Rainfall anomalies are a significant driver of cropland expansion

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Edited by Anthony J. Bebbington, Clark University, Worcester, MA, and approved March 18, 2020 (received for review June 22, 2019)

Rainfall anomalies have long occupied center stage in policy discussions, and understanding their impacts on agricultural production has become more important as climate change intensifies. However, the global scale of rainfall-induced productivity shocks on changes in cropland is yet to be quantified. Here we identify how rainfall anomalies impact observed patterns of cropped areas at a global scale by leveraging locally determined unexpected variations in rainfall. Employing disaggregated panel data at the grid level, we find that repeated dry anomalies lead to an increase in cropland expansion in developing countries. No discernible effects are detected from repeated wet events. That these effects are confined to developing countries, which are often dominated by small-holder farmers, implies that they may be in response to reduced yields. The estimates suggest that overall, in developing countries, dry anomalies account for ∼9% of the rate of cropland expansion over the past two decades. We perform several tests to check for consistency and robustness of this relationship. First, using forest cover as an alternative measure, we find comparable reductions in forest cover in the same regions where cropland expands due to repeated dry anomalies. Second, we test the relationship in regions where yields are buffered from rainfall anomalies by irrigation infrastructure and find that the impact on cropland expansion is mitigated, providing further support for our results. Since cropland expansion is a significant driver of deforestation, these results have important implications for forest loss and environmental services.

rainfall variability | agricultural expansion | land use change | deforestation | dams

The variability of rainfall (i.e., anomalies), defined as deviations of annual rainfall from long-run averages, is an old and recurring challenge (1, 2) that threatens agricultural systems (3) and disproportionately impacts the developing world (4). Many of the world's poorest countries which have a disproportionately high dependence on agricultural employment, rapidly expanding populations, and elevated levels of water stress also endure strong variability of rainfall (4). Since the middle of the 20th century, anthropogenic climate forcing has doubled the joint probability of years that are both warm and dry in the same location (5) with tropics and subtropics facing more record-breaking dry events (6). While the effects of rainfall variability on crop yields and productivity have been widely studied (3, 4, 7–11), the consequences on changes in cropland area and by extension deforestation are less well understood (3, 12) and are yet to be quantified at a global disaggregated scale.

We study this relationship using data at the 0.5° grid cell level (∼55 km at the equator), for 171 countries from 1992 to 2015. Over this time period, there is extensive variation in rainfall over time and space. Defining a rainfall anomaly as a variation in precipitation that is at least 1 SD from the mean, *SI Appendix*, Table S1, shows the distribution of these anomalies. With the exception of large deserts like the Sahara and Gobi, nearly all areas of the world has experienced rainfall anomalies.

We find that repeated dry anomalies increase cropland expansion specifically in developing countries, which are characteristically dominated by small-holder farming, implying that cropland is expanded to compensate for lower yields. Two tests corroborate the results. First, comparable reductions in forest cover due to repeated dry anomalies are found in the same regions where cropland expands. Second, in places where infrastructure buffers yields from rainfall anomalies, cropland expansion halts. Finally, we conduct a two-stage analysis to directly discern the impact of rainfall-induced productivity shocks on cropland expansion. We find that when rainfall anomalies reduce agricultural productivity, we observe a resulting increase in cropland expansion, with 1- to 2- and 3-y lags.

Prior studies have shown that land conversion for agriculture remains a significant driver of deforestation (13–19). Over the past decade, the world has lost 2.3 million km^2 of forested land (20) with a substantial portion of this loss attributed to the ever-expanding agricultural frontier (18). Land under cultivation is expected to continue to increase well into the future to feed growing populations (21). As a consequence, land clearing has emerged as one of the major contributors to climate change and is believed to be responsible for about 6 to 17% of anthropogenic CO_2 emissions (22). Given the scale of deforestation, improving understanding of the relationship between rainfall variability and cropland expansion remains critical to developing adaptation responses that protect natural habitats, limit greenhouse gas emissions from land use change, and meet the growing demand for food. Here we provide global-scale evidence about the consequences of repeated rainfall anomalies on cropland expansion and deforestation using geographically and temporally disaggregated data.

Significance

Rainfall anomalies are known to have deleterious impacts on agricultural yields, but the resulting consequences on cropland expansion remain uncertain. We study the differential scale of these impacts around the world. We find that repeated dry anomalies increase cropland expansion specifically in developing countries, which are characteristically dominated by small-holder farming, implying that cropland is expanded to compensate for lower yields. Two tests corroborate the results. First, comparable reductions in forest cover due to repeated dry anomalies are found in the same regions where cropland expands. Second, in places where infrastructure buffers yields from rainfall anomalies, cropland expansion halts. Understanding the synchronous challenges facing agriculture and the environment will be critical to inform appropriate policy interventions.

Author contributions: E.Z., J.R., and R.D. designed research; E.Z. and J.R. performed research; E.Z. and J.R. analyzed data; and E.Z., J.R., and R.D. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1910719117/-/DCSupplemental.

First published April 27, 2020.

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Knowledge of how changes in agricultural productivity impact cropland expansion remains contested and uncertain (23–32). On one hand, factors that increase the profitability of agriculture and in particular the returns to investments from expansion (extensification) could induce greater land clearing in equilibrium (27–29). Such an outcome would be consistent with conventional economic theories based upon risk averse behavior (33). Conversely, it has been argued that higher yields, or greater profitability per unit of land, allow for the same amount of income to be obtained from a smaller area. By this line of reasoning, productivity and profitability increases are necessary to curb cropland expansion incentives. Variants of this argument have been termed the subsistence hypothesis (29). A related corollary is that increases in crop yield ought to reduce cropland expansion, referred to as the Borlaug hypothesis (29).

Like the economic theories, the empirical evidence remains mixed and ambiguous. Empirical tests using cross-country differences have found little evidence that increases in agricultural productivity lead to falls in cropped area, as conventional theories based on models of risk aversion would predict (30, 31). In contrast, evidence from general equilibrium modeling studies (32) and other microeconomic studies has found suggestive evidence for the reverse (23, 24). These complex relationships ultimately depend on local constraints such as the availability of land and factors that influence the profitability of expansion (29). This study does not attempt to test these hypotheses directly but is related to this empirical literature in so far as it seeks to determine whether exogenous (rainfall-induced) shocks to agricultural productivity curb or enhance incentives to expand cropland.

For our empirical exercise, we construct a panel dataset from geographically and temporally disaggregated weather, agricultural, and land use data, disaggregated at the level of a 0.5° grid cell (*Materials and Methods*). Using disaggregated data is critical since rainfall tends to exhibit significant spatial variability that is considerably higher than that of temperature. Globally, the within-country coefficient of variation is 1.9 times as large for precipitation as it is for temperature in the year 2000 (0.055 for precipitation versus 0.029 for temperature). Aggregated levels of precipitation would therefore mask the considerable spatial heterogeneity causing important statistical distortions that can have direct impacts on the results.

The empirical challenge is to isolate the impact of rainfall variations from other factors, which it could be correlated with. For instance, it is plausible that better levels of rainfall attract more migrants, which in turn induce agglomeration effects. In this case, correlations between rainfall and economic outcomes would be conflated and biased upward reflecting the consequences of features such as agglomeration, rather than the weather. To address these problems we focus on exogenous and unexpected variations in rainfall, combined with a rich set of fixed effects, which allows us to disentangle and causally identify the effects of rainfall from other confounding factors. Specifically, we examine the consequences of plausibly exogenous deviations of rainfall from its long-run mean in each grid cell (*Materials and Methods*). Thus, a grid cell observation in a year of normal rainfall acts as a control for the same grid cell observed in a year of a deviation or an anomaly, while year fixed effects and other controls account for differences in the grid cell from one year to the next, which might impact cropland expansion. Much like the standardized precipitation index, we define anomalies as deviations from the long-run average by using the z score. Dry anomalies are defined as z scores below -1, and wet anomalies are defined as z scores above $+1$.

We investigate how these locally determined exogenous and unexpected variations in rainfall impact observed patterns of cropland expansion as well as agricultural productivity (measured by net primary productivity). By examining the outcomes of interest directly—a physical measure of yields on the intensive margin and changes in cropped area on the extensive margin—we avoid relying on assumptions about mechanisms that might lead to these changes.

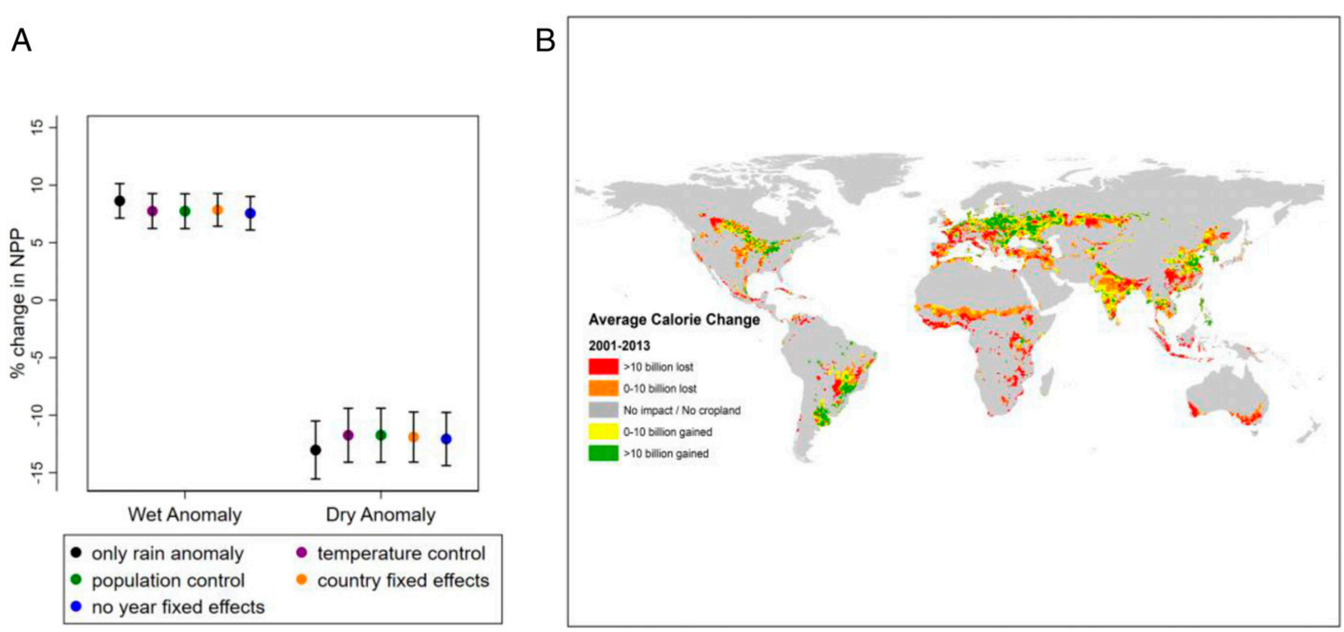

Fig. 1. Rainfall anomalies and agricultural productivity. (*A*) The impact of rainfall anomalies on agricultural productivity (measured by NPP) and plots the coefficients on wet anomalies and dry anomalies for separate regressions. All models include country-specific time trends, grid cell fixed effects (except for the orange dot), and year fixed effects (except for the blue dot). Error bars represent 95% confidence intervals. An extended table of results is provided in *SI Appendix*, Table S2. (*B*) The results of a simulation where average change in NPP due to rainfall anomalies is converted into net kilocalories gained/loss in each grid cell from the years 2001 to 2013.

We perform three additional tests for supportive evidence. First, we test a two-stage model which directly measures the impact of rainfall anomaly-induced agricultural productivity changes on cropland expansion. These results corroborate the reduced-form estimates of the main analysis. Next, we change the dependent variable in the main model and examine the relationship between repeated rainfall anomalies and deforestation, instead of cropland expansion in the same sample of grid cells and years. Since cropland often expands into forested areas or pastureland, we would expect to see a corresponding reduction in forest cover in regions which experience cropland expansion (13–19). Finally, we examine if regions where agricultural productivity is buffered from the impact of rainfall anomalies by irrigation infrastructure see changes in cropland expansion. This is a further test that the mechanism leading to expanded cropland is indeed rainfall-induced changes in agricultural productivity.

Results

Impact of Rainfall Anomalies on Productivity and Cropland Expansion. A number of multivariate statistical models are estimated to tease out the effect of rainfall variability on global cropland expansion and agricultural productivity. Here we discuss results using the preferred model, while additional results are supplied in *SI Appendix*.

Using a satellite-based estimate of agricultural yields—net primary production (NPP), which is a common unit of productivity across different crop types (*Materials and Methods*)—on cropland-designated areas from the European Space Agency (ESA) satellite database, we estimate the nonlinear impact of dry anomalies and wet anomalies on changes in agricultural productivity. Since weather variables tend to be correlated over time in the same location, we also control for a quadratic function of temperature to account for the well-established response of yields and the overall economy to temperature increases (34–36). Across models, we control for unobserved time-invariant heterogeneity at the grid cell level using grid cell fixed effects to capture soil type, socioeconomic characteristics, and other geographical characteristics that affect yield growth as well as year fixed effects to capture year-specific anomalies that are common to all grid cells to account for common contemporaneous trends, like global price changes and economic growth. In addition, we control for country-specific trends to capture variation in socioeconomic indicators and policies across countries. The rich set of controls helps to isolate the unexpected deviations in rainfall facilitating causal inference (*Materials and Methods*).

Fig. 1*A* confirms that rainfall anomalies lead to contemporaneous changes to agricultural production shocks and quantifies the magnitude of the impact globally. On average, productivity increases in response to wet anomalies and decreases with dry anomalies. Dry anomalies lead to an 11 to 12% decrease in agricultural productivity per year globally. Wet anomalies, on the other hand, increase crop productivity by ∼8 to 9%. These results hold across a variety of alternative model specifications that control for temperature exposure (Fig. 1*A*, purple dot) as well as population (Fig. 1*A*, green dot), replacing grid cell fixed effects with country fixed effects (Fig. 1*A*, orange dot) and eliminating year fixed effects (Fig. 1*A*, blue dot). These results are also robust to alternative thresholds used to identify cropland-designated areas in the ESA data (*SI Appendix*, Fig. S1) as well as an alternative measure of a rainfall anomaly that uses the standardized precipitation index (*SI Appendix*, Fig. S2). The findings are consistent with prior literature that finds adverse effects of rainfall shortfalls on yields both globally (3) and regionally (7, 8, 10).

Such rainfall-induced changes in agricultural production have perceptible implications for global and local food security. Converting the magnitudes of loss and gain in NPP into kilocalories for human consumption (10, 34), we find that dry anomalies amount to an average annual reduction of 82.7 trillion kilocalories between 2001 and 2013, assuming a 2,000 kcals per day, per person consumption or 730,000 kcals per person, per year. After accounting for losses of solar energy due to transportation, processing and crop residue (37), a rough conversion of 1 $gC/m^2/y$ of NPP into 1 kcal for human consumption is used to arrive at these estimates (10).

Over the same time period, wet anomalies generate an average annual gain of 47.5 trillion kilocalories. Thus, on net, there is an average loss of 35.3 trillion kilocalories per year—enough to feed 48 million people every day (Fig. 1*B*). Fig. 1*B* shows that these losses (in shades of orange and red) are unevenly distributed around the globe.

Next, we examine the impact of rainfall anomalies on changes in cropland. Similar to the above analysis on agricultural productivity, a global satellite measure of land use from the ESA is used (*Materials and Methods*). The regression specification is similar, with one difference. Expanding cropland, particularly when it requires spreading onto virgin fields or into forested areas, can require a large, upfront fixed cost. For this reason, we expect that contemporaneous impacts of variable rainfall will likely be muted, but repeated anomalies over the medium term could induce expansion as an adaptation strategy. We therefore measure the number of years in the past decade for which there was a dry anomaly or wet anomaly. We then estimate the impact of the lagged count of dry anomalies and wet anomalies on cropland expansion, after controlling for all possible confounders previously used in the agricultural productivity regressions. The distributions of these dry anomalies and wet anomalies are fairly similar, with more than half of the observations receiving zero or one dry anomaly and wet anomaly event in the previous 10 y and less than 4% of observations receiving 5 or more (*SI Appendix*, Table S1).

Main results of our cropland analysis are shown in Table 1. Rainfall variability is found to have a significant, but heterogeneous, effect on cropland expansion. For each year within the past 10 y which experienced a dry anomaly, cropland expanded by ∼0.02% on average across the globe and 0.03% in developing countries (defined as low-income and middle- income countries according to the World Bank; *SI Appendix*, Table S3). Although these increases in cropland appear to be quite minor, the mean increase in cropland over the sample period is 0.44% globally and 0.50% in developing countries. The average grid cell experienced 1.4 dry anomalies over the past 10 y, implying that dry anomalies account for ∼7.4% of global cropland expansion on average. In developing countries, dry anomalies account for ∼9.0% of total cropland expansion on average.

On the other hand, there is no discernible impact of dry anomalies on cropland expansion in high-income countries. This could reflect the fact that wealthier farmers have access to greater irrigation resources and savings, and if incomes are buffered against stochastic rainfall anomalies, there is little reason to alter behavior. Repeated wet anomalies do not show a robust impact on cropland expansion (Table 1); the coefficient estimates are small and not statistically significant ($P > 0.10$). Since wet anomalies are associated with higher agricultural productivity (Fig. 1*A*), the results suggest that the response of farmers in developing countries is asymmetric, with a greater sensitivity to cumulative and persistent declines in agriculture productivity than cumulative increases in agricultural productivity.

These results remain robust to a host of changes in data and model specifications. They are robust to two alternative cropland datasets derived from moderate resolution imaging spectroradiometer (MODIS) (MCD12Q1) that follows the International Geosphere-Biosphere Program (IGBP) classification and the University of Maryland (UMD) classification scheme as provided in ref. 38 (*SI Appendix*, Table S4). In developing countries,

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Table 1. Impact of rainfall anomalies on cropland expansion

	Cropland area			Forest area
Dependent variable	Full sample	High income	Developing	Developing
No. wet anomalies	0.000092	0.000109	0.000079	0.000810^{+}
	(0.000)	(0.000)	(0.000)	(0.000)
No. dry anomalies	0.000233*	0.000126	0.000321*	−0.001101**
	(0.000)	(0.000)	(0.000)	(0.000)
N	1,022,457	295,545	704,664	704,664
R-sq	0.332	0.297	0.338	0.321

Dependent variable in columns 2 to 4 is the 5-y average annual change in log cropland area in a grid cell, while in column 5 it is the 5-y average annual change in log forest area in a grid cell. All regression models include grid cell fixed effects; year fixed effects; country-specific trends; and controls for contemporaneous precipitation, temperature, and population. No. wet anomalies (dry anomalies) denotes number of wet (dry) anomalies in 10 y indicating the number of years, of the prior 10 y, for which annual precipitation in the grid cell was at least 1 SD higher (lower) than the long-run mean of the grid cell. SEs are clustered at the province–year level. Statistical significance is given by $^{+}P < 0.10$, $*P < 0.05$, $**P < 0.01$, and $***P < 0.001$.

dry anomalies account for ~21.5 to 15.9% of total cropland expansion, on average, depending on the classification used (*SI Appendix*, Table S4) which is approximately double the impact found with the ESA cropland data. Although the impact ranges between 9.0 and 21.5% across various cropland datasets due to differences in the temporal extent of the datasets and the varying methods used to classify cropland, results across all cropland datasets show a consistent impact of dry anomalies in expanding cropland. The results are also robust to using an alternative weather dataset from the Climatic Research Unit (*SI Appendix*, Table S5), using the standardized precipitation index in place of the main rainfall anomaly measure (*SI Appendix*, Table S6), calculating changes in cropland over different time periods (*SI Appendix*, Table S7), and using rainfall anomalies over the growing season in sub-Saharan Africa where we are able to explicitly identify the growing season for each grid cell (*SI Appendix*, Table S8). *SI Appendix*, Table S9, examines the sensitivity of the main results to explicit controls for economic factors such as distance to market that are otherwise subsumed in the grid cell fixed effects in the main model. Distance to market is proxied by estimated travel time to the nearest city for each grid cell in our analysis using data from ref. 39. *SI Appendix*, Table S10, tests for differential results in locations that are more likely to be dominated by large agricultural producers by identifying grid cells where soy and palm oil production are dominant—commodities that are known to be farmed at commercial scales (40). Point estimates in both *SI Appendix*, Tables S9 and S10, show that dry anomalies continue to remain a significant predictor of cropland expansion after controlling for market access and where the dominance of commercial agriculture measured by soy and palm oil is limited. This suggests that the behaviors identified here are prominent among the smaller farms in developing countries.

Overall, consistent and robust results are obtained for dry anomalies. These anomalies reduce yields unambiguously. In developing countries, in particular, they lead to a compensating expansion of cropland area, with a quantitative impact that is large relative to current rates of cropland expansion. Taken together, these results are consistent with a safety-first response (41, 42) by poor farmers who seek to achieve a certain target level of income or output.

Estimating a Two-Stage Relationship between Rainfall Anomalies, Agricultural Productivity, and Cropland Expansion. In the prior analysis we demonstrate that rainfall anomalies significantly impact agricultural productivity, as well as cropland expansion. Here we test directly how rainfall anomaly-induced changes in agricultural productivity impact cropland expansion. Empirically, there are statistical complications with testing the direct impact of changes in agricultural productivity on changes in cropland expansion. It is unclear a priori if it is changes in agricultural productivity which cause subsequent changes in cropland extensification or if larger-scale farmers are simply more productive. Thus, a simple statistical association between agricultural productivity and cropland expansion using ordinary least squares (OLS) could lead to a potentially biased regression estimate. This is seen in Table 2, column 2, where more productive agriculture is correlated with expanding cropland. To correct for this problem, a two-stage instrumental variable approach (2SLS) is used in column 3 that uses rainfall anomalies as a source of exogenous productivity variation to predict agricultural productivity. This has the dual benefit of both correcting for the endogeneity bias discussed above, as well as directly testing the specific impact of rainfall anomaly-induced variation in NPP on cropland expansion. Results show that upon this correction, rainfall anomaly-induced crop productivity declines do not cause a contemporaneous change in cropland expansion but induce expansions in cropland 1, 2, and 3 y later. The delayed effects of rainfall anomalies are consistent with our main results where we find that productivity-reducing dry rainfall anomalies, summed over a 10-y period, lead to cropland expansion. Overall, the two-stage results provide further supporting evidence that farmers in developing countries respond to declining yields by expanding cropland.

Is There a Similar Relationship between Rainfall Anomalies and Deforestation? To ascertain if we observe a similar relationship between rainfall anomalies and deforestation as with cropland, we replace the model of cropland changes with a model of forest cover changes. In Table 1, column 5, we estimate a model that explains how rainfall variability impacts changes in forest cover in each grid cell. For each year within the past 10 y which experienced a dry anomaly, forested areas decreased by ~0.1% on average in developing countries, a large effect compared to the sample mean of 0.9%. Overall, dry anomalies therefore account for 15% of total forest reduction on average. While this result does not determine the pathways through which dry anomalies induce forest cover loss, the similarity of estimated magnitudes provides further corroborating evidence of the prominent role that agricultural expansion plays in driving deforestation in the developing world but also the important role of rainfall variability in governing land use changes.

As a further check, to confirm more directly the link between the two, we also estimate a naïve model which relates changes in cropland to changes in deforestation (*SI Appendix*, Table S11). Across all model specifications, changes in cropland strongly predict contemporaneous changes in deforestation, with a 10% increase in cropland in a grid cell corresponding to a 0.7 to 1.0% reduction in forest cover. The contemporaneous response suggests that planted areas move directly into existing forest

Table 2. **Impact of rainfall shock-induced NPP changes on cropland expansion, two-stage least squares estimation**

Cropland area	OLS	2SLS
log(NPP), t	0.000694**	0.001062
	(0.000227)	(0.001092)
log(NPP), t-1	0.000383⁺	−0.002956***
	(0.000210)	(0.000888)
log(NPP), t-2	0.000347⁺	−0.003722***
	(0.000178)	(0.001026)
log(NPP), t-3	0.000000	−0.002993**
	(0.000120)	(0.001115)
N	54,956	54,934
Kleibergen–Papp LM-stat		1,509.62
Kleibergen–Papp LM *P* value		0.0000
Kleibergen–Papp F-stat		183.56

Dependent variable is log cropland area in each grid cell. All regression models include controls for year fixed effects, country–year trends, population temperature and precipitation. Column 2 also controls for grid cell fixed effects, and column 3 controls for country fixed effects as well as distance to the nearest city, CTI, and terrain roughness. Robust clustered SEs are in parentheses. In the first stage regressions, indicator variables for a wet and dry rainfall anomaly are included as instruments, in the same year as NPP. The regressions pass diagnostic tests for instrument relevance (Kleibergen–Papp LM test) and the test for weak instruments (Kleibergen–Papp Wald test) providing supporting evidence about the validity of the instrumental variables. Statistical significance is given by ⁺$P < 0.10$, *$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$.

frontiers. Planted areas can also expand into existing pasture lands, pushing pastures into forested areas. In this scenario, additional time might be needed to displace cattle to forest frontiers, thus delaying the impact of cropland expansion on forested areas (43). Even though the dynamic interaction between forest loss and cropland expansion can certainly vary by location, the results still suggest that rainfall variability remains a key variable in understanding deforestation–agriculture trade-offs.

Can Investments Which Buffer Agricultural Productivity against Rainfall Anomalies Also Buffer against Cropland Expansion? In this section, we test for further corroborative evidence that the relationship between repeated dry anomalies and cropland expansion is driven by impacts on agricultural productivity. We first show that agricultural productivity is not sensitive to rainfall variability in the command area of large irrigation dams. We then test if cropland expansion due to dry rainfall anomalies ceases to occur in these regions. We isolate grid cells which fall within the command area of each irrigation dam (*SI Appendix*, Fig. S3) in the Global Reservoir and Dam (GRanD) v1database—defined as potential recipients of irrigation services (refs. 44 and 45 and *SI Appendix*, Fig. S4)—and empirically establish the spatial threshold over which the largest agricultural benefits accrue (25 to 50 km downstream) (*Materials and Methods*).

To examine if access to irrigation infrastructure can mitigate the impact of rainfall anomalies on agricultural productivity, we use a similar empirical strategy as in the main analysis but also include the number of upstream irrigation infrastructure facilities in the regression equation, as well as interaction terms between the number of upstream irrigation facilities and the rainfall anomaly variables.

We apply a two-stage instrumental variables approach (2SLS) when estimating the impact of irrigation infrastructure to address biases that arise due to the nonrandom placement of infrastructure (*Materials and Methods*). Estimates of the influence of upstream dams on crop productivity are shown in Table 3. OLS results that do not correct for placement bias are reported in *SI Appendix*, Table S12. The 2SLS regression estimates show that the direct impact of dams is significant ($P < 0.05$), suggesting that dams boost productivity. These regressions pass diagnostic tests for instrument relevance (Kleibergen–Papp LM test) and the test for weak instruments (Kleibergen–Papp Wald test) providing supporting evidence about the validity of our instrumental variables. Additionally, results show that an additional upstream dam increases NPP growth by 7%. Having access to an upstream dam also buffers the adverse effects of a dry anomaly (that is, the coefficients on the interaction term of dry anomaly and upstream dams and the coefficient of the dry anomaly variable are of opposite sign). Upstream dams also decrease the sensitivity of NPP to wet anomalies. These results show that with irrigation infrastructure, the loss in productivity is dampened. If true, this ought to limit the safety-first response of cropland expansion seen in developing regions that are impacted by dry anomalies.

To test if this is the case, a similar specification is used for the cropland analysis. To facilitate interpretation, the variables indicating precipitation anomalies are transformed into binary variables. Given the distribution of anomalies, we show results for 2+, 3+, and 4+ y of anomalies, out of the last 10 y. Only around 3% of observations experience five or more wet anomalies or dry anomalies (*SI Appendix*, Table S1), making statistical inference noisy beyond 4+ y. Results are displayed in columns 3 to 5 of Table 3. Column 3 focuses on impacts due to 2+ rainfall anomalies in the last 10 y, column 4 focuses on 3+ rainfall anomalies, and column 5 indicates 4+ rainfall anomalies. The coefficient on the interaction between multiple dry anomalies and upstream irrigation facilities is negative and significant in all three 2SLS models. This implies that when irrigation reduces sensitivity to rainfall anomalies, farmers no longer respond to multiple years of dry anomalies by expanding cropland. Across all 2SLS models, the impact of multiple wet anomalies, as well as the interaction between upstream dams and wet anomalies, remains largely insignificant.

Collectively, these results show that when farmers are equipped with productivity-enhancing irrigation infrastructure that buffers against rainfall-induced anomalies, incentives to expand cropland in the face of repeated dry anomalies disappear.

We caution that these results do not comment on the net benefits of dam construction or irrigation infrastructure. Here we are examining only the command areas of large dams with relatively greater storage capacity. Regions that are in the control area of dams or farther downstream are excluded and have been shown in other studies to be adversely affected by dams (10, 46, 47). Nevertheless, the results demonstrate that when agricultural productivity is no longer sensitive to rainfall anomalies, cropland expansion ceases to occur in response to rainfall anomalies.

Discussion

The global competition for agricultural land and forest resources remains central to policy discussions striving for a food-secure and low-carbon future and seeking to balance development and environmental goals. However, the relationship between agricultural productivity, cropland expansion, and deforestation continues to remain a subject of debate. The results in this paper make a narrow yet important contribution to this debate, by examining specifically how rainfall-induced changes in productivity impact the dynamics of cropland expansion. We first show, independently, how exogenous rainfall anomalies impact both changes in agricultural productivity, as well as cropland expansion. The results suggest that the response of farmers in developing countries is asymmetric, with a greater sensitivity to cumulative and persistent declines in agriculture productivity than cumulative increases in agricultural productivity through a compensating expansion of cropland area. We then conduct a two-stage analysis which directly links these rainfall-induced fluctuations in agricultural productivity to cropland expansion.

Table 3. Impact of irrigation infrastructure on agricultural productivity and cropland expansion

		Cropland Area		
	Agricultural Productivity	X = 2	X = 3	X = 4
No. upstream dams	0.0743*	0.037420*	0.038960***	0.028461***
	(0.031)	(0.015)	(0.007)	(0.005)
Wet anomaly	0.1886***			
	(0.022)			
Wet anomaly × no. upstream dams	−1.0743***			
	(0.220)			
X + wet anomalies		0.000123	0.000528	0.001135*
		(0.000)	(0.000)	(0.000)
X + wet anomalies × no. upstream dams		0.001480	−0.010607	−0.013812
		(0.013)	(0.013)	(0.021)
Dry anomaly	−0.1338***			
	(0.009)			
Dry anomaly × no. upstream dams	0.1905**			
	(0.070)			
X + dry anomalies		0.001124**	0.002153***	0.001796***
		(0.000)	(0.000)	(0.000)
X + dry anomalies × no. upstream dams		−0.023459^{+}	−0.04423***	−0.018970**
		(0.014)	(0.007)	(0.006)
N	63,154	703,512	703,512	703,512
Kleibergen–Papp LM-stat	107.6	123.471	180.597	141.091
Kleibergen–Papp LM *P* value	0.000	0.0000	0.0000	0.0000
Kleibergen–Papp F-stat	25.32	30.491	44.888	35.107

Dependent variable in column 2 is the change in log NPP in a grid cell. Dependent variable in columns 3 to 5 is the 5-y average annual change in log cropland area in a grid cell. All regression models include controls for year and country fixed effects as well as temperature, population, country–year trends, terrain roughness, aquifer presence, and CTI. Columns 3 to 5 also control for annual precipitation. X + wet (dry) rainfall anomalies is a time-varying dummy variable indicating if rainfall was at least 1 SD higher (lower) than the long-run mean of the grid cell for X or more years out of the prior 10 y, where X is given in the second row. Upstream dams is a count variable which indicates the number of upstream dams from the grid cell. Statistical significance is given by $^{+}P < 0.10$, $^{*}P < 0.05$, $^{**}P < 0.01$, and $^{***}P < 0.001$. Robust clustered SEs are in parentheses. The regressions pass diagnostic tests for instrument relevance (Kleibergen–Papp LM test) and the test for weak instruments (Kleibergen–Papp Wald test) providing supporting evidence about the validity of the instrumental variables. Additional details are provided in *Materials and Methods* and *SI Appendix*.

These results again and more directly demonstrate that repeated dry anomalies cause an increase in cropland expansion due to reduced yields. They also rule out other possible mechanisms that may also be induced by dry anomalies, such as forest fires or tree mortality.

The findings of this paper are consistent with that of the subsistence hypothesis (29) which hypothesizes that as farms become more productive, small-holder farmers who are attempting to achieve a subsistence level of production will require less agricultural land. However, it is the inverse result that is found—i.e., that when rainfall anomalies reduce productivity of land, farmers respond by increasing their use of cropland.

These results have important policy implications. We estimate that 9% of cropland expansion in the developing world can be attributable to rainfall-induced productivity anomalies. This is already a nontrivial amount, and given expectations that climate change will generate additional rainfall variability, we should expect this trend to increase. Thus, without policy action, there is a likelihood of a vicious cycle where rainfall variability induces expansion of cropland into forests, removing important carbon sinks, exacerbating climate change impacts, and inducing further rainfall variability.

The first and foremost risk that a small-holder farmer may face is that they will fail to achieve a subsistence level of income due to uncertain production driven by rainfall anomalies. As demonstrated, investments in irrigation infrastructure are one way to diminish the impact of rainfall anomalies that is felt by farmers and reduce their need to react to rainfall anomalies. In fact, previous research has shown that farmers increase their own private irrigation investments in response to dry rainfall anomalies (11). By eliminating the risk of rainfall anomalies, farmers are more likely to find themselves in a different paradigm guided by expected utility theory, where risk is reduced by reducing exposure to rainfall anomalies which can be achieved through cultivating less land.

Our analysis has several caveats. When estimating the impact of rainfall variability, we focus on one specific type of variability: variation from year to year. Previous research (7) shows that intraseasonal rainfall variability can have an even larger impact on crop yields. Estimating the impact of intraseasonal variability is relatively straightforward when dealing with a small geographic area, where growing seasons are homogenous or well known. At the global level, however, measuring this impact is much more difficult as it would require very detailed knowledge on crop choices (which will be endogenously determined with respect to rainfall variation, adding an additional layer of complexity) and assumptions about cropping seasons. Because we examine annual variation, rather than growing season variation, it is likely that we are underestimating the true impact of increased rainfall variability during the growing season. While our results demonstrate the ability of large irrigation infrastructure to mitigate the impact of rainfall anomalies across both margins, other policies may also be equally as effective. Policies which reduce the exposure of a farmer's income to rainfall variability, such as safety nets, weather-based crop insurance, or incentives to grow more weather-resilient crops, can also change a farmer's calculus when deciding how to respond to anomalies.

Conclusion

In sum, results in this paper document a robust global impact of rainfall anomalies on agricultural production across both the extensive and intensive margins. As global climate change is expected to increase rainfall variability in the future (2, 48), our results demonstrate that the production of agriculture is likely to become riskier. Our results provide a plausibly causal reaction to this risk in developing countries in the form of an expansion of cropland. On average, dry anomalies account for ∼7.4% of global cropland expansion and 9% of cropland expansion in the developing world.

Although global policies have been trending toward forest conservation to limit greenhouse gases and conserve biodiversity, these economic forces have the potential to counteract some of the effects of these policies.

Materials and Methods

In order to estimate the impact of rainfall anomalies on extensive and intensive agriculture, a global, gridded dataset was created, with grid cells 0.5° × 0.5° in size. Several global rasters were extracted to these grid cells at an annual basis. For estimates in changes in cropland we use a new land cover dataset developed by the ESA's Climate Change Initiative that provides consistent information on 37 land cover classes based on the United Nations Land Cover Classification System for a period of 24 y from 1992 to 2015 at a 300-m resolution. The data rely on state-of-the-art reprocessing of four different satellite missions [Medium Resolution Imaging Spectrometer (MERIS), Satellite Pour l'Observation de la Terre- Vegetation (SPOT-VGT), Advanced Very High Resolution Radiometer (AVHRR), and Project for On-Board Autonomy, with the V standing for Vegetation (PROBA-V)]. We use a cross-walking table from ref. 49 that characterizes plant functional types across the ESA classes to guide the grouping of classes into a single cropland category and forest category. The categories are then aggregated to the 0.5° grid by calculating the percent of cropland or forest in each 0.5° grid. In *SI Appendix*, we also show results using the latest version of the time-varying MODIS dataset called MCD12Q1 that follows the IGBP legend descriptions as well as the UMD classification scheme as provided in ref. 38. The most recent version of the MODIS Land Cover Type product is Collection 5.1, which includes adjustments for significant errors that were detected in Collection 5 of the MCD12Q1 product. *SI Appendix*, Table S13, lists the land use classes from the different datasets that were used in classifying pixels as cropland. Like with ESA, the cropland pixels are then aggregated to the 0.5° grid by calculating the percent of cropland in each 0.5° grid.

Data on rainfall and temperature are from Willmott and Matsuura (50). This dataset contains monthly observations in a 0.5° grid for the entire world from 1900 to 2014. Using these data, we calculate locally defined annual rainfall z scores. We then define dry anomalies as years when the z score is less than −1 and wet anomalies as years when the z score is greater than 1. Put another way, dry (wet) anomalies indicate years when rainfall is at least 1 SD below (above) the long-run mean for that grid cell. In *SI Appendix*, we show that results using anomalies defined only over the local growing season are similar in magnitude and direction, though are statistically noisier (*SI Appendix*, Table S8), compared to the global results that rely on anomalies over the entire year, using data from sub-Saharan Africa, where high-quality data on growing seasons are available from HarvestChoice (https://www.ifpri.org/project/harvestchoice).

In order to measure changes in agricultural productivity at a global grid-level scale, we exploit a satellite- based estimate of NPP as a proxy following the past literature in economics (10, 51) and remote sensing (52–54) since it facilitates aggregation and provides a common unit of productivity across different crop types (55). NPP is linearly related to the amount of solar energy that plants absorb over a growing season (56) and is measured in grams of carbon per square meter. We use the annual MOD17A3 measures from 2000 to 2013 generated by the Numerical Terradynamic Simulation Group at the University of Montana (57) which corrects for cloud contamination prevalent in MODIS land products. Since our interest is in estimating NPP from cropland, we use the ESA land cover dataset described earlier to identify cropland pixels where cropland makes up more than half of the share of the total land area (55%). We also use other thresholds of cropland coverage (35, 45, 65, and 75%) in robustness checks in *SI Appendix*. Our final data measure changes in NPP for each 0.5° grid cell that contained cropland in the year 2000. We use a time-invariant crop area map from the beginning of our sample period in order to isolate and identify changes in productivity (intensive margin) separately from changes in cropland (extensive margin).

We complement our dataset with additional grid cell characteristics. Our equations control for population in a grid cell. The population data comes from Gridded Population of the World (GPWv3) (58). GPW offers population data at the 0.5° grid cell level for the entire globe, at 5-y intervals between 1990 and 2015. The data are linearly interpolated when annual observations are required as with the NPP analysis. The main result remains consistent without the inclusion of population as a control variable as well as with using a newer version of GPW data, namely, GPWv4, that is also available at 5-y intervals but with a shorter time frame starting from the year 2000 (*SI Appendix*, Table S14). This provides further supporting evidence that the type of population data used is not driving the results.

In certain specifications, we also control for the physical geography of the grid cell that may affect the sensitivity to rainfall anomalies. The first measure we use is a grid cell's wetness index, the compound topographic index (CTI) derived from HYDRO1k; it is time-invariant, correlates with soil moisture, and is a function of the slope and the upstream area contributing to a river's flow. Additionally, we also control for other time-invariant factors like terrain roughness by using the SD of elevation in a grid cell and presence of an underlying unconsolidated aquifer.

To provide further support and evidence that the nonlinear effects identified by wet and dry anomalies separately is most appropriate for our analysis, in *SI Appendix* we create a variable called net anomaly which is the difference between the number of positive anomalies and negative anomalies over the last decade. Specifically, it is (number of annual positive anomalies) − (number of annual negative anomalies). Therefore, if on balance the grid cell experiences more positive anomalies than negative anomalies in the past 10 y, this difference is positive. When we include such a linear term, the coefficient is negative, implying that as the number of positive anomalies increase, cropland expansion diminishes (*SI Appendix*, Table S15). However, this point estimate is noisy and not statistically significant. Finally, we use World Bank Income group classifications to identify high-income countries and developing countries. Classifications are based on mean per-capita gross national income (GNI) in 2015 where developing countries have GNI per capita between \$1,025 and \$12,475 (encompassing low income, lower–middle income, and upper–middle income), and high-income countries are above \$12,475. *SI Appendix*, Table S16, presents summary statistics of the main variables.

To estimate the impact of rainfall anomalies on cropland extensification and forest cover changes, we employ panel regression analysis. Our strategy relies on the fact that short-run deviations from long-run precipitation are exogenous. We expect that contemporaneous impacts of variable rainfall will likely be muted, but repeated anomalies over the medium term could induce extensification as an adaptation strategy. We therefore calculate for each grid cell the number of years in the past 10 y for which precipitation was at least 1 SD above or below the mean. We chose 10 y as the cutoff as it is a long enough time period to exploit significant variation in the independent variable and for impacts on the extensive margin to materialize. We also include a host of controls as well as unobserved characteristics using cell or country fixed effects, year fixed effects, and a country–trend interaction which neutralizes any country-level trends. Formally, we estimate the following equation:

$$\Delta \log(Crop_{it}) = \alpha_1 + \alpha_2 Prec10^-_{it} + \alpha_3 Prec10^+_{it} + +X_{it}'\lambda + f_c(t) + \theta_t + \gamma_i + \varepsilon_{it}, \quad [1]$$

where $\Delta \log(Crop_{it})$ is the percent change in cropland over the past 5 y in grid cell i in year t^1, $Prec10^-_{it}(Prec10^+_{it})$ is the number of dry (wet) rainfall anomalies greater than 1 SD within the last 10 y, $f_c(t)$ are country-specific time trends, θ_t are year fixed effects, and γ_i are grid cell fixed effects. We choose 5 y to smooth out any contemporaneous or idiosyncratic factors that may impact changes in cropland over any given year. X_{it} is a vector of control variables which includes log of population, contemporaneous mean annual temperature (°C), and contemporaneous precipitation (mm/y). This is because sowing decisions could be informed by information about current year rainfall. α_2 and α_3 are our coefficients of interest and measure how repeated dry anomalies or wet anomalies, respectively, can impact the percentage change in cropland. The impact on forest cover change is similarly estimated. In our baseline results we cluster SEs at the province–year level.

To estimate the contemporaneous impact of rainfall anomalies on intensification, we estimate a similar equation:

$$\Delta \log(NPP_{it}) = \alpha_1 + \alpha_2 Prec^-_{it} + \alpha_3 Prec^+_{it} + +X_{it}'\lambda + f_c(t) + \theta_t + \gamma_i + \varepsilon_{it}, \quad [2]$$

where NPP_{it} is net primary productivity in grid cell i in year t, $Prec^-_{it}(Prec^+_{it})$ is a binary variable which indicates if there was a dry (wet) rainfall anomaly in grid cell i and year t, θ_t are year fixed effects, γ_i are grid cell fixed effects, and $f_c(t)$ are country-specific time trends. Finally, X_{it} is a vector of control variables, including log of population, and a quadratic term for mean annual temperature (°C). α_2 and α_3 are our coefficients of interest and measure how a dry anomaly or wet anomaly, respectively, can contemporaneously impact the percentage change in NPP. In our baseline results we cluster SEs at the province–year level.

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To estimate the impact of large dams, we use an instrumental variables approach to correct for placement bias. The GRanD v1 dataset, from the Socioeconomic Data and Applications Center (SEDAC), is used to identify the location of large irrigations dams (refs. 44 and 45 and *SI Appendix*, Fig. S4). In *SI Appendix* we give a detailed explanation of how grid cells were mapped to dam command areas. Dams are more likely to be built in areas where they will have the largest impact on agricultural productivity. Moreover, placement can also be influenced by unobservable factors such as politics. Analysis that does not correct for these inherent placement biases is likely to lead to biased estimates that are not causally interpretable. To derive causally interpretable estimates that account for these biases, we exploit geographical variation in the suitability for dam construction closely following past literature (46, 10). By focusing solely on the impacts of variation in dam placement resulting from geographic factors such as the gentleness of a river slope, we can isolate other determinants of placement that could also affect the outcomes of interest and cause bias. In this way, we choose instruments that can predict the suitability for irrigation dam construction. For instance, rivers with gentle but nonzero slopes are required to create long reservoirs for capturing water, and constructing canals will allow the water to reach the irrigated fields via gravity. In sum, we include three instrumental variables: the length of all rivers within a 25 to 50 km buffer around the centroid of each grid cell (i.e., the same region where we calculate the presence of dams), the share of these rivers which have a slope that is suitable for irrigation dams, and a country's historic propensity for dam construction. We first predict dam construction using the instruments and find evidence for the importance of a gentle river gradient and river length in increasing dam construction (*SI Appendix*, Table S17). In the second stage, we use fitted values of dams in place of the observed values to correct for the bias. The methods and instruments are elaborated upon in *SI Appendix*.

To identify soy and palm oil-dominated grid cells we use data on the geographical distribution of agricultural crops from ref. 59. They provide a 5 arc min $\times$ 5 arc min raster dataset encompassing 137 crops. For each cell in the raster, we report harvested area in hectares. We aggregate the harvested area variable at the lower resolution of our dataset, i.e., 0.5° $\times$ 0.5°. We then rank all crops in each grid cell and identify the crop that occupies the largest amount of harvested area in the grid cell. We then identify grid cells whose main crop is either soy or palm oil. Distance to market is measured using estimated travel time to the nearest city for each grid cell in our analysis using data from ref. 39 which provides a global raster of travel times to the nearest city of 50,000 people or more, for the year 2000. We calculate the mean value for each grid cell and include this variable in our regression.

All data used in this analysis are publicly available from the ESA (https://www.esa-landcover-cci.org/) and the Numerical Terradynamic Simulation Group (https://www.ntsg.umt.edu/project/modis/default.php). Observed temperature and precipitation data are available from http://climate.geog.udel.edu/~climate/.

ACKNOWLEDGMENTS. For helpful comments and support, we are grateful to the seminar participants at Stanford University (Center on Food Security and the Environment); the joint Oxford University & World Bank workshop on Water, the Economy, and Sustainable Development; and to Gregory Amacher, Paul Carrillo, Sébastien Desbureaux, Ryan Edwards, Ram Fishman, Marie Hyland, Asif Islam, Arun Malik, Scott Moore, Aude-Sophie Rodella, Wally Falcon, and two excellent anonymous reviewers. Andres Fernando Chamorro Elizondo provided stellar research assistance. All errors are our own.

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