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Authors

Burney, Jennifer

McIntosh, Craig

Lopez-Videla, Bruno

et al.

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Empirical modeling of agricultural climate risk

Jennifer Burney[a,b,1], Craig McIntosh[a,1], Bruno Lopez-Videla[c,2], Krislert Samphantharak[a], and Alexandre Gori Maia[d]

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Effective policies for adaptation to climate change require understanding how impacts are related to exposures and vulnerability, the dimensions of the climate system that will change most and where human impacts will be most draconian, and the institutions best suited to respond. Here, we propose a simple method for more credibly pairing empirical statistical damage estimates derived from recent weather and outcome observations with projected future climate changes and proposed responses. We first analyze agricultural production and loan repayment data from Brazil to understand vulnerability to historical variation in the more predictable components of temperature and rainfall (trend and seasonality) as well as to shocks (both local and over larger spatial scales). This decomposed weather variation over the past two decades explains over 50% of the yield variation in major Brazilian crops and, critically, can be constructed in the same way for future climate projections. Combining our estimates with bias-corrected downscaled climate simulations for Brazil, we find increased variation in yields and revenues (including more bad years and worse outcomes) and higher agricultural loan default at midcentury. Results in this context point to two particularly acute dimensions of vulnerability: Intensified seasonality and local idiosyncratic shocks both contribute to worsening outcomes, along with a reduced capacity for spatially correlated ("covariate") shocks to ameliorate these effects through prices. These findings suggest that resilience strategies should focus on institutions such as water storage, financial services, and reinsurance.

financial institutions | climate change | Brazil | adaptation | agriculture

Significance

Climate change can affect agriculture across levels–from plants to farms to institutions–but these impacts are difficult to measure and project consistently. We propose a statistical approach for estimating the sensitivity of agricultural systems to different dimensions of climate change and modeling future shifts that incorporate human adaptation. Applying this in the Brazilian context reveals that climate has a powerful effect on yields and agricultural revenues and drives default for a large public sector bank. Future projections suggest increased yield and revenue volatility at midcentury, along with higher rates of climate-driven default that create correlated risks for financial institutions. This approach is thus able to capture often hard-to-model emergent climate risks and inform more tailored approaches to building resilience.

Agriculture is a fundamental linkage between climate change and human welfare in the anthropocene (1). Because agricultural production is susceptible to harm from unsuitable environmental conditions (vulnerability), a key question is the extent to which agricultural systems can adjust—either ex ante or ex post—to the effects of a changing climate (adaptive capacity) and maintain desired function in a warming world (resilience) (2). Understanding adaptive capacity and building resilience in agricultural systems requires the ability to predict biophysical and management responses to weather, as well as shifts in broader systemic factors such as food prices and the credit institutions that support farming (3). A well-understood difficulty in measuring these relationships is that changes in environmental factors like temperature and rainfall will have different effects depending on whether they are anticipated (in which case proactive adaptation may be possible), spatiotemporally correlated (in which case systemic factors like prices and insurance would be expected to respond, potentially dampening adverse impacts), or idiosyncratic and unanticipated (in which case national and local institutions may better diversified in terms of risk, but larger-scale smoothing mechanisms like price changes or declarations of emergency are unlikely).

While there are many potential ways to model the responses of coupled human–natural systems to climate change, detailed case studies and statistical analyses using observations of the recent past form the core of the field (4). Three principal findings have emerged from this empirical climate change impacts literature. First, different sources of weather variation trigger different types of adaptation (5, 6), with anticipated changes eliciting a broader range of adaptive strategies than changes that are unanticipated and may thus have more constrained responses (2, 7–9). Second, in many contexts including Brazil, a key dimension of climate change is that the variance of weather outcomes is expected to increase, in some cases more so than the levels (10, 11). Third, weather variation is likely to have highly nonlinear effects on key human outcomes (12–14), and understanding how agricultural systems respond to extreme events is critical (15–19).

The existing empirical literature has taken a wide range of approaches to impact analysis at various spatial and temporal scales, but advances have largely focused on estimation of the effect of weather variation on human outcomes as representative of longer-run shifts in climate (20–22). A central concern in this work has been

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[1]To whom correspondence may be addressed. Email: jburney@ucsd.edu or ctmcintosh@ucsd.edu.

[2]Lopez-Videla's contributions were made prior to joining Amazon.

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robust causal identification based on isolation of system response to the unpredictable component of weather versus more predictable components like cross-sectional averages (23) and long-run trends (8, 24). An overarching methodological thrust has thus been toward highly localized estimates based on shocks that are statistically well identified in terms of past exposure but may only capture a small component of projected changes in future climate. Deviations from historical mean conditions provide an as-if random source of variation for statistical estimation, but they represent only one form of anticipated climate change and may reflect the component to which the ability to adapt may in fact be weakest.

Here, we propose a straightforward framework for balancing statistical identification goals with a more holistic approach to adaptation and credible projection in a parametric but parsimonious way that avoids the use of fixed effects or other regression techniques that remove certain sources of variation that are relevant when considering the future. We use agricultural productivity, revenue, and loan data from Brazil to show how this method facilitates interpretation of different adaptation margins in both past and future, and then demonstrate how it can be used for understanding the adaptive potential of specific policy interventions in the Brazilian context.

Modeling Approach

Briefly (*Materials and Methods*), the heart of our technique is a spatiotemporal decomposition of the variation in temperature and precipitation into five distinct terms: a) the original local average of temperature and precipitation, b) the time trend in each location, c) the normal (monthly average) seasonal deviation from these trends in each location, d) the spatiotemporally correlated, or "covariate," shocks in each time period relative to components (a–c), and e) idiosyncratic shocks, or the remaining local variation after accounting for trends, seasonal deviations from trends, and covariate shocks in each time period. This decomposition is shown in schematic form in *SI Appendix*, Fig. S1. For the Brazilian context explored here, "local" is defined as the municipality level (the smallest for which panel data on agricultural outcomes is publicly available), and "covariate" is defined at the national level. However, as discussed below, these spatial scales could be adjusted for other contexts and analyses.

Decomposition approaches are useful for partitioning a signal into its component parts; however, in contrast with methods like spectral density decomposition (time series) or empirical orthogonal functions (EOF), the approach described here has several features that make it attractive for studying impacts and adaptation applications. First, this decomposition can be applied in the same way to historical and forecast data (e.g., from climate models), and so allows a close mapping of estimated damages from the recent past to predicted changes in the future (Fig. 1 shows this analogous structure across past and future). Second, the decomposition maps to interpretable spatial and temporal features and thus provides a well-defined way of thinking about vulnerability, adaptation, and resilience of agriculture to climate change. Specifically, the components of this decomposition suggest distinct system response margins with different degrees of adaptive capacity, and thus provide clarity about matching policies to different dimensions of vulnerability (*SI Appendix*, Table S1 provides some examples in the Brazilian context).

Three components of the decomposition are highly predictable and so present the greatest scope for proactive adaptation. The cross-sectional averages of temperature and precipitation, which form the time-zero mean for each location, represent baseline weather expectations, but by definition do not move with climate change and as so are best thought of as origin period intercepts (and perhaps historical suitability). Time trends in temperature and precipitation are separately estimated for each location and represent the long average estimate of how weather is changing over time based on local experience (8); these motivate longer-run adaptive shifts in agricultural systems to be optimized for future climate (1). From here, predictable seasonal variation is defined as the monthly average deviation around the location-specific mean and time trend. Increases in seasonality amplitude indicate an intensification of the annual cycle around the long-run trend and would be expected to elevate the importance of innovations like water storage, as well as savings and credit institutions that might help farmers withstand (and perhaps even leverage) the

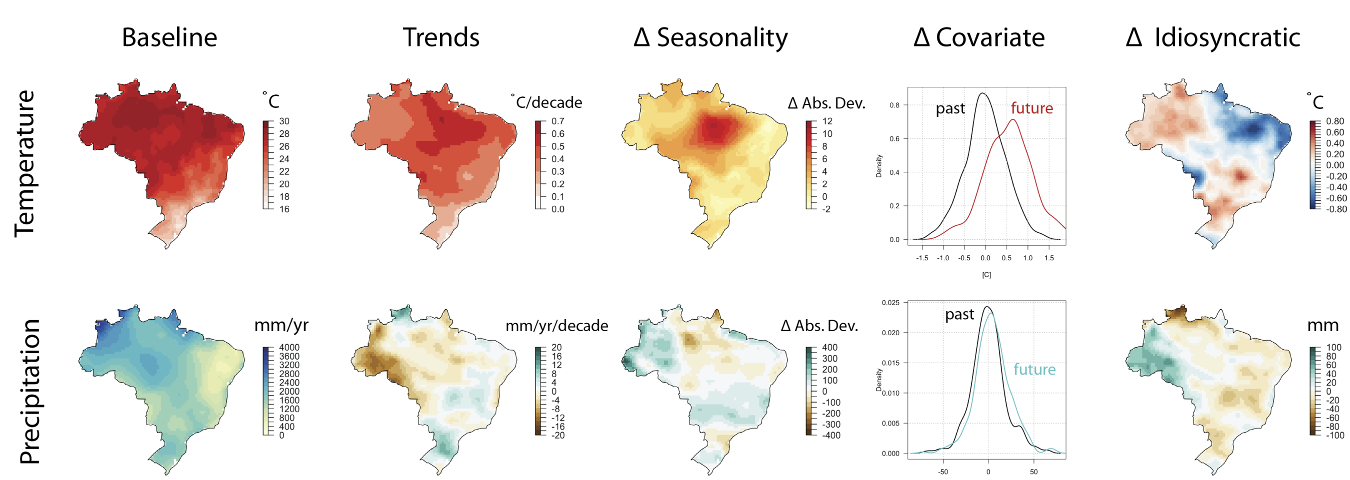

Fig. 1. The spatial nature of Brazil's historical and projected climate changes, with temperature shown in the *Top* row and precipitation in the *Bottom* row. The *Left* column shows baseline average annual temperature and total annual precipitation in the recent past (1991 to 2020) and the second column shows decadal trends for temperature and precipitation. The third column shows the difference in total seasonal magnitude (summed average absolute monthly deviations) between the future and the recent past (2040 to 2069 to 1991 to 2020). The fourth column shows the projected change in covariate (national-scale) temperature and precipitation shocks, and the final column shows the projected average changes in local idiosyncratic shock magnitudes between future and recent past. A detailed example of this decomposition for a sample of Brazilian municipalities is shown in *SI Appendix*, Fig. S1.

enhanced seasonal swings. These three dimensions of variation added together represent the linear seasonally adjusted predicted weather outcome for a location.

Covariate and idiosyncratic shocks make up the residual component of weather variation. After removing local-level intercepts, linear time trends, and average seasonality as described above, we calculate the covariate shock as the average remaining variation across the whole country for each time period. The spatial scale at which covariate shocks are calculated is an important design choice; because their contemporaneous nature would be expected to induce large-scale responses in prices and policies, we also examine the implication of defining covariate shocks instead at the regional or state level. From a policy perspective, the nature of local climatic variation, the spatial scale, and scope of institutions like water-sharing agreements or economic markets that distribute shocks across space, and the scope of operations of the institutions best placed to respond to covariate shocks would determine the appropriate covariate scale definition. Finally, the idiosyncratic shock is the remaining local variation not explained by any of the other terms.

Paired with estimates of historical sensitivity, shocks provide an important window into higher moments of climate vulnerability in the future. As with trends and seasonality, covariate and idiosyncratic shocks also suggest distinct adaptation margins and potential policy responses. While the welfare benefits of large safety-net programs will rise with the magnitude of correlated shocks, these shocks become more difficult to smooth domestically and motivate access to global capital pools and reinsurance markets. Integration with global markets can be both a source of insulation from covariate shocks (if they arise domestically) and a source of exposure to them (if the global market is the source of the shock). Increased exposure to idiosyncratic shocks stresses the importance of transport infrastructure (25), local risk pooling mechanisms (26), the deepening of financial services, and the use of indemnity insurance given that weather index insurance may generally be better at picking up correlated rather than idiosyncratic shocks (27). While the shocks in this decomposition are estimated as residuals, the covariate shock in particular may be partially predictable (such as during regional-scale disturbances like ENSO or a shift in India's monsoon timing), meaning that climate forecasting is one form of institutional adaptation to these shocks.

To demonstrate this decomposition approach, we first use retrospective analysis to measure productivity and economic vulnerability to the decomposed dimensions of weather variation. We aggregate weather data at the annual level – summed (P) or averaged (T) over the growing season – to examine yields and revenues of the country's main crops, using municipality-level data from 1990 to 2014. At the monthly level, we also examine the repayment performance of agricultural loans made by Brazil's main public development bank within the state of Bahia, between 2012 and 2017. We then use the estimated coefficients from the retrospective analysis to project future impacts, linking them to bias-corrected down-scaled climate model projections for Brazil that we have decomposed in the same way as the historical data. Vulnerability to climate change can then be isolated to the dimensions that are both found to drive damages and to be changing in the future. This provides focus to a conversation about the specific investments that can promote resilience in a given context. We discuss the implications for Brazil, including for a major investment in the semiarid region of the country (construction of water cisterns).

Results

Changes in Brazil's Climate. Fig. 1 provides preliminary motivation for the proposed climate decomposition. It shows the spatial variation in Brazil's mean climate and decadal trends from the recent past (1991 to 2020), as well as projected changes in total seasonal amplitude (sum of average monthly deviations), changes in recent and projected covariate shock distribution, and projected changes in idiosyncratic shock sign and magnitude across the country. These last three columns are presented as changes between midcentury (2040 to 2069) and the recent past (1991 to 2020), and suggest that in expectation, the overall structure of climate change in Brazil will involve all components of the decomposition.

A representative example of this decomposition is shown for four municipalities in *SI Appendix*, Fig. S1 and Table S2 show the results of the monthly decomposition of historical temperature and rainfall for the full country for the years 1990 to 2017, using the whole country to define the "covariate" shock. The SD within municipalities is displayed as well, since this is the term that is important to an individual considering weather changes in a given location. The penultimate column indicates the level at which each of the decomposed terms varies. The dominant source of total variation in temperature is seasonal variation within a single location, while for rainfall it is cross-sectional differences in means that have the greatest SD. Given the erratic nature of local rainfall, we unsurprisingly find a large residual variation in the idiosyncratic rainfall shock, while for temperature the idiosyncratic and covariate shocks have similar spread.

SI Appendix, Table S1 provides a conceptual mapping of the decomposed weather dimensions to existing potential policy responses that best match each. In columns 2 to 4, we provide a subjective assessment of credibility in each of three empirical steps: estimation in historical weather data, statistical analysis of agricultural or lending responses to weather variation in the historical data, and decomposition of the future weather forecasts. In terms of the dimensions relevant to climate change, the trend term is least credibly estimated in historical data (especially in short time series) while the shock terms are most credible. In the forecasts, the trend may be the most credible dimension of prediction while the idiosyncratic variance in particular may depend in part on model assumptions and the desired scale of analysis (i.e., the choices made for statistical downscaling). This suggests that it is the seasonal and covariate terms that have the highest combined credibility across past and future. The final column discusses the very heterogeneous policy responses that would be suggested by the intersection of vulnerability and change in each of these dimensions. The two most predictable components of climate change (trends and seasonality) are susceptible to distinct forms of adaptation; the former requiring a secular shift in agricultural technology with the latter also being addressable by technologies like water storage and financial services. Specific policies introduced in Brazil to address heightened seasonal variation include sustainable water management (28) and agroforestry (29). Increases in idiosyncratic shock variance can be dealt with a smaller spatial scales via storage, transport infrastructure, and diversification, while increases in covariate shocks will undermine these local solutions, requiring larger-scale institutional solutions and at the limit require reaching into global risk pools via sovereign borrowing and international reinsurance.

Association between Climate Components and Agricultural Production and Revenue. Because agricultural outcomes are typically measured and reported at the annual level (30), we aggregate our weather decomposition data over crop-specific growing seasons (31) and link them to annual agricultural productivity (production per hectare) and revenue data (in constant Brazilian Reals) for 5,430 Brazilian municipalities. The three terms measured in deviations will tend to have their variation removed by the taking of annual averages; for perennial crops and total annual revenues, we therefore take the absolute value of the seasonal, covariate, and idiosyncratic deviations and average these at the municipal-year level. We then use ordinary least squares regression to estimate the best-fit parameters defining the surface that relates the weather decomposition to each outcome (*Materials and Methods*).

The results of this analysis for maize, soybean, and sorghum yields and revenues are shown in Fig. 2, *SI Appendix*, Figs. S2 and S3, and Tables S3–S8. Maize, soybean, and sorghum are three field crops grown at similar times within their regions of production in Brazil (*SI Appendix*, Fig. S2) but are subject to very different marketing dynamics. Soybeans are predominantly exported and Brazil is a global production leader; maize is consumed both at home and exported; sorghum is largely used domestically for animal feed. For each crop, we fit models with and without quadratic seasonal and shock terms and also estimate responses where the covariate shock is constructed nationally (for the whole country), by region, and by state (i.e., over successively smaller areas of reference). Finally, we compare our decomposition results to a more standard fixed-effects model that includes quadratic terms in both temperature and precipitation (*SI Appendix*, Tables S3–S8). As described above, such models are the standard in the literature and are equivalent to analysis conducted in anomaly space, where the statistical parameters estimated relate deviations from local average weather parameters to deviations from local average outcomes (12, 20, 32).

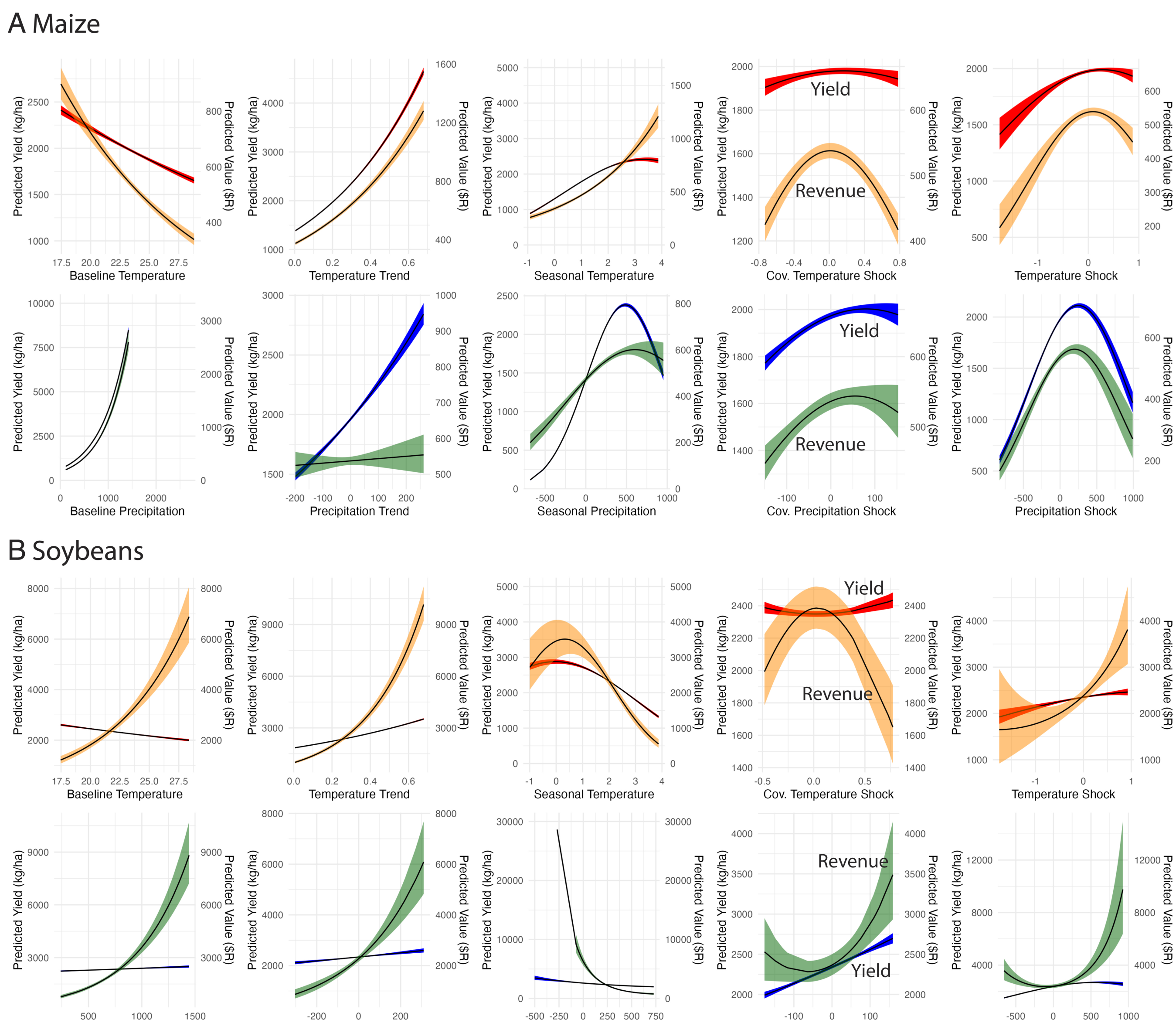

Fig. 2. The marginal impacts of different components of weather on municipality (*A*) maize and (*B*) soybean yields and revenues in Brazil. Black lines show the predicted central tendency with shading indicating the CI. Red and blue curves show the yield response of each crop to temperature and precipitation, respectively; orange and green curves show the revenue responses of each crop to temperature and precipitation, respectively. Curves correspond to the coefficients shown in column 2 of each *SI Appendix*, Tables S5–S8.

We first note that the R^2 for our maize yield models ranges from 0.63 to 0.65; the standard fixed effects model has a higher overall R^2 (0.81), but the within R^2 is only 0.03, meaning that the location- and year-specific intercepts are explaining almost all of the variation in such models, and none of that signal is used to identify climate impacts on outcomes. For revenues our fit is weaker; this is expected given the contributions of other factors to revenues, but we can nevertheless explain a substantial share of the variation in these variables ($R^2 = 0.22$) with our decomposed weather terms (compared to a total & within R^2 of 0.83 and 0.02, respectively, for the fixed effects models). The fits for sorghum and soybeans are weaker than for maize, and especially for soybean revenues, where we would expect nonclimatic factors to play a much larger role than for the other crops. However, the climate decomposition still explains a much larger portion of the variance in yields and revenues than the within-location variation of the climate variables in the standard fixed effects models.

The cross-sectional intercepts terms provide marginal effects consistent with the idea of Brazil as an environment in which cooler and wetter locations are more productive, but the coefficients for the temperature trend terms have the opposite sign. This evidence of adaptation over time could arise from the historical expansion of cropland into new biomes, as well as colder southern regions of Brazil being able to exploit prolonged summers to plant a second off-season crop ("milho safrinha"). The seasonal (accumulated) terms both show optimal values with strong downturns above and below. We would expect to see the "normal is best" relationship for the shock terms, meaning that both yield and revenue are highest when the shocks are small. Indeed, this is the case for the idiosyncratic temperature shock, which is associated with negative yields one either side of zero. The precipitation shocks are centered slightly above zero, conveying that some extra moisture is beneficial on average, but again large departures from optimal are detrimental. For both maize and sorghum, the shock impacts are stronger fractionally in yields than in revenues, indicating that nonclimate forces may dampen the effects. With soybeans, these dynamics are different. The contributions of the shock terms to marginal changes in yields and revenues are much larger. And while the precipitation shock terms are still inverse-U shaped in yields, they have the opposite association with revenues. This may be due to the fact that shocks are interacting with global markets: Brazil represents roughly half of global exports and so even on the international market the price mechanism insulates revenue from shocks to output. Looking across pairs of columns, we compare more localized measures of covariate shocks. Decreasing the size of the unit at which correlated shocks are measured mechanically absorbs more of what was previously idiosyncratic (because idiosyncratic variation is residual, and the covariate means at a localized level capture more spatial variation by definition). Most of our results are quite stable across ways of calculating covariate shocks, although there are cases of sign reversals and the curvature of the idiosyncratic shock in particular appears sensitive to the way that the covariate shock is calculated (*SI Appendix*, Fig. S4). For soybeans, the dynamics change, and whereas a national-level covariate precipitation shock triggers price compensation, a state-level covariate precipitation shock does not; nevertheless, a local (idiosyncratic) precipitation shock still results in some price compensation at the state level.

Association between Climate Components and Loan Performance. The broad set of financial institutions that support investments in the face of uncertainty are an important holder of agricultural risks, and recent evidence has emerged as to the magnitude of the exposure that banks have to weather risk (27, 33). To probe this relationship in the Brazilian context, we pair our same decomposed weather shocks with data on the universe of agricultural loans made in the state of Bahia by our partner financial institution (a large public-sector lender) between 2012 to 2017. Bahia represents the diversity of biomes and agricultural systems in the country, with modern systems producing grains in the Midwest and fruits in the São Francisco River Valley, along with lower-technology family farming production in the semiarid region. Summary statistics for the universe of loans are provided in *SI Appendix*, Table S9, along with some basic information about borrower demographics and their own resilience investments. *SI Appendix*, Figs. S5 and S6 show the distributions of loan performance and climate shocks across time and space, respectively. We do not recalculate the weather decomposition for this restricted data, so for each month and municipality, the trends and shocks are those derived from the national analysis over the time period used above.

Because loan performance (i.e., being in delinquency or default) is assessed monthly, we pair loan data with monthly climate decomposition data. Results from this analysis are shown in *SI Appendix*, Figs. S7 and S8 and Table S10. We find significant associations between higher baseline temperatures and both delinquency and default, and a consistent nonlinear association between increased seasonality and increased probability of delinquency or default. The response to idiosyncratic temperature shocks is more muted, but idiosyncratic precipitation shocks—which we expect to drive yields but not to affect prices through market mechanisms—generate both delinquency and default. Interestingly, the dynamics of the covariate shocks are the opposite: Covariate shocks are associated with reduced delinquency and default rates, indicating that these shocks may have been more predictable, or that price effects might have mitigated some climate risk (the effect sizes are smaller than for seasonal dynamics or idiosyncratic shocks). These nuanced results illustrate the value of decomposing weather variation into its component parts, given that (e.g.) increases in precipitation variance across locations have an opposite effect on the credit system as an increase in the variance of highly localized precipitation shocks.

SI Appendix, Fig. S9 shows the distribution and spatial correlations of climate variables and loan performance across the study region. Although average climate shocks are more strongly spatially correlated than loan delinquency and default over the study period, we nevertheless find that the two are statistically related (*SI Appendix*, Table S11). That is, when temperature idiosyncratic shocks are more highly correlated, we see a stronger spatial correlation in loan delinquency and default. While intuitive, this nevertheless points to a potential for emergent risks to financial institutions like bank branches that must hedge against correlated risk.

Future Risks. To understand potential future agricultural sector impacts, we pair our impact estimates from the models presented above with bias-corrected spatially downscaled climate model output for Brazil. A subset of these results are shown in Fig. 3, with the breakdown of contribution by each component of the weather decomposition shown in *SI Appendix*, Fig. S10. The mean shifts in pooled maize yields and revenues are small (*Left* column), but the pooled results belie important shifts within the country. Importantly, over a 25 y projection, future climate produces one much lower-yielding year (and one lower-revenue

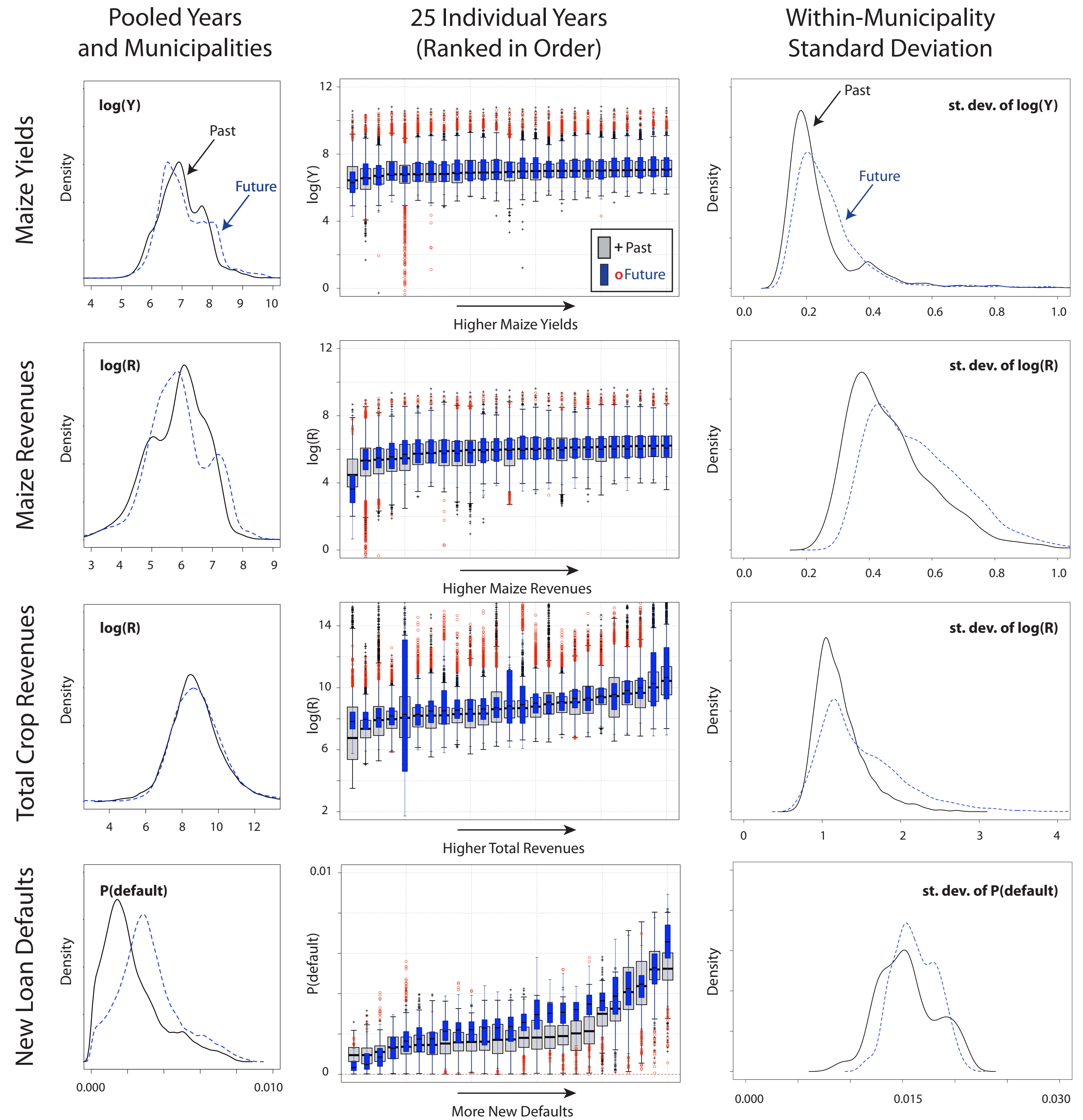

Fig. 3. Past and future projected agricultural sector impacts. The *Left* column shows the pooled distributions of past (black solid line, 1990 to 2014) and future (blue dashed line, 2045 to 2069) municipality-level maize yields, maize revenues, total agricultural revenues, and rates of new loan defaults. The *Center* column shows the municipality-level variation within each year, where years are ranked from lowest to highest by median. Gray/black boxes and outliers show past performance, and blue/red outliers show future. The *Right* column shows the distribution of within-municipality variation (SDs) across the 25 past and future projected years. *SI Appendix*, Figure S11 shows the total past and future projected loan delinquency and default rates.

producing year), as well as at least one additional year with a much larger lower tail across municipalities (center column). Across yields and revenues, the variance of outcomes is significantly larger in the future than the past, and this is the case both within years and within municipalities (center and right columns, respectively). For defaults, a mean shift is clear, with more defaults predicted in the future, and uniformly higher predicted rates year on year, and a higher future variance. In other words, productivity and revenue become more unpredictable but loan default worsens. Taken as a whole country, the drivers of these shifts are not uniform (*SI Appendix*, Fig. S10), in part because predicted changes in climate components are nonuniform Fig. 1. Although mean shifts in any one component of the climate for the whole country may be small, the shifts in each contribute to worsened loan performance in the future (*SI Appendix*, Fig. S10, *Bottom Right*).

Using the Decomposition to Quantify Adaptive Capacity. There are two ways in which this approach can refine assessment of adaptive capacity in a quantitative manner (see ref. 2 for a discussion of the dimensions of adaptive capacity). First, if there is variation in access to technologies intended to address vulnerability, the terms in the decomposition can be interacted with this variation to assess whether outcomes are less sensitive to different dimensions of weather risk in the presence of the technology. In the Brazilian context, one obvious public policy thrust aimed at insulating producers against rainfall risk is water storage. From the bank screening data, we have information on the presence of farm-level water storage infrastructure, and in particular cisterns. This form of adaptation is of interest in Brazil and similar agro-ecosystems given large-scale government efforts to foster construction of water storage, such as the "One Million Cisterns Program"—a key public policy to promote access to water for human consumption and food production in the poorest and driest areas of the country. In 2017, the Brazilian Agricultural Census found more than one million cisterns in Brazil, 90% in the semiarid region and 81% in family farms. While the placement of such infrastructure is not exogenous or randomly assigned, we might expect that the selection bias from endogenous placement will lead them to be sited where rainfall risk is worst, while the treatment effect should be in the opposite direction (although it is also possible that farmer wealth mutually drives cistern access and lower vulnerability, which would generate correlation in the direction of our hypothesis).

To investigate whether these investments have decreased vulnerability, we estimate versions of our default model that interact binary variables for cistern access with the temperature and precipitation terms developed above. This enables a comparison of how households with and without water storage differentially withstand exposure to the components of weather in trying to avoid default. Our expectation is that small-scale water infrastructure will dampen the effect of seasonal variation and also play a role in mitigating the extent to which precipitation shocks drive loan repayment. The results of this analysis are shown in Fig. 4 and *SI Appendix*, Figure S12 and Table S12. Indeed, the vulnerability of repayment to seasonal and idiosyncratic precipitation variation is particularly dampened by the presence of cisterns. While a large empirical literature uses related techniques to study reductions in vulnerability, how to parameterize weather shocks is an open question with many researcher degrees of freedom, and our decomposition provides a principled and policy-relevant way to achieve this.

Second, we can consider impacts on resilience by starting from the forecasted changes that the decomposition of future weather suggests are in store. As demonstrated in Fig. 1, Brazil is projected to be warmer and to see substantial increases in seasonality, as well as greater covariate and idiosyncratic temperature shocks. Technologies that generate good economic outcomes under these future conditions can be said to promote resilience. We can therefore tie the heterogeneous vulnerabilities revealed in Fig. 4 to the forecast changes shown in Fig. 1 to say that, because cisterns appear particularly well suited to enhance the capacity to manage increasing temperatures and seasonality, they will promote resilience. The fact that they indicate a potential worsening of outcomes under the increasingly covariate temperature shocks suggests that additional institutions may be necessary to enhance resilience in this dimension. (Ultimately, a cistern can only store water that arrives, so in extreme regional-scale hot and dry conditions, this adaptation would be less effective in reducing risk. Similarly, cisterns would not do much to facilitate adaptation to extreme regional-scale flooding events).

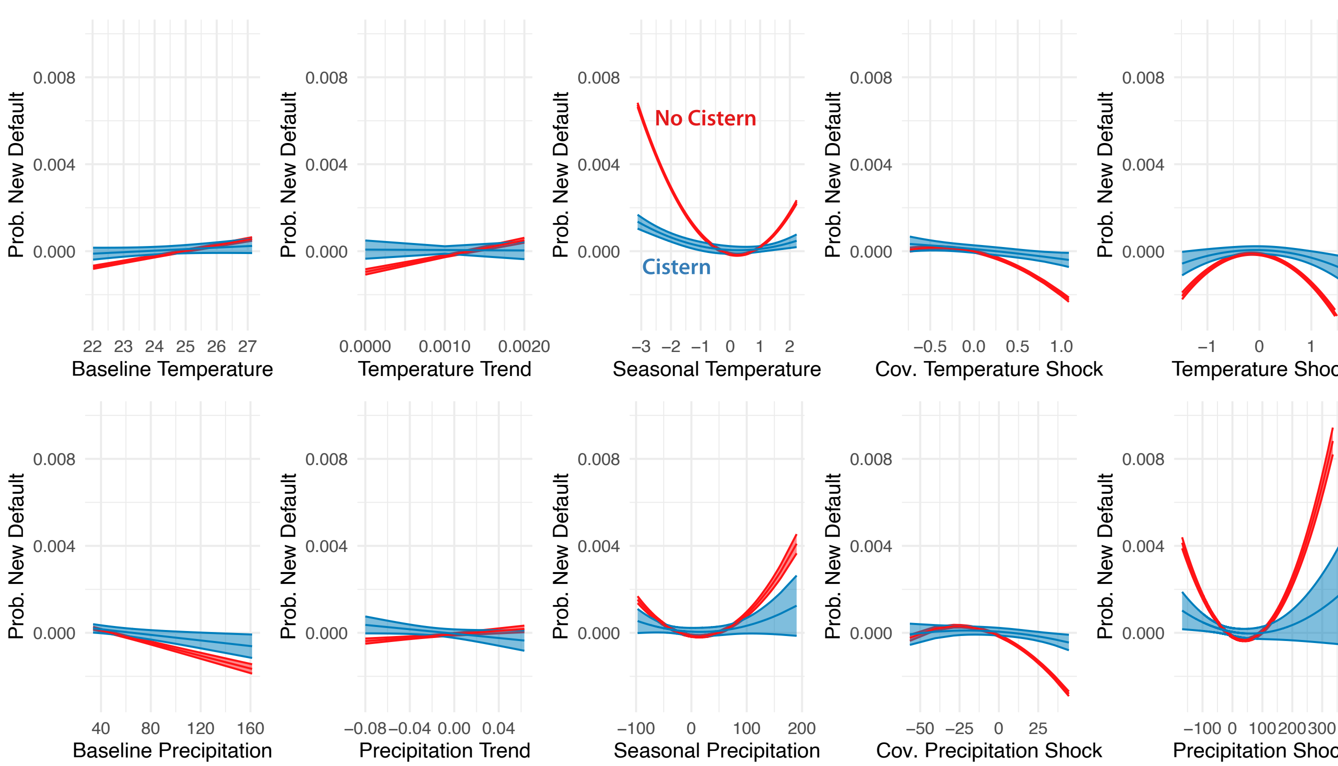

Fig. 4. The marginal impacts of different components of weather on new loan default, where all weather components are allowed to vary based on whether or not a farmer has access to a water cistern. *SI Appendix*, Figure S12 shows the analogous results for overall default; coefficients can be found in *SI Appendix*, Table S12.

Discussion

Here, we show that the ability to pair historical and future data in a straightforward manner moves forward our understanding of the human impacts of climate change and indicates increasing weather-driven problems in Brazil's agricultural system. We find that climate change in Brazil is expected to have negative impacts that ripple across the agricultural sector—from yields to revenues to loan repayment performance of agricultural borrowers. We achieve this using an approach of estimating the statistical relationships between agricultural outcomes and a decomposition of weather variables into components that can each change independently and correspond to different potential adaptation margins. We find very strong relationships between this weather decomposition and agricultural outcomes and also find weather to be a significant determinant of repayment (although the R^2 here is substantially lower than for agricultural outcomes). And importantly, we are able to identify that different components of weather appear to contribute to modeled future outcomes. Local idiosyncratic precipitation shocks are detrimental to all outcomes, but the nature of the shock and the degree to which it is spatially correlated matters. Importantly, the increasing correlation structure of such shocks (for example at the national level as shown in Fig. 1) raises the fear that existing endogenous price effects (i.e., higher prices if production drops) may only go so far, and we would expect more detrimental financial impacts that trickle up to portfolio- and institution-level risk in the financial sector as the climate warms.

We find some preliminary evidence that investments in resilience infrastructure like cisterns (even though their adoption is endogenous in this analysis) do weaken the link between seasonal weather fluctuations and agricultural loan repayment, and are overall associated with better performance. So intentional design around resilience not only has the capacity to help individual producers but also to build resilience into the financial sector. Efforts to provide physical and financial infrastructure to enhance resilience will be all the more important as climate extremes become more spatiotemporally correlated across large producing regions like Brazil. Promising efforts in the Brazilian context include The Agricultural Climate Risk Zoning program (ZARC), a risk management tool that provides planting guidance and soil-specific extension for more than 40 crops, and the national agricultural insurance program PROAGRO (which requires farmers to comply with ZARC recommendations).

This research does point to a role for more nuanced and integrated climate information for stakeholders, practitioners, and policymakers. While provision of weather data to producers has had mixed results (e.g., refs. 34–37), this is in part due to a mismatch between need and the utility of the information provided. Moreover, efforts to harmonize information across a range of actors have been limited. Because the decomposition used here can be constructed in the same way in the historical and future climate data, this approach poses in parallel the two key questions: "to what has the system been vulnerable" and "what is changing" and can tie those different margins closely to their respective adaptation policies. In particular, coordinated monitoring of evolving shocks—to know whether they are covariate or idiosyncratic—is an obvious point where harmonized information to farmers, local institutions, and institutions covering larger spatial scales (including banks and potential social safety net programs) would be especially powerful. We note however that one red flag raised by this analysis is that financial institutions like banks could use this type of information to more effectively screen out the types of borrowers who would most benefit from access to credit or other financial services.

Our approach attempts to strike an important methodological balance. There has long existed a tension between empirical estimation of climate impacts in the recent past and credible projection of impact estimates into the future. The focus on statistical inference and causal identification in the empirical impacts literature has led to methods that identify very local causal impacts. However, these methods often rely on use of fixed effects and other control structures that remove sources of variation that may be meaningful in the future as the structure of climate evolves and changes. In addition, forward projection of these types of results requires strong assumptions about adaptation (typically that there is none), and also that the structure of climate stays the same such that the variation used in statistical identification has the same distribution as the overall structure of the climate shift in the future (32). This is likely not to be the case given the simple fact that all locations are warming, but hydrological shifts are occurring in both directions in different locations (38). The method we propose here trades off some causal identification for flexibility in projection. Use of standard fixed effects models would liken all future changes to idiosyncratic shocks. Our results here suggest that such an approach misses important structural features in future climate that would correspond to very different strategic or policy responses.

We note that our approach is but one realization of an attempt to link empirical statistical impact estimates and future climate projections in a more credible manner. Efforts to assess the different forms this approach might take (including through ML and AI-based approaches) would be especially fruitful. The proposed framework may be most useful in that it offers a concrete method for linking empirical approaches with deep, local, and often mixed-methods research on the different dimensions of vulnerability and adaptation, because local strategies and policies can be empirically tied to specific components of climate and tested for their impact (actual or projected) over larger spatial and temporal scales. Scholars of vulnerability, adaptation, and resilience in Brazil and more broadly have long called for a more integrated understanding of these issues that effectively connects knowledge and stakeholders across scales (34, 39, 40), and ensures that adaptations have a systems perspective and do in fact build resilience (41–43).

We conclude by noting that even a country as large as Brazil offers somewhat limited degrees of freedom and relatively small overlap between agricultural and financial institution data. This is in part due to legal frameworks and norms in the financial sector that do not require institutions to preserve records beyond a certain length of time. Our analysis shows how a concerted effort to link longer records of climate, agricultural production and revenue data, and agricultural loan data in key producing regions would assist in understanding, characterizing, and predicting climate impacts across the agricultural sector. Importantly, it would allow for exploration of different margins and spatial scales of correlation of shocks, as well as benchmarking adaptation efforts aimed at different margins and scales. Such an effort could form a core component of sustained assessment (44) and help more closely align stakeholder and practitioner needs with academic research.

Materials and Methods

Climate Data. We use historical monthly gridded temperature and precipitation data from the University of Delaware (45) as the main input to historical impact estimation. For future projections, we an ensemble member from the Hadley

Earth System model (HadGEM-ES) (46) contributions to the CMIP5 (47, 48), using RCP8.5, that was bias corrected and spatially downscaled (49–51). We note that the model has a high equilibrium climate sensitivity, but is one of the ESMs that performs best for Brazil, and outperforms the CMIP5 ensemble mean for precipitation metrics (52–54); it is also one of the ESMs selected for coordinated regional downscaling experiments (55, 56). We show results for only one ensemble member for clarity, but note that model-based uncertainty could easily be assessed by applying decomposition methods to multiple ensemble members or multiple models.

Agricultural Data. Agricultural data are from the Brazilian Institute of Geography and Statistics (IBGE; Instituto Brasileiro de Geografia e Estatística) Municipal Agricultural Production data (30). Growing seasons were derived from Sacks et al. (31), and climate exposures were aggregated over crop-specific production seasons between 1990 and 2017.

Financial Data. Data on the universe of agricultural loans from 2012 to 2017 in the State of Bahia were provided by our partner financial institution. We compiled loan-level information into monthly status (binary indicators of whether a loan was in delinquency or default at the end of that month) and merged these data with municipal weather decomposition data at the monthly level to analyze how the different components of our spatiotemporal weather decomposition were related to agricultural loan performance.

Decomposing Weather Variation. We begin with monthly historical weather data on average temperature and precipitation for spatial unit *i* (municipalities) in month *m* and year *t*. The steps in the decomposition of the historical data are as follows:

1. Estimate the linear time trend in temperature for unit *i*, calculate $\hat{T}_{trend_{it}} \equiv E_t(T_{it})$.
2. Calculate the base value of expected temperature for each unit as $\hat{T}_{i0} \equiv E(T_{i0})$.
3. Calculate seasonality for every location as the average deviation in a month from the linear time trend above: $\bar{T}_{im} \equiv E_m(T_{im} - \hat{T}_{trend_{it}})$. These three components represent a simple forecast of the first moment of temperature for each unit (mean, linear time trend, and seasonality). The remaining terms are residuals around this predictable component.
4. The "covariate" shock is then the residual that is common to all units: $\hat{T}_{shock_t} \equiv E_t(T_{imt} - (\hat{T}_{i0} + \hat{T}_{trend_{it}} + \bar{T}_{im}))$.
5. Finally, the "idiosyncratic" shock is the component of the residual that is not correlated: $\hat{T}_{shock_{imt}} \equiv T_{imt} - (\hat{T}_{i0} + \hat{T}_{trend_{it}} + \bar{T}_{im} + \hat{T}_{shock_t})$.

To understand nonlinearity in the response function, it would be ideal to allow for flexibility in each of the four terms that capture change in the climate. Imposing a linear functional form on the way that the decomposed variables drive outcomes implicitly imposes that the variance of weather has no independent effect on outcomes, independent of a shift in the mean. A large literature shows this to be an unreasonable assumption for agricultural outcomes in particular (12, 16–18, 24), and so we estimate quadratic functions of these sources of variation in order to be able to fit and then predict the impact of future changes in the variance of the decomposed weather variables. In each dimension, variance has a distinct interpretation (increases in the variance of predictable seasonal rainfall may be easier to adapt to than unpredictable changes in the variance of covariate shocks, for example). Given the identification and power problems present in the estimation of the time trend terms, we do not attempt to measure nonlinear time trends. We do however use quadratics in the seasonal variation, the correlated shock, and the idiosyncratic shocks (for which we have strong panel identification and many degrees of freedom) to study the effects of changes in the variance of weather outcomes.

Empirical Strategy. The estimation on the historical data (described here for agricultural loan data) is conducted by regressing monthly outcome Y_{imt} on the five decomposed weather terms above and three quadratic terms for both temperature T and precipitation P:

$$\begin{aligned} Y_{imt} = \alpha_0 &+ \tau_1 \hat{T}_{i0} + \tau_2 \hat{T}_{trend_{it}} + \tau_3 \bar{T}_{im} + \tau_4 \bar{T}^2_{im} \\ &+ \tau_5 \hat{T}_{shock_t} + \tau_6 \hat{T}^2_{shock_t} + \tau_7 \hat{T}_{shock_{imt}} + \tau_8 \hat{T}^2_{shock_{imt}} \\ &+ \rho_1 \hat{P}_{i0} + \rho_2 \hat{P}_{trend_{it}} + \rho_3 \bar{P}_{im} + \rho_4 \bar{P}^2_{im} + \rho_5 \hat{P}_{shock_t} \\ &+ \rho_6 \hat{P}^2_{shock_t} + \rho_7 \hat{P}_{shock_{imt}} + \rho_8 \hat{P}^2_{shock_{imt}} + \epsilon_{imt}. \end{aligned}$$

Because the distributions of yields and revenues across Brazil are not normally distributed, we estimate these models with logged outcomes.

Future Projections. We decomposed bias corrected and downscaled climate data for Brazil (2040 to 2069) in the same manner as in the historical period. We then paired the parameters estimated from our regression models with forecast information about each of the decomposition components.

Data, Materials, and Software Availability. Data and analysis code can be found at https://github.com/jaburney/AgResilienceBrazil (57).

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Author affiliations: [a]School of Global Policy and Strategy, University of California San Diego, La Jolla, CA 92093; [b]Scripps Institution of Oceanography, University of California, San Diego, La Jolla, CA 92037; [c]Department of Economics, University of California San Diego, La Jolla, CA 92093; and [d]Universidade Estadual de Campinas, São Paulo, Brazil

Author contributions: J.B., C.M., B.L.-V., and K.S. designed research; J.B., C.M., B.L.-V., and K.S. performed research; J.B., C.M., and B.L.-V. contributed new reagents/analytic tools; J.B., C.M., B.L.-V., and A.G.M. analyzed data; and J.B., C.M., B.L.-V., and A.G.M. wrote the paper.

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