Global Patterns of Crop Production Losses Associated with Droughts from 1983 to 2009

WONSIK KIM, TOSHICHIKA IIZUMI, AND MOTOKI NISHIMORI

*Institute for Agro-Environmental Sciences, National Agriculture and Food
Research Organization, Tsukuba, Ibaraki, Japan*

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ABSTRACT

Droughts represent an important type of climate extreme that reduces crop production and food security. Although this fact is well known, the global geographic pattern of drought-driven reductions in crop production is poorly characterized. As the incidence of relatively more severe droughts is expected to increase under climate change, understanding the vulnerability of crop production to droughts is a key research priority. Here, we estimate the production losses of maize, rice, soy, and wheat from 1983 to 2009 using empirical relationships among crop yields, a drought index, and annual precipitation. We find that approximately three-fourths of the global harvested areas—454 million hectares—experienced drought-induced yield losses over this period, and the cumulative production losses correspond to 166 billion U.S. dollars. Globally averaged, one drought event decreases agricultural gross domestic production by 0.8%, with varying magnitudes of impacts by country. Crop production systems display decreased vulnerability or increased resilience to drought according to increases in per capita gross domestic production (GDP) in the countries with extensive semiarid agricultural areas. These changes in vulnerability accompany technological improvements represented by per capita GDP increases. Our estimates of drought-induced economic losses in agricultural systems offer a sound basis for subsequent assessments of the costs of adaptation to droughts under climate change.

1. Introduction

Droughts have received continuous attention, given that they represent a key type of climate extreme that causes food production losses and thus spikes in food prices (Field et al. 2012; Dai 2011; Heim 2002; FAO 2012; Esper et al. 2017). A study based on historical records reports that droughts reduced global crop production by 10% from 1964 to 2007 (Lesk et al. 2016). Global climate models have predicted that drought conditions will intensify in major breadbaskets of wheat and maize (e.g., North America and Europe; Seneviratne et al. 2012) and that climate change will cause droughts to become more persistent and more extensive in the coming decades (Dai 2013; Trenberth et al. 2014). The global demand for food is anticipated to double by 2050 because of population growth, dietary change, and bioenergy use (Davies et al. 2009; Tilman et al. 2011), and an annual rate of yield increase of 2.4% is necessary to meet this

demand without clearing additional land (Ray et al. 2013). However, the reported recent increases in the yields of key crops—maize, rice, soy, and wheat, which together account for two-thirds of food calories worldwide—are far lower than this rate at 1.6% (FAO 2017a). Under pressure, the Sustainable Development Goals (SDGs) of the United Nations (UN) aimed to achieve the eradication of poverty and hunger by 2030 (UN 2018), and droughts are a major threat to achieving these goals (FAO et al. 2017; FAO 2015; Field et al. 2012). Thus, an understanding of the timing, location, and magnitude of drought-induced damage is critical. For the first time, to the best of our knowledge, we present crop-specific and spatially explicit geographic patterns of drought-induced yield losses and the associated national-level economic losses in crop production. We also show that decreases in the vulnerability of crop production systems to drought have accompanied increases in the per capita gross domestic production (GDP) in recent decades. This result can inform the extent to which the technological improvements represented by per capita GDP are necessary to increase the resilience of crop production systems to droughts under climate change.

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Corresponding author: Wonsik Kim, wonsik@affrc.go.jp

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FIG. 1. Global patterns of the coefficients reflecting the correlations between yield anomaly Ω and drought magnitude Z from 1983 to 2009. Negative correlations indicate yield losses produced by droughts (red), whereas positive correlations indicate yield gains (blue). The gray areas represent statistically insignificant regions (those with p values ≥ 0.05), and the white areas indicate regions where either a crop is not harvested or yield data are not available. The pie chart describes the ratio of the harvested area to the total harvested area written in the center (Portmann et al. 2010) given the five ranges of Pearson correlation coefficients presented on the scale bar.

2. Method and data

The global drought-induced yield losses and economic losses for maize, rice, soy, and wheat from 1983 to 2009 are estimated as follows:

- 1) The percentage yield anomaly at year t is calculated from one grid cell ($0.5^\circ \times 0.5^\circ$) to another using the spatially explicit global yield dataset (Iizumi et al. 2018, <https://doi.org/10.20783/DIAS.528>) for the period from 1983 to 2009:

$$\Omega_t = \frac{\omega_t - \bar{\omega}_t}{\bar{\omega}_t} \times 100, \quad (1)$$

where ω indicates the crop yield (tons per hectare, t ha^{-1}) and $\bar{\omega}$ is the 5-yr centered moving average (t ha^{-1}) expressed as

$$\bar{\omega}_t = \frac{1}{5} \sum_{i=-2}^2 \omega_{t+i}. \quad (2)$$

The $\bar{\omega}$ denominator in Eq. (1) avoids yield loss overestimation owing to yield amount; the average over 5 years in Eq. (2) reveals the maximum global

percentages of statistically significant areas of the correlation between yield anomaly and drought magnitude in all crops (the upper half of Table A1 of appendix A and Fig. 1).

- 2) The drought magnitude at year t , which is 3-month aggregation of the standardized precipitation index (SPI; appendix B) before harvest, is calculated grid cell by grid cell:

$$Z_t = - \begin{cases} \sum_{j=0}^1 \zeta_{12-j,t-1} + \zeta_{1,t}, & H = 1, \\ \zeta_{12,t-1} + \sum_{j=0}^1 \zeta_{2-j,t}, & H = 2, \\ \sum_{j=0}^2 \zeta_{H-j,t}, & H \geq 3, \end{cases} \quad (3)$$

where H is the harvested month in 2000 (Sacks et al. 2010, <http://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php>) and $\zeta_{j,t}$ is the 6-month SPI in month j in year t . The aggregation over 3 months reveals maximum global percentages of statistically significant areas of the correlation

between yield anomaly and drought magnitude in all crops (the lower half of Table A1 of appendix A, and Fig. 1); for the case in which harvesting occurs in January ($H = 1$) or February ($H = 2$), SPI values in December and November or December in the previous year ($t - 1$) are required, respectively; note that the minus operator is multiplied by the computed 3-month sum of SPI. As a result, a larger Z value indicates more severe drought conditions.

- 3) A linear regression analysis between the annual time series of Ω and Z calculated in steps 1 and 2 is performed from one grid cell to another to determine the Pearson correlation coefficient r (Fig. 1) and the regression coefficients—intercept a and slope b (e.g., Fig. 2). We used the data in only the years with $Z \geq 0$ (dry years) to capture drought impacts on yield. The inclusion of data in years with $Z < 0$ (wet years) can be a source of errors in addressing drought–yield relationships because of influences of excess water on crops in wet years.
- 4) The regression coefficients a and b are separately associated with the average annual precipitation κ in the period from 1983 to 2009 (Figs. 3a,b). This parameterization enables us to estimate the drought-induced yield losses in the locations where no significant correlation between Ω and Z was obtained in the step 3 (Fig. 1). Using the gridcell values of a and b for the locations where a significant correlation ($p < 0.05$) was obtained, the median values of a and b are separately calculated for every 20th-percentile bin of κ . These medians are related to the precipitation ranges for all crops as $\alpha = 8.5 - 3.7\kappa$ and $\beta = 7.9 - 3.3\kappa$ (Figs. 3a,b). Note that these α and β functions are estimated without points—a negative intercept in Fig. 3a and a positive slope in Fig. 3b—of rice ranging from 1.5 to 1.8 m yr^{−1} because this range leads to yield gain by drought.
- 5) The percentage drought-induced yield loss at year t is calculated on a per-gridcell basis using

$$Y_t = \alpha + \beta Z_t, \quad (4)$$

where Z is the forcing variable calculated in step 2 and α and β are calculated in step 4 with the κ of the grid cell. The calculated Y sometimes has a negative value—yield gain under drought conditions. To limit our analysis to only the yield loss associated with droughts, we deem that the cases with positive Y values—yield loss under drought conditions—are effective data. Note that the grid cells for rice in which precipitation ranges

FIG. 2. Examples of linear regression analyses between yield anomaly Ω and drought magnitude Z . Red indicates that droughts lead to yield losses near Eagle Butte, South Dakota, United States (45.0°N, 101.6°W), and blue indicates they lead to yield gains near Abadia dos Dourados, Minas Gerais, Brazil (18.5°S, 47.5°W). Here, r represents the Pearson correlation coefficients, and p is the probability of the test being rejected when the correlation coefficient equals 0 using a two-tailed t test.

between 1.5 and 1.8 m yr^{−1} are masked out worldwide because these gridcell data are not considered in the modeled relationship between κ and α (or β) value in step 4.

- 6) The average yield loss per drought event from 1983 to 2009 (Fig. 4) is estimated on a per-gridcell basis using

$$\bar{Y} = \frac{1}{n} \sum_{t=1}^n Y_t, \quad (5)$$

where n is the number of years with positive Y values for 27 years (1983–2009) and represents the number of drought events.

- 7) The national-level drought-induced economic loss for four target crops from 1983 to 2009 (Fig. 5) is calculated using

$$E = \sum_{\text{crops}} \left[P \sum_{\text{gridcells}} \left(A \sum_{t=1}^n \bar{\omega}_t \frac{Y_t}{100} \right) \right], \quad (6)$$

where P is the average producer price by crop [U.S. dollars per ton (\$ t^{−1})] from 2004 to 2006 (FAO 2017a). If P is unavailable for a given country, the average P value of the other countries on the same continent is substituted (asterisks

FIG. 3. Variations in (a)–(c) the linear regression coefficients and (d) the irrigated area (Portmann et al. 2010) by crop because of the average annual precipitation κ from 1983 to 2009. The circles and the vertical and horizontal tails denote the medians and the standard deviations, respectively. The red lines in the (a) and (b) indicate the regression line among all circles in each panel except for one blue circle of rice representing the range of $1.5 \leq \kappa < 1.8 \text{ m yr}^{-1}$.

in Fig. 5b). Term A is the gridcell harvested area (ha) in 2000 (Portmann et al. 2010, http://www.uni-frankfurt.de/45218031/data_download), $\bar{w}$ (t ha⁻¹) is the year-to-year average yield calculated in step 1,

and Y (%) is the year-to-year yield loss estimated in step 5.

8) The agricultural gross domestic production is estimated using

$$\text{AGDP} = \frac{\text{Value} - \text{Added agricultural percentage of GDP}}{100} \times \text{GDP}, \quad (7)$$

where the value-added agricultural percentage of GDP is the GDP share of the agricultural sector

(%; World Bank 2017). GDP (\$) is gross domestic production.

FIG. 4. Global patterns of average drought-induced yield loss per drought event $\bar{Y}$ from 1983 to 2009. The gray areas represent regions where the effects of droughts are not detected in harvested areas, and the white areas represent regions where either a crop is not harvested or yield data are not available. The pie chart represents the ratio of the harvested area to the total harvested area written in the center (Portmann et al. 2010) given the five ranges of yield losses indicated on the scale bar.

3. Results and discussion

a. Sensitivity of yield anomaly to drought

Globally, the harvested areas of different crops with significant correlations between Ω and Z from 1983 to 2009 account for 21–73 million hectares (Mha; Fig. 1). Wheat displays the most extensive area of correlations (73 Mha, 34% of its global harvested area), followed by maize (41 Mha, 27%), rice (31 Mha, 19%), and soy (21 Mha or 28%). Drought-induced yield losses, which are indicated by negative correlations (red areas in Fig. 1), are seen in the Great Plains of North America, the Pampas of South America, Mediterranean Europe, southeast Africa, southeast Australia, and Indochina. Although drought-induced yield gains, which are indicated by positive correlations (blue areas in Fig. 1), also emerge in some parts of East China and the Brazilian Highlands, these correlations may partly reflect increases in yields due to abundant solar radiation without accounting for precipitation deficits accompanying crop water stresses. In the case of wheat (Fig. 1d), these results are comparable to Fig. 2d of Zampieri et al. (2017) estimated by the standardized precipitation evaporation index and the national yields except for the United States; the wheat yield losses of the Great Plains are relatively too small to reflect the total yield

anomalies in the United States. We find that the sensitivity of Ω to Z —the slopes of regression lines such as those shown in Fig. 2—varies by location and depends on the average annual precipitation κ (Fig. 3). In broad terms, the sensitivity of the yield anomaly—the absolute value of the regression slope—increases as the annual precipitation decreases without considering the sort of crop (Fig. 3b). However, the intercept on the Z axis (Fig. 3c), the Z threshold for negative Ω (Fig. 2), which is the drought definition in this study, is not significant according to κ ; the threshold for rice is lower than those for the other crops while statistically insignificant.

b. Global estimation of drought-induced yield loss

The harvested areas that experienced yield losses by droughts correspond to 161 Mha (75% of global harvested area by each crop) for wheat, 124 Mha (82%) for maize, 102 Mha (62%) for rice, and 67 Mha (91%) for soy (Fig. 4). The global averages of drought-induced yield losses per drought event $\bar{Y}$ are 8% for wheat, 7% for maize and soy, and 3% for rice; these losses correspond to 0.29, 0.24, 0.15, and 0.13 t ha⁻¹ from 1983 to 2009, respectively. Lesk et al. (2016) reported that the loss of cereal is 4.9%–5.2% for the period of 1964–2007 using the superposed epoch analysis. Our findings are quantitatively comparable to this result.

FIG. 5. The 25 countries that have large cumulative drought-induced economic losses E for the period from 1983 to 2009. The data on the national producer prices of staple crops and the national-level agricultural gross domestic product (AGDP) in 2005 were obtained from FAO et al. (2017) and World Bank (2017), respectively. The red crosses are based on the EM-DAT data published by CRED (2017). An asterisk denotes the country for which the P value is replaced by the average P on its continent, and the two-character country code is based on the International Organization for Standardization (ISO) standard 3166.

In addition, our estimate for soy, which is the crop the most sensitive to drought in our study—91% of its global harvested area is damaged by drought—is the first published global estimate to date. As expected, our findings confirm that semiarid regions (Bailey 1979) are more vulnerable to drought than other areas across the globe, and wheat is the most vulnerable to drought in terms of the area that experiences yield losses and the proportional losses because the proportions of irrigated area for this crop are lower although κ is lower than those of the other crops considered here (Fig. 3d). Remarkably, the most insensitive crop to drought is rice (Fig. 4b), and this result could be delivered by its larger irrigation area than the others (Fig. 3d; blue).

c. Global estimation of drought-induced economic loss

The worldwide aggregated national E for the four crops from 1983 to 2009 corresponds to \$166 billion (B). Maize is associated with the largest economic loss (\$58 B or 35% of the global total E), followed by wheat (\$47 B or 28%), rice (\$37 B or 22%), and soy (\$24 B or 14%). Approximately 93% of the aggregated loss is associated with the 25 most vulnerable countries, and 56% is concentrated in China and the United States only because of the large areas of cropland in these countries (Fig. 5a). The estimates for E presented here are comparable to the data contained in the Emergency Events Database

(EM-DAT) of the Center for Research on the Epidemiology of Disasters (CRED 2017), which is a global dataset that describes the economic losses and damage caused by disasters, as shown in Figs. 5a and 6. In our estimate, 26% of the yearly economic losses by country overlaps with drought years recorded in EM-DAT because EM-DAT has rigorous drought criteria for disasters (<https://www.emdat.be/explanatory-notes>). The United States is comparable to EM-DAT and the data from the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NOAA NCEI 2018). CRED does not record an economic damage value for 1988, and the NCEI estimate of this value is \$20 B. The NOAA National Climate Program Office (1988) reported damage of \$4.7 B for maize and \$3.7 B for soy in 1988. Our estimate of \$8.6 B for this year (United States in Fig. 6) is comparable with these values if we consider that the NCEI incorporates agricultural products for which the prices are higher than those of cereal crops and the total livestock feeding cost—vegetables, fruits, and hay for livestock (Smith and Matthews 2015).

d. Economic damage caused by drought-induced crop losses

Drought damage measured as a percentage of agricultural gross domestic production (AGDP) may have

FIG. 6. Temporal trends in aggregated national-level drought-induced economic losses for all crops: maize, rice, soy, and wheat, and the recorded drought events from 1983 to 2009 published in EM-DAT by [CRED \(2017\)](#). Blue arrows denote drought events covering a single year, red arrows indicate multiyear droughts, and yellow arrows indicate drought events without economic loss data.

relevance for international or national-level policy makers who allocate resources to the reduction and prevention of drought damage. The worldwide relative economic loss per drought corresponds to 0.8% of the national AGDP calculated as the average for 119 countries that experienced drought-related losses from 1983 to 2009. The crops with the largest impact on the

global AGDP are wheat (39%), followed by maize (36%), rice (21%), and soy (4%). Only two crops—wheat and maize—account for three-fourths of drought-induced damage to AGDP. Interestingly, these percentages are relatively larger gaps with the percentage of global total E ([section 3c](#)) on wheat (11%) and soy (−10%). These results indicate that wheat is more

FIG. 7. Relationships between the per capita GDP (World Bank 2017) and the average drought-induced yield loss $\bar{Y}$ produced by individual drought events from 1983 to 2009 (see Fig. 4). The colors of the circles denote the average annual precipitation κ given the five ranges of κ indicated on the scale bar, the sizes of the circles denote the percentages of agricultural GDP to GDP (World Bank 2017), and the two-character country codes are based on the ISO standard 3166 (see Fig. 5). The blank country codes indicate that AGDP data are not available at World Bank (2017). The solid line presents the regression line among the orange and yellow circles for which κ values are less than 0.9 m yr^{-1} , which is the average κ where our target crops are harvested.

vulnerable in high AGDP countries and that soy is more resilient in these countries. Figure 5b presents the 25 countries most vulnerable to AGDP. The crops with the largest impacts on the 25 countries are maize (40%), followed by wheat (37%), rice (18%), and soy (5%), and these values are not very different from the global values, except for changing the order between maize and wheat; maize is the most vulnerable crop in these countries. Remarkably, 68% are countries with $\kappa \leq 0.9 \text{ m yr}^{-1}$, which is a global average value of the annual precipitation in the crop harvested areas in our study.

Importantly, our analysis suggests that $\bar{Y}$ values in developed countries are lower than those in developing countries where semiarid agricultural areas ($\kappa \leq 0.9 \text{ m yr}^{-1}$; the circles colored with orange and yellow in Fig. 7) are extensive, and the AGDP makes up a relatively large proportion in developing countries (the circle size in Fig. 7). These results indicate that developing countries whose economies rely heavily on agriculture are constrained by water resources, and then are more vulnerable to droughts. Meanwhile, most of the average yield losses decrease with increasing per capita GDP in the countries where $\kappa < 0.9 \text{ m yr}^{-1}$. This result shows that the prevalence of advanced agricultural technologies, for example, irrigation systems (Playán and Mateos 2006; Pereira et al. 2002), breeding (Cattivelli et al. 2008; Duick 2005), and crop management (Bodner et al. 2015; Farooq et al. 2009), in developed countries tends to reduce drought-induced yield losses, while maize cultivated in the U.S. Midwest had no reduction during 1995–2012 (Lobell et al. 2014). Considering the expected increases in per capita GDP in the future, this process will likely be accompanied by investments in agricultural research and development and the transfer of technologies to developing countries. In particular, the expansion of irrigated crop areas (Fig. 8; Siebert et al. 2015; Fischer et al. 2014) will be activated and then improved drought resilience will be expected in all crops. Improved drought management should contribute to increases in the on-farm incomes of small household farmers and to food security in drought-prone regions across the world (FAO 2017b).

e. Limitations and uncertainty

Our findings have limitations; in particular, the estimated damages in western Africa and western Asia are more uncertain than those for other regions because the estimates for these two regions depend on sparse measurements of precipitation and yields, which are employed to calculate the drought magnitudes and yield anomalies in our study (Schneider et al. 2014; Iizumi et al. 2014). The uncertainties that originate in

FIG. 8. The relationship between the area equipped for irrigation (Siebert et al. 2015) and the per capita GDP (World Bank 2017) for major countries equipped for irrigation.

the limitations of the available data also propagate into our damage estimates because of the use of a fixed crop calendar year, harvested area, and producer prices for drought magnitudes and economic losses. Although the soil water balance is not explicitly considered in our analysis, the simplicity of the standardized precipitation index (WMO 2012) helps us to reduce the uncertainty associated with the parameters and forcing variables used in other drought indices (Zargar et al. 2011; Burke and Brown 2008; Keyantash and Dracup 2002). Finally, our results depend substantially on the quality of the precipitation data presented in the Water and Global Change (WATCH) Forcing Data applied to ERA-Interim data (WFDEI) dataset (Weedon et al. 2014).

4. Conclusions

The UN is promoting zero hunger as one of the sustainable development goals to transform our world. To achieve this goal, the UN targets global sustainable and resilient agricultural production systems that strengthen the capacity for adaptation to drought and other disasters to achieve double agricultural production by 2030. This study improves our understanding of the spatial and temporal patterns of crop-specific drought-related damage. Therefore, this study has utility for policy makers in national governments and international organizations who wish to identify locations in which drought risk management should be

TABLE A1. Global percentages of statistically significant areas for the correlation between yield anomaly Ω and drought magnitude Z by crop according to time scales of the average year in Eqs. (1) and (2) and the aggregate month in Eq. (3). The boldface numerals indicate the selected time scales for this study to maximize the areas (Fig. 1).

Time scale	Maize	Rice	Soy	Wheat
Average year for Eqs. (1) and (2)				
3	24	17	25	31
5	27	19	28	34
7	25	18	26	34
9	23	17	28	32
11	23	15	27	31
13	21	15	23	30
Aggregate month for Eq. (3)				
1	26	19	29	31
2	26	19	29	31
3	27	19	28	34
4	26	18	28	34
5	25	16	27	34
6	23	13	24	34

prioritized. Improved drought management should contribute to increases in the on-farm incomes of small household farmers and to food security in drought-prone regions across the world. These outcomes represent a target of the SDGs promoted by the UN for the coming decade.

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APPENDIX A

Best Time Scales

We choose 5-yr average and 3-month aggregation (Table A1) to obtain the maximum global percentages of statistically significant areas (Fig. 1).

APPENDIX B

Standardized Precipitation Index

We use the SPI (McKee et al. 1993) for a drought index because of its popularity (Bachmair et al. 2016; WMO 2012; Zargar et al. 2011; Sivakumar et al. 2011) to estimate agricultural drought at common points (Lu et al. 2017; Vicente-Serrano et al. 2012). Under the hypothesis that monthly precipitation $x_{j,t}$ aggregated at

time scale k is normally distributed (Edwards and McKee 1997; Cancelliere et al. 2007), SPI in month j in year t is

$$\zeta_{j,t}^{(k)} = \frac{X_{j,t}^{(k)} - \mu_j^{(k)}}{\sigma_j^{(k)}}, \quad \text{where} \quad (\text{B1})$$

$$X_{j,t}^{(k)} = \sum_{i=0}^{k-1} x_{j-i,t}, \quad (\text{B2})$$

$$\mu_j^{(k)} = \sum_{i=0}^{k-1} \mu_{j-i}, \quad \text{and} \quad (\text{B3})$$

$$\sigma_j^{(k)} = \sum_{i=0}^{k-1} \sigma_{j-i}, \quad (\text{B4})$$

and μ_j and σ_j are the mean and the standard deviation of x at month j for at least 30 years (=360 months; McKee et al. 1993), respectively. The Global Precipitation Climatology Centre (GPCC) monthly precipitation in WFDEI (Weedon et al. 2014, [ftp://rfdata:forceDATA@ftp.iiasa.ac.at](ftp://rfdata.forceDATA@ftp.iiasa.ac.at)) is used as x for SPI computation. We examined the averaging time period for SPI from 1- to 12-month intervals in preliminary analysis and selected the 6-month period for this study because the highest Pearson correlation coefficient between yield anomaly Ω and drought magnitude Z was achieved when the 6-month SPI was used.

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