions from each component (Eq. 2), by calculating the logarithmic mean Divisia Index (Eq. 3, example for yield). This approach was applied to every two consecutive years to estimate the contributions of each component to annual national production loss caused by production shocks as:

$$\Delta P_t = P^t - P^{t-1} = \sum_i Y_i^t A_i^t F_i^t - \sum_i Y_i^{t-1} A_i^{t-1} F_i^{t-1} \qquad (1)$$

$$\Delta P_t = \Delta Y + \Delta A + \Delta F \qquad (2)$$

$$\Delta Y = \sum_i (P_i^t - P_i^{t-1}) / (ln\, P_i^t - ln P_i^{t-1}) \times ln(\frac{Y_i^t}{Y_i^{t-1}}) \quad (3).$$

Random Forest and Cross-Validation

We applied a Random Forest machine learning algorithm to evaluate the correlation between each agricultural variable (e.g., planted area, harvestable fraction, yield, and production) and a suite of climate variables (Table S3). “Random Forests” is a non-parametric statistical method, using decision trees to make regression or classification and is robust to overfitting [53]. This method has been previously applied in the analysis of yield or production anomalies in association with climate variables [20,54].

The Random Forest model was built to examine the relationship between the anomalies (i.e., deviations from an overall trend) of each agricultural variable and all climate indicators for each crop. All data was randomly partitioned into an 80%/20% split for training and validation. Hyperparameters (i.e., number of trees to build, maximum depth of the tree, minimum leaf node size, and number of features to use for splitting) used in each model were tuned based on a Grid Search approach [55]. To estimate and compare the variance explained by climate for each agricultural variable, we calculated R^2 values from cross-validated predictions. We further generated “variable importance ranks” to assess the relative effect of the climate indicators on each agricultural variable for each crop.

Acknowledgments: This study was supported in part by the Gerard J. Mangone Climate Change Science & Policy Hub at the University of Delaware. K.F.D. acknowledges support by the United States Department of Agriculture National Institute of Food and Agriculture grant 2022-67019-37180 and University of Delaware General University Research Fund.

Author contributions: Conceptualization: DW, KFD. Methodology: DW, JAG, TI, NR, KFD. Validation: DW. Visualization: DW. Writing – original draft: DW, KFD. Writing – review & editing: DW, JAG, TI, NR, KFD.

Competing interest: Authors declare that they have no competing interests.

Data availability: All underlying raw data are publicly available online. County-level harvestable fraction, planted area, yield, and production data for the US are available at https://www.nass.usda.gov/Quick_Stats/Lite/index.php. Climatic data from PRISM database are available at https://prism.oregonstate.edu/. Growing period data are available at https://www.nass.usda.gov/Publications/Todays_Reports/reports/fcdate10.pdf.

Code availability: R code for shock detection is derived from Gephart et al. (https://github.com/jagephart/Shock_Detection). R code for decomposition and Python code for Random Forest analysis are available at https://github.com/Dongyang2020/US_Shock.

Figure Captions

Fig. 1. Production shock frequency and hotspot maps for study crops. The left panel (a) shows the production shock per county from 1978 to 2020. The asterisk indicates a statistically significant trend ($P < 0.05$, two-sided; corn: $p = 0.015$; cotton: $p = 0.009$; soybeans: $p = 0.017$). N represents the total number shocks for the whole time period. The right panel (b) shows the maps of shock frequency in each county over the study period. The total number of counties (n) examined is included in the bracket. Values higher than 0.1 are displayed in red.

Fig. 2. Proportion of production shocks co-occurring with different component shocks. Solid brackets indicate yield-related shocks, and dashed brackets include area-related shocks. Note that a small fraction of production shocks co-occurred with both yield and area-related shocks. The fraction of total detected production shocks that did not have co-occurring shocks with any of the three components are not shown in this figure. The two main reasons for no co-occurrence are because 1) the changes in the three components are minor but amplify one another; or 2) there is high variability in the time series of one or more of the components and a shock is not statistically detectable.

Fig. 3. Annual contribution from planted area, harvestable fraction, and yield to shock-related production losses. For each year for a specific crop, counties with production shocks were summed to represent the national production loss due to production shocks. Each component's contribution to the total loss was then calculated via shock decomposition [30]. The gap years (e.g., 1979 for cotton) mean that no production shock was detected across all counties for that crop.

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Fig. 4. Explained variance from Random Forest regressions. Predictor variables are the climate variables listed in Table S3. Response variables are the anomalies of the three agricultural components.

Box 1. Production outcomes of component shocks.

Crop production is calculated as the product of yield and harvested area. Harvested area can be further separated into planted area times harvestable fraction (calculated as the ratio of harvested to planted area). Each of these components can suffer a sudden loss independent of the other but still have the same consequences for production outcomes, as shown in the illustration below. In the first scenario, a smaller amount of area is planted compared to the other two scenarios, but there are no shocks to harvestable fraction or yield. In the second scenario, only half of the planted area was harvestable but yield was unaffected. In the third scenario, there is no difference between planted area and harvested area but yield is reduced by half. Across all of these scenarios, shocks in different components contribute to the same amount of production loss. In addition, should more than one component experience a shock at the same time, this would collectively amplify the resultant production shock. Note that these scenarios presume single season per year, and the sum of seasonal production is additionally required for multi-cropping systems.

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Accepted Manuscript
Version of Record at: https://doi.org/10.1038/s41893-023-01152-2

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