Crop-damaging temperatures increase suicide rates in India

Tamma A. Carleton[a,b,1]

[a]Agricultural & Resource Economics, University of California, Berkeley, CA 94720; and [b]Global Policy Lab, Goldman School of Public Policy, University of California, Berkeley, CA 94720

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More than three quarters of the world's suicides occur in developing countries, yet little is known about the drivers of suicidal behavior in poor populations. I study India, where one fifth of global suicides occur and suicide rates have doubled since 1980. Using nationally comprehensive panel data over 47 y, I demonstrate that fluctuations in climate, particularly temperature, significantly influence suicide rates. For temperatures above 20 °C, a 1 °C increase in a single day's temperature causes ∼70 suicides, on average. This effect occurs only during India's agricultural growing season, when heat also lowers crop yields. I find no evidence that acclimatization, rising incomes, or other unobserved drivers of adaptation are occurring. I estimate that warming over the last 30 y is responsible for 59,300 suicides in India, accounting for 6.8% of the total upward trend. These results deliver large-scale quantitative evidence linking climate and agricultural income to self-harm in a developing country.

climate | suicide | agriculture | weather impacts | India

Each year, over 130,000 lives are lost to self-harm in India (1). The causes of these deaths are poorly understood; drivers of suicidal behavior remain disputed across scientific disciplines, and nearly all evidence comes from developed country contexts (2–4). Despite lack of substantiation, public debate in India has centered around one possible cause of rapidly rising suicide rates: increasing variability of agricultural income (5, 6). Drought and heat feature prominently in these claims; climate events are argued to damage crop yields, deepening farmers' debt burdens and inducing some to commit suicide in response. With more than half of India's working population employed in agriculture, one third lying below the international poverty line, and nearly all experiencing rising temperatures due to anthropogenic climate change, these arguments appear plausible. However, the relationship between economic shocks and suicide is controversial (3, 4, 7–9), and, in India, the effect of income-damaging climate variation on suicide rates is unknown. Although the national government has recently announced a $1.3 billion climate-based crop insurance scheme motivated as suicide prevention policy (10), evidence to support such an intervention is lacking. Existing work has found that agricultural yields in India rely heavily on growing season temperature and precipitation (11, 12), but it is unclear to what extent, if any, this sensitivity to climate influences suicide rates. Previous studies of income variability affecting suicide in India are anecdotal (5) or qualitative (13–17), and none attempt to identify and synthesize quantitative relationships between climate, crops, and suicides. To fill this knowledge gap, I use a data set from India's National Crime Records Bureau (NCRB), which contains the universe of reported suicides in the country from 1967 to 2013. I pair these data with information on agricultural crop yields and high-resolution climate data to identify the effect of climatic shifts on suicide rates, and to test whether agricultural yields are a mechanism through which these effects materialize. Although my analysis is most directly applicable to India, it also contributes to building a broader understanding of the effect of climate on suicide throughout the developing world.

My empirical strategy relies on a simple thought experiment in which I observe two identical populations, alter the climate in one, and compare suicide rates in this "treatment" population to those in an unaltered "control." In the absence of such an experiment, I emulate this comparison by observing a population within India under different climate realizations over time, allowing the same population to function as both treatment and control. After accounting for secular trends, year-to-year changes in the climate are plausibly random, and amount to many ongoing approximations of my ideal experiment (18). Because this approach isolates random variation in climate, other common factors associated with both suicide and the climate are unlikely to confound the analysis. Therefore, a causal interpretation of estimated regression coefficients is reasonable, even though the climate itself was not experimentally manipulated.

I analyze the relationship between annual suicide rates, measured for each of India's 32 states and union territories, and cumulative exposure to temperature and rainfall using a regression model that accounts for time-invariant differences across states in unobservable determinants of suicide rates, such as religion or history, as well as regional time trends in suicide rates that may derive from shifting cultural norms or suicide contagion effects, among many other possible forces. Under my estimation strategy, two key empirical concerns remain. First, the functional form of the relationship between suicide rates and climate variables has minimal precedent in existing literature. I therefore use a flexible nonlinear model and show robustness of my results to alternative functional form assumptions. Second, the channels through which adverse climate conditions may affect suicide rates are not immediately discernible, yet are of central policy relevance. To this end, I distinguish between climate conditions that damage crops and those that have no

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Significance

Suicide is a stark indicator of human hardship, yet the causes of these deaths remain understudied, particularly in developing countries. This analysis of India, where one fifth of the world's suicides occur, demonstrates that the climate, particularly temperature, has strong influence over a growing suicide epidemic. With 47 y of suicide records and climate data, I show that high temperatures increase suicide rates, but only during India's growing season, when heat also reduces crop yields. My results are consistent with widely cited theories of economic suicide in India. Moreover, these findings have important implications for future climate change; I estimate that warming temperature trends over the last three decades have already been responsible for over 59,000 suicides throughout India.

Author contributions: T.A.C. designed research, performed research, analyzed data, and wrote the paper.

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[1]Email: tcarleton@berkeley.edu.

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effect on agricultural yields. I do so by estimating differential impacts of climate during growing and nongrowing seasons, using the arrival and departure of the southwest summer monsoon to define seasonality (see *SI Appendix* for details). In additional mechanisms tests, I use spatial heterogeneity and temporal lags to assess the mediating factors between climate and suicide.

Results

I find that temperature during India's main agricultural growing season has a strong positive effect on annual suicide rates (Fig. 1 *A* and Table 1). For days above 20 °C, a 1 °C increase in a single day's temperature during the growing season increases annual suicides by 0.008 per 100,000 people, causing an additional 67 deaths, on average across India; this amounts to a 3.5% increase in the suicide rate per SD (σ) increase in temperature exposure. In contrast, temperatures in the nongrowing season have no identifiable impact on suicide rates. This finding is robust to inclusion of state-specific trends and national-level shocks to the suicide rate (Table 1), distinct methods for averaging gridded climate data across pixels within a state (*SI Appendix*, Table S5), alternative degree day cutoff values (*SI Appendix*, Table S6), controlling for irrigation (*SI Appendix*, Table S10), and alternative definitions of the growing season (*SI Appendix*, Table S11).

The differential response of suicide to temperature in the growing and nongrowing seasons is consistent with an agricultural channel in which heat damages crops, placing economic pressure on farming households, members of which may respond to such hardship with suicide. These crop losses may also permeate throughout the economy, causing both farming and nonfarming populations to face distress as food prices rise and agricultural labor demand falls. To further test this mechanism, I use district-level yield data covering 13 Indian states from 1956 to 2000 to estimate an identical regression model to that described above, now measuring the response of crop yields to variations in the climate. I find that yields mirror suicides in their response to temperature, falling with rising growing season temperatures but reacting minimally to nongrowing season heat (Fig. 1 *E* and *F*), a result identified in many other parts of the world (12, 19, 20). For growing season days above 20 °C, annual yields fall by 1.3%/σ. This finding is robust to the same specification checks listed above for suicide (*SI Appendix*, Tables S4, S5, S7, and S11). The striking similarity between the responses of suicide and yield to temperature suggests that variations in temperature affect suicide rates through their influence over agricultural output.

India's agriculture is predominately rain-fed and dependent on the timing and duration of the monsoon, making growing season rainfall critical for crop growth (21), as well as a potential driver of suicide. As expected, growing season precipitation

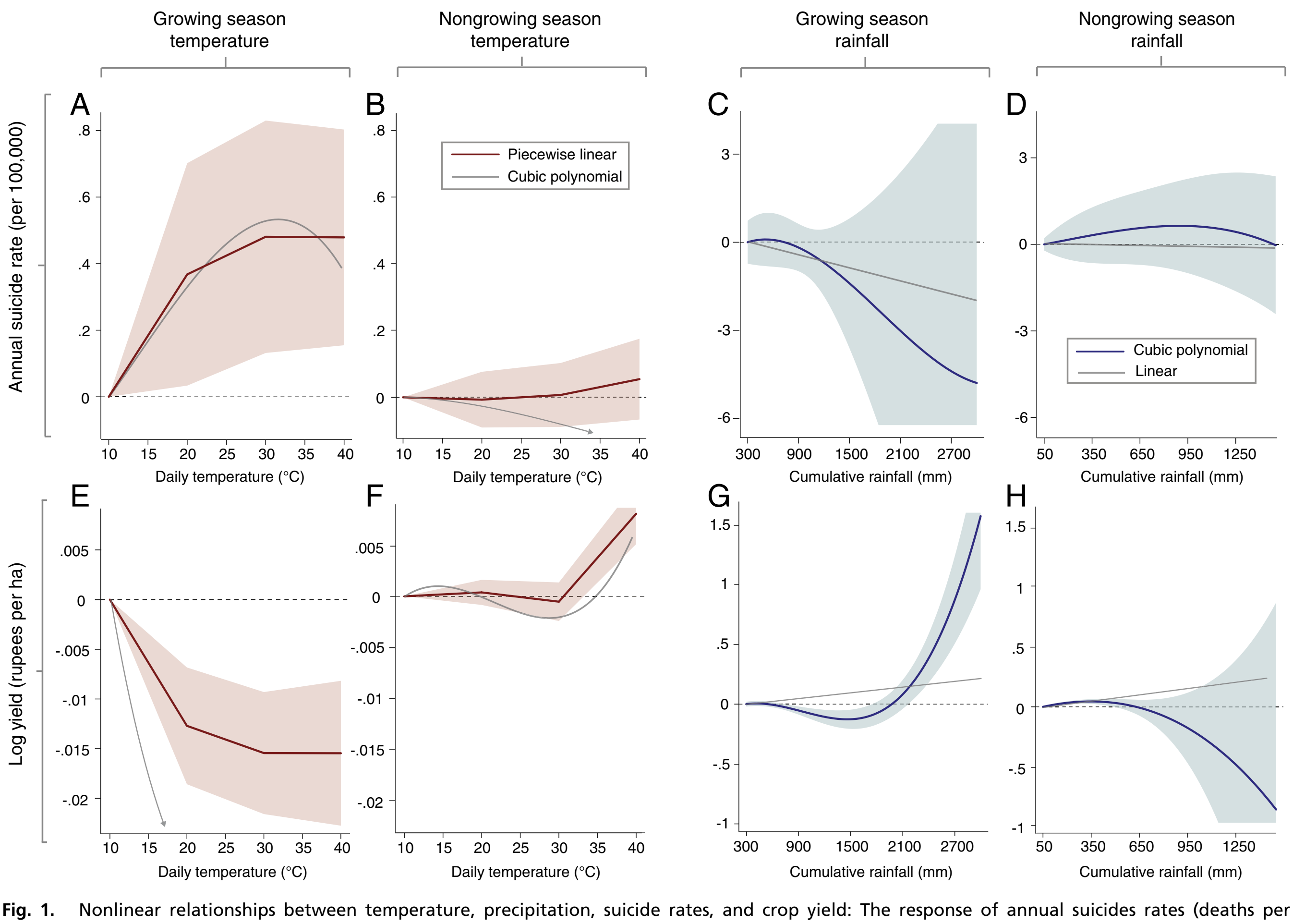

Fig. 1. Nonlinear relationships between temperature, precipitation, suicide rates, and crop yield: The response of annual suicides rates (deaths per 100,000 people) to (*A*) growing season and (*B*) nongrowing season temperatures. Response of annual suicide rates to cumulative (*C*) growing season and (*D*) nongrowing season rainfall. (*E–H*) Analogous relationships for log annual yield, valued in rupees per hectare. The slopes of the responses in *A*, *B*, *E*, and *F* can be interpreted as the change in the annual suicide rate or log yield caused by one day's temperature rising by 1 °C. The slopes of the responses in *C*, *D*, *G*, and *H* can be interpreted as the change in the annual suicide rate or log yield caused by one additional millimeter of rainfall. All graphs are centered at zero.

Table 1. **Effect of heat exposure on suicide rates and yield values, by agricultural season**

Variable	Suicides per 100,000			100 × log yield, rupees per hectare		
	State trends	Year fixed effects	State trends + year fixed effects	State trends	Year fixed effects	State trends + year fixed effects
Growing season						
Degree days below threshold, °C	0.003***	0.000	0.004***	0.013	−0.019	−0.003
	(0.001)	(0.001)	(0.001)	(0.009)	(0.018)	(0.013)
Degree days above threshold, °C	0.007***	0.009**	0.008**	−0.017***	−0.020*	−0.019*
	(0.002)	(0.004)	(0.003)	(0.006)	(0.010)	(0.010)
Nongrowing season						
Degree days below threshold, °C	−0.001	−0.009*	−0.003*	0.002	0.007	0.001
	(0.001)	(0.004)	(0.002)	(0.003)	(0.005)	(0.004)
Degree days above threshold, °C	−0.002*	0.002	0.001	0.010***	0.018***	0.010*
	(0.001)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)

Coefficients represent the effect of 1 d becoming 1 °C warmer on the annual suicide rate (suicide deaths per 100,000 people) or annual yield (log rupees per hectare), where the degree day threshold is 20 °C. All regressions include a cubic polynomial of seasonal precipitation (coefficients not shown). Suicide regressions include state fixed effects, report standard errors clustered at the state level, and are estimated with 1,434 observations. Yield regressions include district fixed effects, report standard errors clustered at the district level, and are estimated with 11,289 observations. Models with state trends include linear state-specific time trends; models with year fixed effects include annual, India-wide indicator variables. ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$.

positively impacts yields, with an effect of $1.9\%/\sigma$, whereas nongrowing season rainfall (of which there is little) has no statistically distinguishable effect (Fig. 1 *G* and *H*). These yield gains again reflect the response of suicides to climate—suicide rates fall as growing season rainfall increases (Fig. 1 *C* and *D*)—although the relationship is statistically insignificant across most robustness checks (*SI Appendix*, Tables S3–S11). Despite statistical uncertainty, the yield and suicide response functions with respect to rainfall also match in the nongrowing season, where a flat relationship is estimated in both cases. Imprecision in these rainfall estimates for suicide may be due to measurement error introduced by the need to characterize monsoon rainfall at the state level, as there can be important within-state differences in monsoon arrival and withdrawal (21). The district-level agricultural data, in contrast, do not suffer from this problem. Consistent with measurement error, a less parametric estimate of rainfall's effect on suicide separately during each month of the year demonstrates that rain during all growing season months negatively influences suicide rates, but with high uncertainty (*SI Appendix*, Fig. S7). Moreover, results from an alternative empirical model measuring impacts of longer-run trends in climate demonstrate a robust and substantial negative effect of growing season rainfall on suicide rates (*SI Appendix*, Table S9). Under this approach, I find that increasing growing season rainfall by 1 cm is associated with a decrease of ∼0.8 deaths per 100,000, lowering the suicide rate by 7%, on average. Together, these results suggest that rainfall may mitigate suicide rates in India, plausibly through an agricultural channel.

The Agricultural Mechanism. I further examine the agricultural mechanism by including lagged effects in the regression model. If suicides are affected by climate variation through negative agricultural income shocks, there may be delayed impacts: poor harvests in one year may make subsequent conditions more unbearable, as households draw on stored crops or deplete monetary savings. In contrast, if these climate variables influence suicide prevalence purely through direct channels, such as the hypothesized neurological effects of heat exposure on aggressive behavior (22, 23), delayed effects should not materialize. A model that includes lagged climate variables reveals that past growing season temperatures strongly influence suicide rates, with effects that last for ∼5 y (Fig. 2*A*). Similarly, high-precipitation years have a strong lagged effect in which heavy rainfall today causes lower suicide rates in 2 y to 3 y; this beneficial yield shock may enable individuals to save crops and income, making future suicides less likely (Fig. 2*B*). Interestingly, drought appears to have no effect on suicide rates, either contemporaneously or in lagged form (*SI Appendix*, Fig. S8).

Geographic heterogeneity in both suicide and crop yield impacts can be used as an additional means of assessing the channel through which climate drives suicides. I disaggregate suicide response functions by state to detect a clear geographic pattern in which southern states—which are generally hotter, have higher average suicide rates, and display steeper suicide trends over time—have much stronger responses to growing season temperature (Fig. 2*C*). I obtain similar heterogeneous responses of agricultural yields to growing season temperatures for each of the 13 states included in the crop data. Although these estimates have large uncertainty, the correlation between state yield sensitivity and state suicide sensitivity is positive, suggesting that states where agricultural yields are more damaged by high temperatures are also the states where these temperatures increase suicide rates substantially (Fig. 2*D*). Four states that have been at the center of India's public debates regarding agricultural influences on suicide (Maharashtra, Karnataka, Tamil Nadu, and Andhra Pradesh) not only have severe suicide responses to temperature, but also exhibit large negative impacts of temperature on yield.

Adaptation. As anthropogenic climate change raises temperatures throughout the world, a central question for global welfare is the extent to which populations adopt adaptive behaviors to prevent climate damages (18). I conduct four sets of tests to assess the evidence for four distinct hypotheses regarding adaptive behavior in the context of suicide in India: (*i*) locations that are hotter, on average, exhibit lower sensitivity to temperature, as populations acclimatize; (*ii*) locations that are wealthier, on average, exhibit lower sensitivity to temperature, as wealth enables investment in adaptation; (*iii*) temperature sensitivity has declined over time as incomes and access to modern agricultural technologies have risen; and (*iv*) sensitivity to longer-run gradual trends in temperature will be lower than sensitivity to short-run variations in temperature, as populations require time to adapt. My estimation strategies for testing these hypotheses are detailed in *SI Appendix*. Across all four tests, I find no evidence of any type of adaptive behavior. In hotter locations, I detect higher than average sensitivity to temperature, contradicting my first hypothesis (Fig. 3*A*). Temperature sensitivity in wealthier locations is indistinguishable from that in poor locations, failing to support my second hypothesis

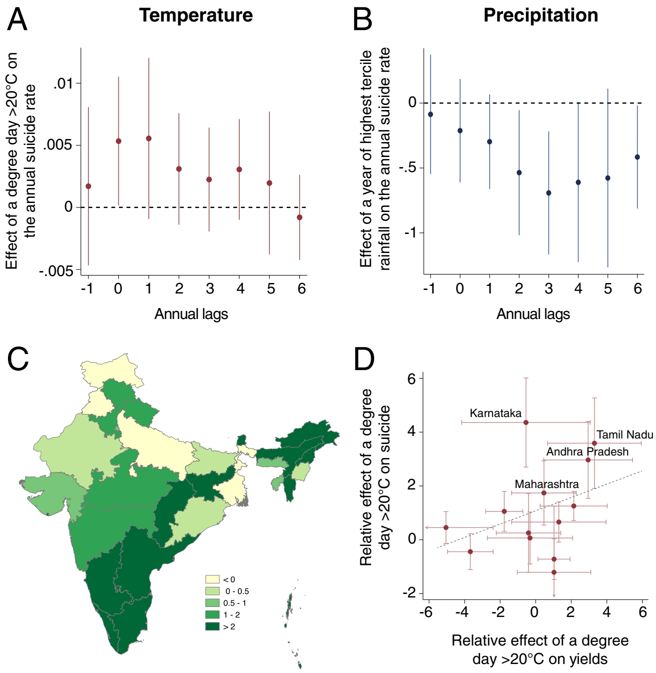

Fig. 2. Evidence for the agricultural income channel. Lagged effects of (*A*) growing season temperature and (*B*) high precipitation (years in which precipitation falls into the highest tercile of the long-run rainfall distribution) on annual suicide rates per 100,000 people suggest an economic mechanism for climate impacts. (*C*) Geographic heterogeneity in the suicide–temperature response, where states are colored by the state-specific temperature sensitivity as a fraction of the average treatment effect. Darker colors indicate more severe responses of suicide to growing season temperature; yellow indicates a negative effect. (*D*) Correlation between state-level suicide sensitivities and the additive inverse of corresponding state-level crop yield sensitivities. Temperature effects are shown as relative to the average treatment effect. Coefficients in all panels were estimated in a degree days model with a cutoff of 20 °C. Standard errors are clustered at the state level for suicide and district level for yield, and 95% CIs are shown around each point estimate.

(Fig. 3*B*). Temperature sensitivity of suicide has remained remarkably stable over time, despite India's robust economic growth and dramatic improvements in agricultural yields over this period (Fig. 3*C*). Finally, the impact of gradual changes ("long differences") is, in contrast to my final hypothesis, more severe than that of short-run variations in temperature (Fig. 3*D* and *SI Appendix*, Table S9). Taken together, these tests reveal no evidence of adaptive behavior in the context of temperature damages to suicide rates in India.

Discussion

As India's suicide rate continues to rise, the causes of these deaths remain heavily debated. In this study, I find that variations in temperature during India's main growing season exert substantial influence over suicide rates. To explore the significance of this effect to total trends in India, I extend my results to calculate the share of this upward trend that is attributable to changes in India's climate over recent decades. In particular, I measure the additional number of deaths attributable to warming growing season temperatures throughout India since 1980 (see *SI Appendix* for details on this approach). I find that, by 2013, temperature trends are responsible for over 4,000 additional deaths annually across India, accounting for ∼3% of annual suicides (Fig. 4). Across all states and all years since 1980, a cumulative total of 59,300 suicides can be attributed to warming, accounting for 6.8% of the national upward trend in suicide rates over this time period.

My study has important limitations. Of primary concern is that I do not have a quasi-experiment in which agricultural incomes were randomly allocated across populations within India and suicide rates were monitored in response. Thus, although I use multiple distinct approaches aimed at pinning down the agricultural mechanism through which climate affects suicide, I do not have a direct test of the common hypothesis that climate-induced economic hardship can lead some individuals to respond with self-harm. Secondly, my empirical strategy relies on estimating the effects of year-to-year variation in temperature and precipitation on suicides within a given state; although this facilitates a causal interpretation of estimated coefficients, it does not guarantee that there are no other factors correlated with both suicide and climate within a state that could confound my estimation. However, the robustness of the effect of growing season temperature on suicide rates across many specifications (*SI Appendix*, Tables S3–S13) and subsamples (Fig. 3) makes such confounding factors extremely unlikely.

Despite these necessary shortcomings, my findings convey important lessons for current and future generations. Suicide rates are a salient indicator of human hardship. My identification of a substantial effect of climate variation on this measure of human suffering in one fifth of the global population provides empirical support for policies that aim to prevent suicides through tools that alleviate the impacts of climate on income, such as crop insurance. These findings are also critical inputs into policy decisions regarding future climate change mitigation and adaptation. As I find no evidence that adaptation has occurred over 47 y in a large and rapidly developing country, and because suicide prevalence is a valuable measure of well-being, the magnitude of effects I detect has important consequences for assessing the likely impact of future climate change on human welfare globally. India alone is predicted to experience an average temperature increase of up to 3 °C by 2050 (24). Without investments in adaptation, my findings suggest that this warming will be accompanied by a rising number of lives lost to self-harm.

Materials and Methods

Suicide and Agricultural Data. Annual suicide data are reported by the Indian NCRB at the state level beginning in 1967 for 27 of India's 29 states and 5 of its 7 union territories. Suicide records are in NCRB's "Accidental Deaths and Suicides in India" report and include the total number of state suicides per year. I calculate suicide rates as the number of total suicides per 100,000 people, with population values linearly interpolated between Indian censuses. I use agricultural data from ref. 25. These are district-level annual yield records for major crops (rice, wheat, sugar, sorghum, millet, and maize) between 1956 and 2000, compiled from Indian Ministry of Agriculture reports and other official sources. These data cover 271 districts in 13 major agricultural states, and provide log annual yield values of a production-weighted index across all crops measured in constant Indian rupees, where prices are fixed at their 1960–1965 averages. Details on these data and summary statistics are provided in *SI Appendix*.

Climate Data. Climate data are generally available at higher spatial and temporal resolution than social outcome data. Although suicides and yields are only measured annually, if the relationship between these outcomes and temperature is nonlinear, daily climate data are required, as annual averages obscure such nonlinearities (26). For daily temperature data, I use the National Center for Environmental Prediction gridded daily reanalysis product, which provides observations in a grid of $\sim 1^\circ \times 1^\circ$. These data include daily mean temperature for each grid over my sample period. To convert daily temperature into annual observations without losing intraannual variability in daily weather, I use the agronomic concept of degree days (details in *SI Appendix*). I aggregate grid-level degree day values to state-level observations using an area-weighted average (see *SI Appendix*, Table S5 for robustness checks using weights based on population and area planted with crops). When these state-level degree day values are summed over days within a year, regressing an annual outcome on cumulative degree days imposes a piecewise linear relationship in daily temperature, in which the outcome response has zero slope for all temperatures less than T^*. Although a body of literature identifies biologically determined cutoffs T^*

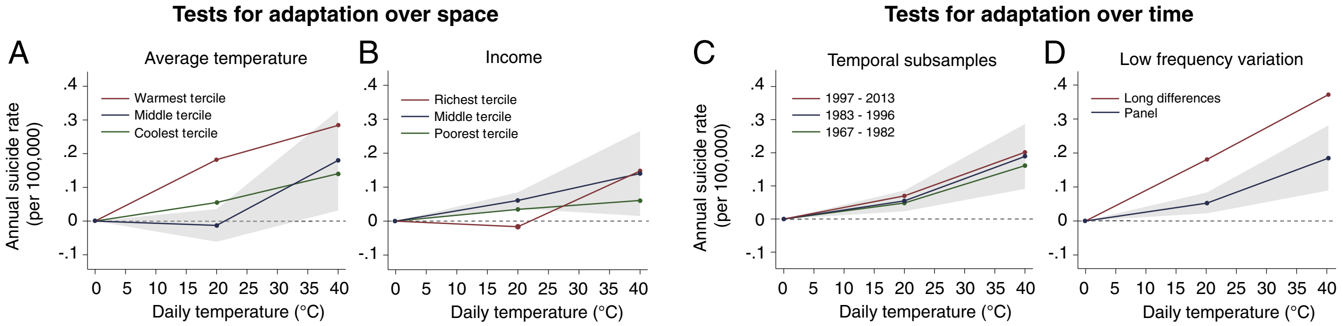

Fig. 3. Four tests of adaptation in the suicide–temperature relationship. Shown is heterogeneity in the suicide response to growing season degree days above 20 °C, (*A*) by terciles of long-run average growing season degree days, (*B*) by GDP per capita in 2010, (*C*) by periods within the sample, and (*D*) across two different estimation strategies ("long differences" estimates the effect of long-run climate trends, and "panel" estimates the effect of year-to-year variation). Shaded areas indicate the 95% CI around (*A* and *B*) the middle tercile response function, (*C*) the period 1983 to 1996, and (*D*) the panel method.

for yields of a variety of major crops, there is no empirical support to draw on in selecting T^* for suicides. Thus, although I use $T^* = 20\,^\circ$C throughout this study, I show robustness for a range of plausible cutoffs based on the distribution of my temperature data, and, in Fig. 1, I estimate a flexible piecewise linear function using four different degree day cutoffs to impose minimal structure on the response function.

Because reanalysis models are less reliable for precipitation data, and because nonlinearities in precipitation that can't be captured with a polynomial appear to be less consistently important both in the violent crime literature (27) and in the agriculture literature (19), I use the University of Delaware monthly cumulative precipitation data to complement daily temperature observations (28). These data are gridded at a $0.5^\circ \times 0.5^\circ$ resolution, with observations of total monthly rainfall spatially interpolated between weather stations. I again aggregate grids up to states using area-based weights, after calculating polynomial values at the grid level first.

Regression Estimation. To identify the impact of temperature and precipitation on suicide rates, I estimate a multivariate panel regression using ordinary least squares, in which the identifying assumption is the exogeneity of within-state, annual variation in cumulative degree days and precipitation. My primary estimation approach uses a flexible piecewise linear specification with respect to temperature and a cubic polynomial function of precipitation. To isolate the impact of economically meaningful climate variation, I separately identify the temperature and precipitation response functions by agricultural seasons (see *SI Appendix* for details). My empirical model takes the general form

$$suicide\_rate_{it} = \sum_{s=1}^{2} \sum_{k=1}^{\kappa} \beta_{ks} \sum_{d \in s} DD_{idt}^{k} + \sum_{s=1}^{2} g_s \left(\sum_{m \in s} P_{imt} \right) + \delta_i + \eta_t + \tau_i t + \varepsilon_{it}, \qquad [1]$$

where $suicide\_rate_{it}$ is the number of suicides per 100,000 people in state i in year t, s indicates season (growing and nongrowing), and $k = 1, \ldots, \kappa$ indicates a set of degree day cutoffs that constrain the piecewise linear response. In my most flexible model, I let $\kappa = 7$ with degree day intervals of 5 °C, and, in my simplest model, I let $\kappa = 2$ and estimate a standard degree day model with just one kink point and two piecewise linear segments. DD_{idt}^{k} is the degree days in bin k (e.g., degree days between 10 °C and 20 °C) on day d in year t in state i, and P_{imt} is cumulative precipitation during month m in year t in state i. I estimate $g(\cdot)$ as a cubic polynomial. State fixed effects δ_i account for time-invariant unobservables at the state level, year fixed effects η_t account for India-wide time-varying unobservables, and state-specific time trends $\tau_i t$ control for geographically differentiated trends in suicide driven by time-varying unobservables. Robustness to different temporal adjustments is shown in *SI Appendix*, Table S8.

Eq. **1** identifies $\hat{\beta}_{ks}$, the season-specific estimated change in the annual suicide rate caused by 1 d in bin k becoming 1 °C warmer. This annual response to a daily forcing variable is described in detail in ref. 26. The polynomial response function for precipitation generates marginal effects of one additional millimeter of rainfall, again estimated seasonally. Due to likely correlation between errors within states, I cluster standard errors at the state level. This strategy assumes that spatial correlation across states in any time period is zero, but flexibly accounts for within-state, across-time correlation. I estimate a nearly identical specification as shown in Eq. **1** for agricultural yields. However, with district-level data, I include district fixed effects and state-specific time trends, and I cluster standard errors at the district level.

Adaptation. Fig. 3 shows results from four sets of tests for evidence of adaptation. The exact specifications for all regression models are shown in *SI Appendix*. All models use a variant of Eq. **1** in which $\kappa = 2$, the degree day

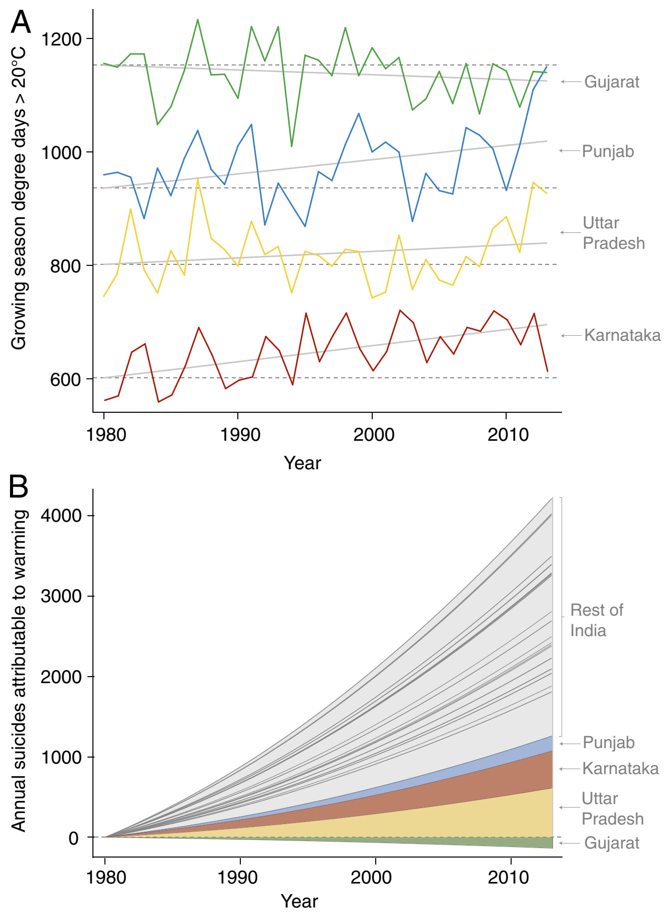

Fig. 4. Attribution of suicides to warming trends in growing season temperatures since 1980: (*A*) trends in degree days above 20 °C during India's main growing season for four example states and (*B*) the total number of deaths annually that can be attributed to warming trends, using the estimated marginal effects of degree days on suicide rates.

cutoff is set to 20 °C, and state-specific linear trends are included. In Fig. 3 *A* and *B*, I estimate Eq. **1**, but add an interaction term between degree days in the growing season and an indicator for the tercile of average growing season degree days that state *i* falls into (Fig. 3*A*) or an indicator for the tercile of average gross domestic product (GDP) per capita that state *i* falls into (Fig. 3*B*). These distributions are defined over all states and all years in the sample. In Fig. 3*C*, I split the 47 y in my sample into three temporal subsamples, and estimate the coefficient on an interaction between growing season degree days and an indicator for each of these three subsamples. In Fig. 3*D*, I estimate a "panel of long differences" empirical model in addition to the standard panel regression in Eq. **1** (29). To do so, I collapse my data to four observations for each state, where each observation measures the 10-y change in suicide rates and climate variables for each decade, and where these changes are "smoothed" by taking 5-y averages at the end points. I then estimate the effect of changes in average degree days and precipitation on changes in average suicide rates.

Attribution of Climate Trends. To compute estimates of the effect of warming temperature trends since 1980, I follow the approach outlined in refs. 18 and 30. I first estimate a state-specific linear trend in growing season degree days above 20 °C for the years 1980–2013. I then generate a detrended degree days residual that is normalized to temperature in 1980 and predict suicide rates using actual and detrended growing season degree days. In so doing, I use the coefficient estimates from the model in Table 1 which includes both state trends and year fixed effects (column 3). The elevated risk of suicide attributable to the trend, relative to the detrended counterfactual, is the difference between these two predictions. Multiplying by the population in each state and each year recovers the total additional number of suicides. Fig. 4*B* displays these additional deaths in each year; integrating over states and years gives the cumulative effect of temperature trends for all of India over the entire period since 1980 (see *SI Appendix* for details).

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Crop-damaging temperatures increase suicide rates in India

Tamma A. Carleton

Supporting Information

1 Materials and methods

1.1 Data appendix

I compiled suicide and climate data at the state level for the years 1967-2013, and agricultural yield and climate data at the district level for the period 1956-2000. Summary statistics for key variables of interest are provided in Table S1.

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Suicide data: 1967 - 2013 (32 states)					
Suicide rate (deaths per 100,000)	11.4	(11.9)	0	73.23	1472
Growing season daily degree days > 20°C	5.32	(2.93)	0	12.23	1645
Nongrowing season daily degree days > 20°C	3.85	(2.83)	0	9.56	1645
Growing season precip. (mm)	1186.18	(626.85)	111.16	4461.3	1598
Nongrowing season precip. (mm)	439.12	(361.48)	5.76	2148.4	1598
Agricultural data: 1956 - 2000 (271 districts)					
Log annual yield (Rupees per ha)	3.92	(0.72)	-1.87	6.45	11289
Growing season daily degree days > 20°C	6.7	(2.6)	0	14.99	11780
Nongrowing season daily degree days > 20°C	4.56	(1.79)	0	9.51	11780
Growing season precip. (mm)	870.55	(467.27)	10.74	4663.99	11780
Nongrowing season precip. (mm)	205.18	(185.12)	0.83	1577.09	11780

Table S1: Summary statistics

Note: Suicide data are from India's National Crime Records Bureau and are reported annually at the state level. Yield data are from [11] and are reported annually at the district level, valued in constant rupees. Growing season is June-September, nongrowing season contains all other months. Precipitation is measured cumulatively. See below for details on the degree days variables.

Note that for estimation throughout the article, I use cumulative degree days, as described in Section 1.1.3, which sums the daily degree day values across an entire season. When reporting standardized effects in the main text, I use the within-state standard deviations in cumulative degree days. The growing season within-state standard deviation of cumulative degree days is 51 in my suicide sample and 44 in my yield sample.

1.1.1 Suicide data

I use annual suicide data as reported by the Indian National Crime Records Bureau (NCRB) at the state or union territory (UT) level from 1967 to 2013. States and UTs included in the data: Adaman & Nicobar Islands, Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Dadra & Nagar Haveli, Daman & Diu, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Lakshadweep, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, Puducherry, Punjab, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh, Uttaranchal, and West Bengal. I calculate suicide rates as the number of total suicides per 100,000 people, with population data linearly interpolated between Indian censuses.

Deaths in general are under-reported in India [4], and the suicide data provided by the NCRB are particularly problematic in this regard. The data are aggregated from district police reports; because attempted suicide was a criminal offense punishable under the Indian Penal Code until 2014, there is likely to be significant under-reporting of suicide as a cause of death. As evidence of this, the NCRB reports 135,000 suicides in India in 2010, while data from a nationally-representative cause of death survey calculates the value at 187,000 [20]. This under-reporting is likely uncorrelated with temperature and precipitation, implying my estimates of the response of suicide to climate provide lower bounds on the true marginal effect.

The evolution over time and space of state level suicide rates in India during my sample period is shown in Figure S1; darker shades indicate higher suicide rates. As a point of reference, suicide rates in the United States are currently approximately 12.5 per 100,000. There is clear spatial heterogeneity, with southern India experiencing the highest suicide rates and largest increases over time. These geographic differences can be seen in more detail for a subset of states in Figure S2. My empirical strategy accounts for this geographic heterogeneity by relying on within-state variation in order to avoid conflation of climate impacts with unobservables, such as cultural norms, political structures, and religious influences. Moreover, I account for spatially varying time trends, due to clearly distinct patterns over time across India (see Section 1.2 below for details).

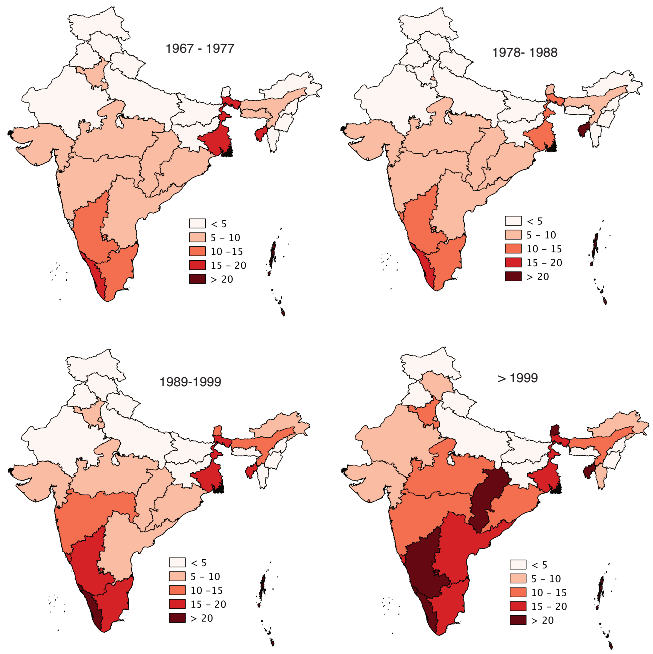

Figure S1: Evolution of suicide rates across space and time

Notes: This figure shows states colored by the average annual suicides per 100,000 people.

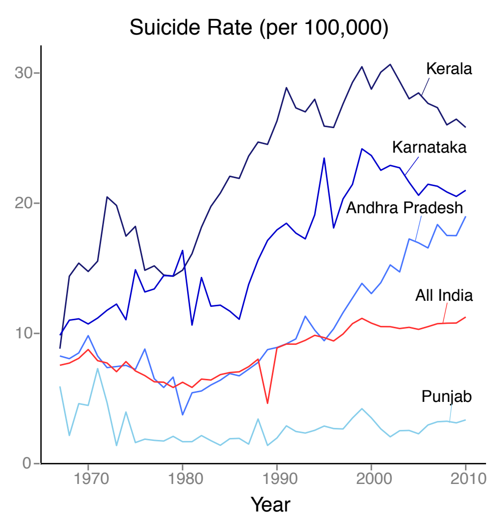

Figure S2: Evolution of suicide rates across time for four selected states, and on average across India

1.1.2 Agriculture data

I use agricultural data from [11]. These are district-level annual yield records for major crops (rice, wheat, sugar, sorghum, millet and maize) between 1956 and 2000, compiled from Indian Ministry of Agriculture reports and other official sources. These data cover 271 districts in 13 major agricultural states: Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. Districts are defined by the 1961 political boundaries. As noted in [4] and [11], these data importantly omit Kerala and Assam, two large agricultural producers that I find also have high rates of suicide. Rather than reporting quantities of each crop, these data provide log annual yield values of a production-weighted index across all crops measured in constant Indian rupees, where prices are fixed at their 1960-1965 averages (see [11] for details).

1.1.3 Climate data

Climate data are generally available at higher spatial and temporal resolution than social outcome data. Although suicides and yields are only measured annually, if the relationship between these outcomes and temperature is nonlinear, daily climate data are required, as annual average temperatures obscure such nonlinearities [16]. While existing studies on temperature and suicide in the epidemiology, sociology, or meteorology literatures do not explore nonlinearities, there are two reasons why they are likely to occur. First, the growing literature on climate and interpersonal conflict reviewed by [6] often identifies nonlinearities in the effect of temperature on violent crime. If we view suicide as a type of violence against oneself, it is possible that a similar relationship exists in this context. Second, [21], among others, have identified a strongly nonlinear response of staple crop yields to temperature. If suicide in India is indeed related to agricultural productivity, then capturing this nonlinearity is important.

For daily temperature data, I use the National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) gridded daily reanalysis product, which provides observations in an irregular grid that is approximately $1^\circ \times 1^\circ$ [18]. These data include daily mean temperature for each grid over my entire sample period. To convert daily temperature into annual observations without losing intra-annual variability in daily weather, I use the agronomic concept of degree days. Degree days are calculated as follows, where T^* is a selected cutoff temperature value and T is a realized daily temperature value:

$$D^{T^*}(T) = \begin{cases} 0 & if \;\; T \leq T^* \\ T - T^* & if \;\; T > T^* \end{cases} \tag{1}$$

Because there are multiple grid cells per state, I aggregate grid-level degree day values $D^{T^*}(T)$ to state-level observations using an area-weighted average (see Table S11 for robustness checks using weights based on population and area planted with crops). When these state-level degree day values are summed over days within a year, e.g. from day t to τ, regressing an annual outcome on cumulative degree days $\sum_{t=1}^{\tau} D^{T^*}(T_t)$ imposes a piecewise linear relationship in daily temperature, in which the outcome response has zero slope for all temperatures less than T^*. While a body of literature identifies biologically-determined cutoffs T^* for yields of variety of major crops, there is no empirical support to draw on in selecting T^* for suicides. Thus, while I use $T^* = 20$°C throughout the study, I also show robustness for a range of plausible cutoffs based on the distribution of my temperature data (see Tables S6 and S7), and in Figure 3 of the main text I estimate a flexible piecewise linear function using four different degree day cutoffs simultaneously to impose minimal structure on the response function (see Section 1.2 below for details).

Due to the fact that reanalysis models are less reliable for precipitation data [2], and because non-linearities in precipitation that cannot be captured with a polynomial appear to be less consistently important both in the violent crime literature [6] and in the agriculture literature [21], I use the University of Delaware monthly cumulative precipitation data to complement daily temperature observations [22]. These data are gridded at a $0.5° \times 0.5°$ resolution, with observations of total monthly rainfall spatially interpolated between weather stations. Again, I aggregate grids up to states and districts using area-based weights, after calculating polynomial values at the grid-level.

1.2 Regression methods

To identify the impact of temperature and precipitation on annual suicide rates, I estimate a multivariate panel regression using ordinary least squares, in which the identifying assumption is the exogeneity of within-state annual variation in degree days and cumulative precipitation. Heterogeneity in suicide rates and in temporal trajectories across states, due to an interplay between unobservable cultural, political and economic factors, implies that cross-sectional variation in climate is endogenous. Thus, I use state and year fixed effects with state-specific time trends to control for time-invariant state-level unobservables, national-level temporal shocks and regional trends.

Without precedent for the functional form of suicide's relationship to climate, my primary estimation approach employs a flexible piecewise linear specification with respect to temperature and a cubic polynomial function of cumulative precipitation. To capture the distinct impact of economically meaningful climate variation, I separately identify the temperature and precipitation response functions by agricultural seasons. My empirical model takes the general form:

$$suicide\_rate_{it} = \sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}\sum_{d\in s}DD_{idt}^{k} + \sum_{s=1}^{2}g_s\left(\sum_{m\in s}P_{imt}\right) + \delta_i + \eta_t + \tau_i t + \varepsilon_{it} \tag{2}$$

Where $suicide\_rate_{it}$ is the number of suicides per 100,000 people in state i in year t, $s \in \{1, 2\}$ indicates the season (growing and nongrowing), and $k = 1, ..., \kappa$ indicates a set of degree day cutoffs that constrain the piecewise linear response. In my most flexible model I let $\kappa = 7$ with degree day intervals of 5°C, and in my simplest model I let $\kappa = 2$ and estimate a standard degree day model with just one kink point and two piecewise linear segments. DD_{idt}^{k} is the degree days in bin k (e.g. degree days between 10°C and 20°C) on day d in year t in state i, and P_{imt} is cumulative precipitation during month m in year t in state i. I estimate $g(\cdot)$ as a cubic polynomial. State fixed effects δ_i account for time-invariant unobservables at the state level, while year fixed effects η_t account for India-wide time-varying unobservables. In most specifications, I include state-specific time trends $\tau_i t$ to control for differential trends in suicide driven by time-varying unobservables. My identifying assumption is that, conditional on these fixed effects and trends, variations in daily temperature and monthly rainfall are as good as randomly assigned. Robustness to different fixed effects specifications is shown in the supplementary tables below.

Separately for each season, Equation 2 allows me to identify $\hat{\beta}_{ks}$, the estimated change in the annual suicide rate induced by one day in bin k becoming 1°C warmer. This annual response to a daily forcing variable is similar to that estimated and described in [9]. The polynomial response function for precipitation generates marginal effects of one additional millimeter of rainfall, again estimated seasonally. Due to likely correlation between errors within states, I cluster standard errors at the state level. This strategy assumes spatial correlation across states in any time period is zero, but flexibly accounts for within-state, across-time correlation.

1.2.1 Mechanism tests

With ideal data, I would estimate separate response functions for farmers and non-farmers to isolate the importance of an agricultural channel. Because my data do not provide the occupation of suicide victims prior to 2001 (and because using only post-2001 data at the state level leaves me statistically under-powered), I utilize a variety of other methods to investigate the validity of the oft-cited agricultural mechanism. The primary approach I take is to compare the significance and magnitude of each coefficient β_{ks} in Equation 2 across seasons. Temperatures and rainfall in June through September have been shown to be most critical for agricultural productivity [4], and thus should dominate the climate-suicide relationship if the agricultural channel is important. In a similar exercise, [12] and [3] demonstrate that monsoon-season precipitation impacts civil conflict and interpersonal crime in India, respectively, more than precipitation outside the growing season. Just as they use these findings as evidence of an agricultural channel through which climate affects crime and conflict, I use my results to identify the presence of an agricultural channel for suicide.

An additional method for examining mechanisms is to "pattern match" response functions [6]. For example, [15] show that the nonlinear relationship between agricultural income and rainfall in Brazil is nearly a perfect inverse of the relationship between land-invasion risk and rainfall. Similarly, [17] match the responses of conflict and income to the timing of the El Niño Southern Oscillation (ENSO), arguing that the results provide support for an income channel. I follow this approach by estimating Equation 2 using the log value of yield as the dependent variable in place of suicide rates. My estimating equation for the yield regression is:

$$
\begin{aligned}
log\_yield_{ct} = &\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}\sum_{d\in s} DD^{k}_{cdt} + \sum_{s=1}^{2} g_s\left(\sum_{m\in s} P_{cmt}\right) \\
&+ \delta_c + \eta_t + \tau_i t + \varepsilon_{ct}
\end{aligned} \tag{3}
$$

Where the subscript c now indicates district, as my agriculture data are at the district-by-year level. δ_c are district fixed effects, η_t are year fixed effects, and $\tau_i t$ are state-specific linear trends. Standard errors are clustered at the district level. I use the response functions uncovered in Equations 2 and 3 to identify matching patterns between suicide and yield.

Finally, I look for further support of economic motives by exploring spatial heterogeneity of impacts.

For temperature shocks, I estimate a model that allows each of India's 32 states and union territories to have a distinct suicide rate response function:

$$suicide\_rate_{it} = \sum_{s=1}^{2}\sum_{k=1}^{\kappa} \beta^{i}_{ks} \times \mathbb{1}[state = i] \sum_{d \in s} DD^{k}_{idt} + \sum_{s=1}^{2} g_s \left(\sum_{m \in s} P_{imt} \right) + \delta_i + \eta_t + \tau_i t + \varepsilon_{it} \qquad (4)$$

I then look at correlations between these state-level temperature responses β^{i}_{ks} and analagous state-level temperature responses for log yield.

1.2.2 Adaptation

Figure 3 in the main text shows results from four sets of tests for adaptation. The exact specification for each regression model is shown below; all models use $\kappa = 2$ with a degree day cutoff of 20°C and include state-specific linear trends.

- **Fig. 3 A: Heterogeneity by long-run average climate**

  I calculate the average degree days over the entire period for each state in the sample, and assign each state to a tercile of high, middle or low average degree days based on the national distribution. Let $avg\_degday\_tercile_i$ indicate the tercile of state i. I estimate:

$$\begin{aligned} suicide\_rate_{it} = &\sum_{s=1}^{2}\sum_{k=1}^{\kappa} \beta_{ks} \times \sum_{d \in s} DD^{k}_{idt} + \sum_{s=1}^{2}\sum_{k=1}^{\kappa} \beta^{2}_{ks} \times \mathbb{1}[avg\_degday\_tercile_i = 2] \sum_{d \in s} DD^{k}_{idt} \\ &+ \sum_{s=1}^{2}\sum_{k=1}^{\kappa} \beta^{3}_{ks} \times \mathbb{1}[avg\_degday\_tercile_i = 3] \sum_{d \in s} DD^{k}_{idt} + \sum_{s=1}^{2} g_s \left(\sum_{m \in s} P_{imt} \right) \\ &+ \delta_i + \tau_i t + \varepsilon_{it} \end{aligned}$$

  Note that in this regression, the first tercile is omitted, such that coefficients β^{2}_{ks} and β^{3}_{ks} are effects for the 2^{nd} and 3^{rd} terciles, relative to the 1^{st} tercile.

- **Fig. 3 B: Heterogeneity by average income**

  I use cross-sectional gross domestic product (GDP) per capita data for each state for the year

2010 from [13] to assign states to terciles of the national income distribution. I estimate:

$$
\begin{aligned}
suicide\_rate_{it} = & \sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}\times\sum_{d\in s}DD_{idt}^{k}+\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}^{2}\times\mathbb{1}[avg\_income\_tercile_i=2]\sum_{d\in s}DD_{idt}^{k} \\
& +\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}^{3}\times\mathbb{1}[avg\_income\_tercile_i=3]\sum_{d\in s}DD_{idt}^{k}+\sum_{s=1}^{2}g_s\left(\sum_{m\in s}P_{imt}\right) \\
& +\delta_i+\tau_i t+\varepsilon_{it}
\end{aligned}
$$

- **Fig. 3 C: Heterogeneity by temporal subsamples**

  I estimate:

$$
\begin{aligned}
suicide\_rate_{it} = & \sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}\times\sum_{d\in s}DD_{idt}^{k}+\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}^{2}\times\mathbb{1}[period=1983-1997]\sum_{d\in s}DD_{idt}^{k} \\
& +\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}^{3}\times\mathbb{1}[period=1997-2013]\sum_{d\in s}DD_{idt}^{k}+\sum_{s=1}^{2}g_s\left(\sum_{m\in s}P_{imt}\right) \\
& +\delta_i+\tau_s t+\varepsilon_{it}
\end{aligned}
$$

  Note that in this regression, the period 1967-1982 is omitted, such that coefficients β_{ks}^2 and β_{ks}^3 are effects relative to this earlier time period.

- **Fig. 3 D: Heterogeneity by frequency of climate variation**

  The "panel" response is estimated as follows, with $\kappa = 2$ and a degree day cutoff of 20°C:

$$
suicide\_rate_{it}=\sum_{s=1}^{2}\sum_{k=1}^{\kappa}\beta_{ks}\sum_{d\in s}DD_{idt}^{k}+\sum_{s=1}^{2}g_s\left(\sum_{m\in s}P_{imt}\right)+\delta_i+\tau_i t+\varepsilon_{it}
$$

  The "long difference" estimate is discussed below.

1.2.3 Long differences estimation

My main estimation strategy exploits year-to-year variation in temperature and precipitation. To test whether there are adaptive behaviors that are infeasible in response to such short-run climate shocks, but become feasible at longer time scales, I estimate a "panel of long differences" empirical model in addition to the standard panel regression, the results of which are shown in Figure 3, panel D of the main text. This strategy follows closely the approach outlined in [5].

I first construct a moving average of the suicide rate and climate variables with a window of 5 years, over the entire sample. I then calculate the 10-year change in this average at four points in my sample: 1970, 1980, 1990 and 2000. That is, I collapse my data to 4 observations for each state in my data, where each observation measures the 10-year change in suicide rates and climate variables for each decade, and where these changes are "smoothed" by taking 5-year averages at the end points. I then estimate the effect of changes in average degree days and precipitation on changes in average suicide rates. This model takes the following form:

$$\Delta suicide\_rate_{i\tau} = \sum_{s=1}^{2} \beta_s \Delta DD^k_{is\tau} + \sum_{s=1}^{2} \gamma_s \Delta P_{is\tau} + \delta_i + \nu_\tau + \varepsilon_{i\tau} \tag{5}$$

Where δ_i are state fixed effects, ν_τ are fixed effect for each of the four decadal starting points in my sample, s indicates the growing and nongrowing seasons, k indicates the degree day cutoff, and Δ indicates the 10-year change in each variable. I report results both including and excluding the state fixed effect δ_i and the decadal starting point fixed effect ν_τ. Results are shown in Section 2.6.

1.3 Impacts of recent climate trends

To compute estimates of the effect of warming temperature trends since 1980, I follow the approach outlined in [7] and [19]. I do not consider trends in precipitation, as my estimates for suicide impacts of precipitation were highly uncertain. Nor do I consider the impacts of warming outside the growing season.

For each state in my data, I estimate a linear trend in growing season degree days above 20°C for the years 1980-2013. Let the predicted value of degree days in state i in year t, as estimated by the trend, be indicated by DD^*_{it}. I then create a de-trended degree days residual that is normalized to temperature in 1980, for every state-year (see Figure S3):

$$DD\_detrended_{it} = DD_{it} - DD^*_{it} + DD^*_{i,1980}$$

I predict suicide rates using actual and de-trended growing season degree days, using coefficient estimates from the model in Table 1 of the main text which includes both state trends and year fixed effects (column 3). The elevated risk of suicide attributable to the trend, relative to the de-trended counterfactual, is the difference between these two predictions, which simplifies to $\Delta s_{it} = \hat{\beta} \times (DD_{it} - DD\_detrended_{it})$, where $\hat{\beta} = 0.008$ as estimated in my preferred empirical model. I multiply Δs_{it} — the increase in the suicide rate attributable to warming — by the population in each

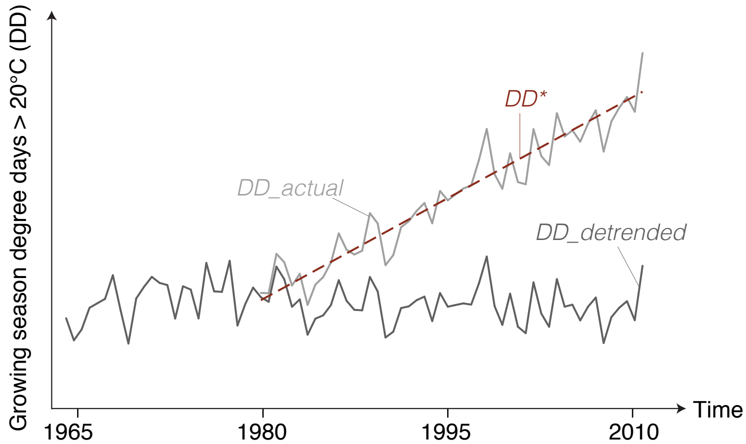

Figure S3: Identifying counterfactual de-trended temperatures, adapted from [7]

state and each year to recover the additional number of suicide deaths. Figure 4 B in the main text displays these additional deaths in each year; integrating over states and years gives the cumulative effect of temperature trends for all of India over the entire period since 1980.

1.4 Assumptions behind ordinary least squares

Throughout this article, I estimate the effect of climate on suicide using ordinary least squares (OLS). It is also possible to model suicide events using nonlinear count models, such as Poisson regression or negative binomial regression, and these approaches may be preferable to OLS when the conditional distribution of the dependent variable is poorly approximated by a normal distribution. While other analyses have modeled causes of suicide using count models (e.g. [14]), I use OLS for two reasons: the relative weakness of assumptions required for consistent estimation of causal effects, and its ease of interpretation.rupees

Distributional assumptions on either the disturbances or the outcome variable, such as normality, are not required in order for OLS regression coefficients to consistently estimate a true population parameter [23]. However, normality of the disturbances is an assumption used to estimate critical values for inference in finite samples. As count data are aggregated to coarser levels of spatial and temporal aggregation, it becomes more likely that the conditional distribution of the outcome variable approximates a normal distribution. In my case, my state-by-year observations are relatively coarse measures. Reassuringly, the residuals from my main regression model very closely approximate a normal distribution, as shown in Figure S4.

In contrast, the assumptions imposed by count models can be much more restrictive. For example,

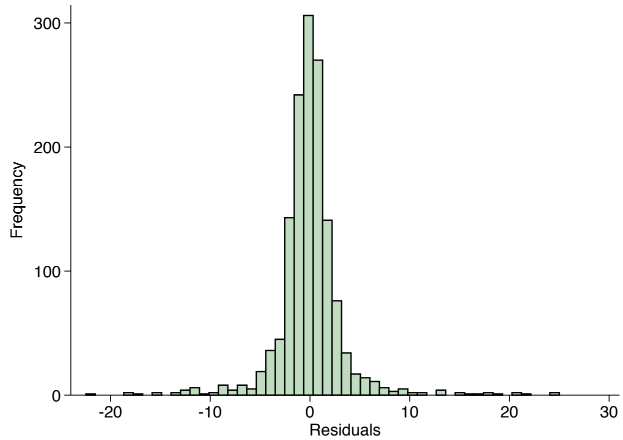

Figure S4: Distribution of residuals from regression model in Equation 2

modeling the data generating process as Poisson imposes the restriction that the mean and variance of the outcome variable are identical (as shown in Table S1, this is not the case in my data). Moreover, the coefficients derived from count models are much more difficult to interpret than those derived from OLS. I therefore follow the literature on climate and mortality (e.g. [10]), as well as the literature studying the socioeconomic drivers of suicide in aggregate panel data (e.g. [1]), and use OLS with the state-by-year suicide rate as an outcome variable.

2 Supplementary tables

2.1 Effect of heat exposure and precipitation on suicide rates and yield values

	Suicides per 100,000			*100×Log yield (rupees/ha)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Growing seas. degree days below threshold (°C)	0.003***	0.000	0.004***	0.013	-0.019	-0.003
	(0.001)	(0.001)	(0.001)	(0.009)	(0.018)	(0.013)
Growing seas. degree days (°C)	0.007***	0.009**	0.008**	-0.017***	-0.020*	-0.019*
	(0.002)	(0.004)	(0.003)	(0.006)	(0.010)	(0.010)
Nongrowing seas. degree days below threshold (°C)	-0.001	-0.009*	-0.003*	0.002	0.007	0.001
	(0.001)	(0.004)	(0.002)	(0.003)	(0.005)	(0.004)
Nongrowing seas. degree days (°C)	-0.002*	0.002	0.001	0.010***	0.018***	0.010*
	(0.001)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)
Growing seas. precip. (cm)	0.115	0.251	0.183	6.048***	4.255***	4.422***
	(0.147)	(0.176)	(0.152)	(0.712)	(0.638)	(0.653)
Growing seas. precip.^{2} (cm^2)	-0.026	-0.027	-0.022	-0.870***	-0.653***	-0.681***
	(0.020)	(0.019)	(0.017)	(0.133)	(0.117)	(0.122)
Growing seas. precip.^{3} (cm^3)	0.001*	0.000*	0.000	0.030***	0.023***	0.024***
	(0.000)	(0.000)	(0.000)	(0.005)	(0.004)	(0.004)
Nongrowing seas. precip. (cm)	-0.031	0.097	0.033	1.496**	2.974***	3.103***
	(0.206)	(0.221)	(0.237)	(0.596)	(0.775)	(0.746)
Nongrowing seas. precip.^{2} (cm^2)	0.013	0.003	0.014	0.282	-0.300	-0.365
	(0.030)	(0.035)	(0.033)	(0.323)	(0.401)	(0.377)
Nongrowing seas. precip.^{3} (cm^3)	-0.001	-0.001	-0.001	-0.071*	-0.018	-0.011
	(0.001)	(0.001)	(0.001)	(0.037)	(0.050)	(0.045)
Observations	1,434	1,434	1,434	11,289	11,289	11,289
R-squared	0.908	0.893	0.916	0.840	0.842	0.849
State Trends	YES		YES	YES		YES
Year FE		YES	YES		YES	YES

Table S2: Effect of heat exposure and precipitation on suicide rates and yield values, by agricultural season

Notes: Temperature coefficients represent the effect of one day becoming 1°C warmer on the annual suicide rate (suicide deaths per 100,000 people) or annual yield (log rupees/ha), where temperature effects are differentially estimated for days below 20°C and above 20°C and for the growing and nongrowing seasons in India. Precipitation coefficients represent the effect of seasonal cumulative rainfall increasing by 1cm on the annual suicide rate and annual yield. Columns (1)–(3) include state fixed effects and report standard errors clustered at the state level. Columns (4)–(6) include district fixed effects and report standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.2 Robustness to fixed effects specifications

	Suicides per 100,000			
	(1) OLS	(2) State FE	(3) State FE + State Trends	(4) State & Yr FE + State Trends
Growing seas. degree days below threshold (°C)	0.0046	-0.0040***	0.0026***	0.0037***
	(0.0053)	(0.0010)	(0.0008)	(0.0008)
Growing seas. degree days (°C)	-0.0020	0.0175***	0.0066***	0.0079**
	(0.0040)	(0.0035)	(0.0023)	(0.0031)
Nongrowing seas. degree days below threshold (°C)	-0.0038	-0.0036	-0.0009	-0.0027*
	(0.0025)	(0.0040)	(0.0010)	(0.0016)
Nongrowing seas. degree days (°C)	0.0159***	0.0029	-0.0020*	0.0014
	(0.0040)	(0.0026)	(0.0011)	(0.0026)
Growing seas. precip. (cm)	0.1083	0.3407*	0.1150	0.1826
	(0.8147)	(0.1703)	(0.1465)	(0.1522)
Growing seas. precip.^{2} (cm^2)	-0.0071	-0.0510**	-0.0264	-0.0218
	(0.0789)	(0.0216)	(0.0196)	(0.0171)
Growing seas. precip.^{3} (cm^3)	-0.0001	0.0009***	0.0006*	0.0004
	(0.0013)	(0.0003)	(0.0003)	(0.0002)
Nongrowing seas. precip. (cm)	1.1920*	0.0673	-0.0312	0.0327
	(0.6845)	(0.2126)	(0.2060)	(0.2367)
Nongrowing seas. precip.^{2} (cm^2)	0.0406	-0.0000	0.0133	0.0142
	(0.1395)	(0.0326)	(0.0300)	(0.0330)
Nongrowing seas. precip.^{3} (cm^3)	-0.0065	-0.0005	-0.0009	-0.0009
	(0.0066)	(0.0013)	(0.0011)	(0.0011)
Observations	1,434	1,434	1,434	1,434
R-squared	0.478	0.871	0.908	0.916
State FE		YES	YES	YES
State Trends			YES	YES
Year FE				YES

Table S3: Robustness of the suicide degree day model to various fixed effects specifications

Notes: Regression includes annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Degree day cutoff is 20°C. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

	Log yield (rupees per ha)			
	(1) OLS	(2) District FE	(3) District FE + State Trends	(4) District & Yr FE + State Trends
Growing seas. degree days below threshold (°C)	0.2557***	-0.0116	0.0133	-0.0027
	(0.0377)	(0.0348)	(0.0090)	(0.0127)
Growing seas. degree days (°C)	-0.0376**	0.1453***	-0.0173***	-0.0191*
	(0.0149)	(0.0114)	(0.0060)	(0.0097)
Nongrowing seas. degree days below threshold (°C)	-0.0425***	-0.0784***	0.0019	0.0012
	(0.0107)	(0.0056)	(0.0034)	(0.0044)
Nongrowing seas. degree days (°C)	0.0007	0.0020	0.0101***	0.0100*
	(0.0124)	(0.0075)	(0.0038)	(0.0056)
Growing seas. precip. (cm)	0.6421	8.8834***	6.0476***	4.4222***
	(2.6620)	(0.8961)	(0.7121)	(0.6529)
Growing seas. precip.^{2} (cm^2)	-0.1911	-1.4395***	-0.8697***	-0.6812***
	(0.4707)	(0.1730)	(0.1332)	(0.1222)
Growing season precip.^{3} (cm^3)	0.0155	0.0483***	0.0296***	0.0238***
	(0.0181)	(0.0065)	(0.0048)	(0.0044)
Nongrowing seas. precip. (cm)	26.9092***	14.8560***	1.4962**	3.1032***
	(2.3122)	(1.3260)	(0.5958)	(0.7457)
Nongrowing seas. precip.^{2} (cm^2)	-7.6716***	-6.4903***	0.2816	-0.3646
	(1.3907)	(1.0047)	(0.3230)	(0.3765)
Nongrowing season precip.^{3} (cm^3)	0.6476***	0.5919***	-0.0710*	-0.0114
	(0.1599)	(0.1419)	(0.0372)	(0.0450)
Observations	11,289	11,289	11,289	11,289
R-squared	0.225	0.666	0.839	0.848
District FE		YES	YES	YES
Year FE				YES
State Trends			YES	YES

Table S4: Robustness of the yield degree day model to various fixed effects specifications

Notes: Regression includes annual district-level data for 13 Indian states between 1956 and 2000. Growing season is June-September, Nongrowing season contains all other months. Degree day cutoff is 20°C. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.3 Robustness to weighting schemes for climate data aggregation

	Suicides per 100,000			*100×Log yield (rupees/ha)*		
	(1) area weighted	(2) crop weighted	(3) pop weighted	(4) area weighted	(5) crop weighted	(6) pop weighted
Growing seas. degree days below threshold (°C)	0.0026***	0.0032***	0.0032***	0.0133	0.0180*	0.0177*
	(0.0008)	(0.0004)	(0.0005)	(0.0090)	(0.0097)	(0.0099)
Growing seas. degree days (°C)	0.0066***	0.0050***	0.0058***	-0.0173***	-0.0171***	-0.0170***
	(0.0023)	(0.0016)	(0.0019)	(0.0060)	(0.0060)	(0.0060)
Nongrowing seas. degree days below threshold (°C)	-0.0009	-0.0010	-0.0009	0.0019	0.0014	0.0011
	(0.0010)	(0.0009)	(0.0009)	(0.0034)	(0.0040)	(0.0040)
Nongrowing seas. degree days (°C)	-0.0020*	-0.0021**	-0.0021**	0.0101***	0.0103***	0.0104***
	(0.0011)	(0.0001)	(0.0001)	(0.0038)	(0.0038)	(0.0038)
Growing Seas. precip (cm)	0.1150	0.0159	0.1689	6.0476***	6.0430***	6.0390***
	(0.1465)	(0.0625)	(0.1722)	(0.7121)	(0.7154)	(0.7153)
Growing seas. precip.^{2} (cm^2)	-0.0264	-0.0127	-0.0340	-0.8697***	-0.8687***	-0.8680***
	(0.0196)	(0.0076)	(0.0240)	(0.1332)	(0.1336)	(0.1336)
Growing seas. precip.^{3} (cm^3)	0.0006*	0.0005**	0.0007*	0.0296***	0.0296***	0.0295***
	(0.0003)	(0.0002)	(0.0004)	(0.0048)	(0.0049)	(0.0049)
Nongrowing seas. precip (cm)	-0.0312	-0.2630**	-0.0460	1.4962**	1.4964**	1.4982**
	(0.2060)	(0.1222)	(0.2160)	(0.5958)	(0.5982)	(0.5980)
Nongrowing seas. precip.^{2} (cm^2)	0.0133	0.0498	0.0195	0.2816	0.2829	0.2818
	(0.0300)	(0.0300)	(0.0319)	(0.3230)	(0.3238)	(0.3238)
Nongrowing seas. precip.^{3} (cm^3)	-0.0009	-0.0025*	-0.0013	-0.0710*	-0.0712*	-0.0710*
	(0.0011)	(0.0014)	(0.0014)	(0.0372)	(0.0372)	(0.0372)
Observations	1,434	1,387	1,434	11,289	11,289	11,289
R-squared	0.9083	0.9141	0.9086	0.8401	0.8401	0.8401

Table S5: Robustness of the degree day model to different weighting schemes for aggregation of climate data

Notes: Regressions in columns (1)–(3) include annual data for 32 Indian states between 1967 and 2013, and in columns (4)–(6) include annual data for all districts in 13 Indian states between 1956 and 2000. Growing season is June-September, nongrowing season contains all other months. Degree day cutoff is 20°C. Columns (1)–(3) include state fixed effects and report standard errors clustered at the state level. Columns (4)–(6) include district fixed effects and report standard errors clustered at the district level. All regressions include state-specific linear trends. Crop weights for each grid cell are cropped area fraction; population weights for each grid cell are total population in 2010. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2.4 Robustness to degree day cutoff values

	Suicides per 100,000		
	(1)	(2)	(3)
	15°C	20°C	25°C
Growing seas. degree days below threshold (°C)	0.0026***	0.0026***	0.0024**
	(0.0009)	(0.0008)	(0.0009)
Growing seas. degree days (°C)	0.0062***	0.0066***	0.0087**
	(0.0021)	(0.0023)	(0.0033)
Nongrowing seas. degree days below threshold (°C)	-0.0009	-0.0009	-0.0009
	(0.0013)	(0.0010)	(0.0010)
Nongrowing seas. degree days (°C)	-0.0017	-0.0020*	-0.0027
	(0.0010)	(0.0011)	(0.0022)
Growing seas. precip (cm)	0.1079	0.1150	0.1376
	(0.1450)	(0.1465)	(0.1511)
Growing seas. precip.^{2} (cm^2)	-0.0258	-0.0264	-0.0283
	(0.0195)	(0.0196)	(0.0200)
Growing seas. precip.^{3} (cm^3)	0.0006*	0.0006*	0.0006*
	(0.0003)	(0.0003)	(0.0003)
Nongrowing seas. precip (cm)	-0.0293	-0.0312	-0.0303
	(0.2059)	(0.2060)	(0.2085)
Nongrowing seas. precip.^{2} (cm^2)	0.0132	0.0133	0.0135
	(0.0301)	(0.0300)	(0.0305)
Nongrowing seas. precip.^{3} (cm^2)	-0.0009	-0.0009	-0.0009
	(0.0011)	(0.0011)	(0.0011)
Observations	1,434	1,434	1,434
R-squared	0.9083	0.9083	0.9084

Table S6: Robustness of the suicide degree day model to different degree day cutoffs

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. All regressions include state-specific linear time trends. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

	100 × Log yield (rupees per ha)		
	(1)	(2)	(3)
	15°C	20°C	25°C
Growing seas. degree days below threshold (°C)	0.0113	0.0133	0.0272***
	(0.0093)	(0.0090)	(0.0082)
Growing seas. degree days (°C)	-0.0164***	-0.0173***	-0.0270***
	(0.0058)	(0.0060)	(0.0078)
Nongrowing seas. degree days below threshold (°C)	0.0090*	0.0019	-0.0029
	(0.0054)	(0.0034)	(0.0027)
Nongrowing seas. degree days (°C)	0.0052*	0.0101***	0.0251***
	(0.0029)	(0.0038)	(0.0058)
Growing seas. precip (cm)	6.1603***	6.0476***	5.6173***
	(0.7099)	(0.7121)	(0.6877)
Growing seas. precip.^{2} (cm^2)	-0.8844***	-0.8697***	-0.8136***
	(0.1327)	(0.1332)	(0.1297)
Growing Season precip.^{3} (cm^3)	0.0300***	0.0296***	0.0279***
	(0.0048)	(0.0048)	(0.0047)
Nongrowing seas. precip (cm)	1.4283**	1.4962**	1.6163***
	(0.5975)	(0.5958)	(0.5969)
Nongrowing seas. precip.^{2} (cm^2)	0.3065	0.2816	0.1888
	(0.3244)	(0.3230)	(0.3204)
Nongrowing seas. precip ^{3} (cm^3)	-0.0736**	-0.0710*	-0.0598
	(0.0371)	(0.0372)	(0.0371)
Observations	11,289	11,289	11,289
R-squared	0.8387	0.8388	0.8395

Table S7: Robustness of the yield degree day model to different degree day cutoffs

Notes: Regressions include annual data for all districts in 13 Indian states between 1956 and 2000. Growing season is June-September, nongrowing season contains all other months. All regressions include state-specific linear time trends. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.5 Robustness to alternative temporal adjustments

	(1) Linear trends	(2) Quad. trends	(3) Linear trends + Year FE	(4) Quad. trends + Year FE
Growing seas. degree days below threshold (°C)	0.0026***	0.0035***	0.0037***	0.0046***
	(0.0008)	(0.0011)	(0.0008)	(0.0008)
Growing seas. degree days (°C)	0.0066***	0.0064**	0.0079**	0.0082**
	(0.0023)	(0.0024)	(0.0031)	(0.0031)
Nongrowing seas. degree days below threshold (°C)	-0.0009	-0.0009	-0.0027*	-0.0018
	(0.0010)	(0.0010)	(0.0016)	(0.0013)
Nongrowing seas. degree days (°C)	-0.0020*	-0.0015	0.0014	0.0024
	(0.0011)	(0.0011)	(0.0026)	(0.0025)
Growing seas. precip. (cm)	0.1150	0.1030	0.1826	0.2166
	(0.1465)	(0.1447)	(0.1522)	(0.1502)
Growing seas. precip.^{2} (cm^2)	-0.0264	-0.0268	-0.0218	-0.0253
	(0.0196)	(0.0192)	(0.0171)	(0.0172)
Growing seas. precip.^{3} (cm^3)	0.0006*	0.0006*	0.0004	0.0005*
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Nongrowing seas. precip. (cm)	-0.0312	0.0125	0.0327	0.0421
	(0.2060)	(0.1994)	(0.2367)	(0.2426)
Nongrowing seas. precip.^{2} (cm^2)	0.0133	0.0049	0.0142	0.0152
	(0.0300)	(0.0299)	(0.0330)	(0.0343)
Nongrowing seas. precip.^{3} (cm^2)	-0.0009	-0.0006	-0.0009	-0.0009
	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Observations	1,434	1,434	1,434	1,434
R-squared	0.9083	0.9091	0.9163	0.9173
Linear State Trends	YES		YES	
Quad. State Trends		YES		YES
Year FE			YES	YES

Table S8: Robustness of the suicide degree day model to different time-varying controls

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.6 Panel of long differences

	(1) Deg. days 20°C	(2) Deg. days 20°C	(3) Deg. days 25°C	(4) Deg. days 25°C
Growing seas. degree days (°C)	0.023	0.020	0.037	0.023
	(0.021)	(0.020)	(0.031)	(0.026)
Nongrowing Seas. degree days (°C)	-0.012	-0.004	-0.013	0.008
	(0.012)	(0.011)	(0.016)	(0.017)
Growing seas. precip (cm)	-0.844**	-0.731	-0.829**	-0.723*
	(0.340)	(0.438)	(0.313)	(0.418)
Nongrowing seas. precip (cm)	-0.378	-0.020	-0.360	-0.027
	(0.452)	(0.472)	(0.417)	(0.456)
Observations	116	116	116	116
R-squared	0.408	0.479	0.408	0.478
State FE	YES	YES	YES	YES
Time Period FE		YES		YES

Table S9: Panel of long differences

Notes: Dependent variable in all regressions is the decadal difference in the smoothed suicide rate, where the data are organized as a 4-period panel of 10-year differences. Periods are 1970-1980, 1980-1990, 1990-2000 and 2000-2010. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.7 Irrigation as adaptation

I test whether irrigation is effective at mitigating the temperature response of suicide. I use Ministry of Agriculture data to classify states as heavily irrigated if their share of crop area under irrigation ever exceeds 50% during my sample period. Table S10 shows precipitation and temperature effects on suicide for irrigated and rain-fed states separately. While the results indicate that on average irrigated states have lower suicide rates, accounting for irrigation does not change the findings of my main model, nor is it an identifiable means of adaptation to high temperatures.

	(1) Baseline Model	(2) Irrigation & Temp	(3) Irrigation & Precip
Growing seas. degree days (°C)	0.0056***	0.0056**	0.0049**
	(0.0020)	(0.0028)	(0.0021)
Nongrowing seas. degree days (°C)	-0.0016	-0.0021*	-0.0021*
	(0.0011)	(0.0012)	(0.0012)
Growing seas. precip (cm)	-0.0789	-0.0754	-0.0741
	(0.0475)	(0.0508)	(0.0555)
Nongrowing seas. precip (cm)	-0.0082	-0.0341	-0.0343
	(0.0819)	(0.0998)	(0.1003)
Irrigated		-21.8881***	-23.5120***
		(3.6741)	(2.3590)
Irrigated × growing season degree days (°C)		-0.0026	
		(0.0034)	
Irrigated × growing season precip. (cm)			-0.0105
			(0.0729)
Observations	1,434	1,332	1,332
R-squared	0.908	0.907	0.907

Table S10: Heterogeneity in the degree days model by irrigation prevalence

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Degree day cutoff is 20°C. All regressions include state-specific linear time trends. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.8 Alternative growing season definition

I define the growing season in India to be the months of June through September, based on the average arrival and withdrawal dates of the southwest monsoon, which largely determines the timing of agricultural production throughout the country. However, the monsoon arrives and withdraws differentially throughout India, first arriving in the southeast in late May, and reaching the northwest of the country by the middle of July. Withdrawal occurs in reverse, with the rains first ending in the northeast in early September, but continuing in the southeast until December. Because my approximation of this timing is coarse, in this table I demonstrate robustness of my main results to an alternative definition of the growing season, in which each state is described by a state-specific growing season, the dates of which are obtained from the Indian Meteorological Department.

	Suicides per 100,000		*100×Log yield (rupees/ha)*	
	(1)	(2)	(3)	(4)
	June-Sep. season	State-specific season	June-Sep. season	State-specific season
Growing seas. degree days (°C)	0.0066***	0.0072**	-0.0173***	-0.0177***
	(0.0023)	(0.0032)	(0.0060)	(0.0060)
Nongrowing seas. degree days (°C)	-0.0020*	-0.0023*	0.0101***	0.0100***
	(0.0011)	(0.0012)	(0.0038)	(0.0037)
Growing seas. precip. (cm)	0.1150	0.2327	6.0476***	6.1183***
	(0.1465)	(0.2391)	(0.7121)	(0.6711)
Growing seas. precip.^{2} (cm^2)	-0.0264	-0.0355	-0.8697***	-0.8810***
	(0.0196)	(0.0261)	(0.1332)	(0.1265)
Growing seas. precip.^{3} (cm^3)	0.0006*	0.0007	0.0296***	0.0300***
	(0.0003)	(0.0004)	(0.0048)	(0.0046)
Nongrowing seas. precip. (cm)	-0.0312	-0.1927	1.4962**	1.6372**
	(0.2060)	(0.1697)	(0.5958)	(0.7688)
Nongrowing seas. precip.^{2} (cm^2)	0.0133	0.0296	0.2816	-0.0189
	(0.0300)	(0.0333)	(0.3230)	(0.5408)
Nongrowing seas. precip.^{3} (cm^3)	-0.0009	-0.0010	-0.0710*	-0.0389
	(0.0011)	(0.0011)	(0.0372)	(0.0821)
Observations	1,434	1,434	11,289	11,289
R-squared	0.908	0.908	0.840	0.840

Table S11: Robustness of the degree day model to state-specific growing season definitions

Notes: Regressions in columns (1)–(2) include annual data for 32 Indian states between 1967 and 2013, and in columns (3)–(4) include annual data for all districts in 13 Indian states between 1956 and 2000. The growing season is defined as June-September in columns (1) and (3), and is defined individually by state using data from the India Meteorological Department on average monsoon arrival and withdrawal dates in columns (2) and (4). The nongrowing season contains all other months. The degree day cutoff is 20°C, and all regressions include state-specific linear time trends. Standard errors are clustered at the state level in columns (1)–(2) and at the district level in columns (3)–(4). *** p<0.01, ** p<0.05, * p<0.1.

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2.9 Drought

	Suicides per 100,000		
	(1)	(2)	(3)
Growing seas. degree days (°C)	0.0162***	0.0059***	0.0073**
	(0.0036)	(0.0021)	(0.0031)
Nongrowing seas. degree days (°C)	0.0033	-0.0014	0.0013
	(0.0025)	(0.0011)	(0.0024)
Drought: 20th percentile	-0.3160	0.0417	-0.0439
	(0.3940)	(0.3430)	(0.4440)
Surplus: 80th percentile	-0.3770	-0.3740	0.2940
	(0.2750)	(0.2330)	(0.3370)
Observations	1,472	1,472	1,472
R-squared	0.869	0.908	0.916
State Trends		YES	YES
Year FE			YES

Table S12: Effect of heat exposure and precipitation on suicide rates and yield values

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Temperature coefficients represent the effect of one day becoming 1°C warmer on the annual suicide rate, for days above 20°C in the growing and nongrowing seasons in India. Drought is defined as an indicator equal to one when annual rainfall is in the 20th percentile or below, while surplus is equal to one when annual rainfall is above the 80th percentile, where percentiles are state-specific. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2.10 Robustness to inclusion of a lagged dependent variable

	Suicides per 100,000	
	(1) Main model	(2) AR model
Lagged suicide rate (suicides/100,000)		0.3195***
		(0.0740)
Growing seas. degree days below threshold (°C)	0.0037***	0.0036***
	(0.0008)	(0.0009)
Growing seas. degree days (°C)	0.0079**	0.0067*
	(0.0031)	(0.0033)
Growing seas. precip. (cm)	0.1826	0.1031
	(0.1522)	(0.1849)
Growing seas. precip.^{2} (cm^2)	-0.0218	-0.0151
	(0.0171)	(0.0215)
Growing seas. precip.^{3} (cm^3)	0.0004	0.0004
	(0.0002)	(0.0003)
Observations	1,434	1,400
R-squared	0.9163	0.9270

Table S13: Robustness of the suicide degree day model to inclusion of a lagged dependent variable

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. All regressions include linear state-specific trends and year fixed effects. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3 Supplementary figures

3.1 Degree days across seasons

One concern with using the pattern matching approach I show in Figure 1 of the main text is that temperature may impact suicide during the growing season months only, but for reasons unrelated to agriculture. In particular, there is some evidence that suicide is directly impacted by heat through a psychological mechanism [8]. However, this direct impact is not identifiable in the nongrowing season, despite the presence of many hot days during this period (Figure S5). Across a variety of robustness checks (Table S3-S10), coefficients on high temperatures in the off-season are consistently close to zero and statistically insignificant, suggesting no strong psychological mechanism is at play.

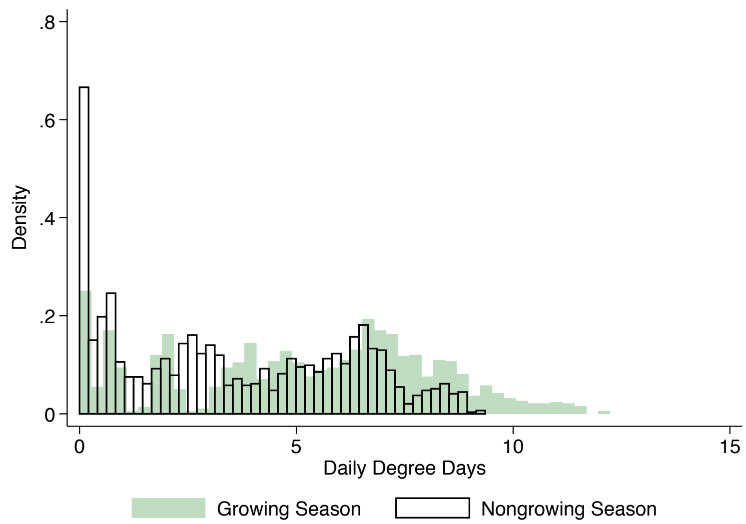

Figure S5: Distribution of cumulative degree days above 20°C in the growing and nongrowing seasons

Notes: This figure shows the distribution of daily degree days above 20°C for the growing and nongrowing seasons, using daily mean temperature for 32 of India's states between 1967-2013. The growing season is June through September, while the nongrowing season is all other months.

3.2 Robustness of piecewise linear response

Figure S6 shows the robustness of my piecewise linear estimation strategy for temperature to a higher order of flexibility. The dotted lines show the response function when estimating Equation 2 and setting $\kappa = 7$, while the solid lines, as in the main text, show the response function when setting $\kappa = 4$. Temperatures below 10°C are not shown, although are included in the regression.

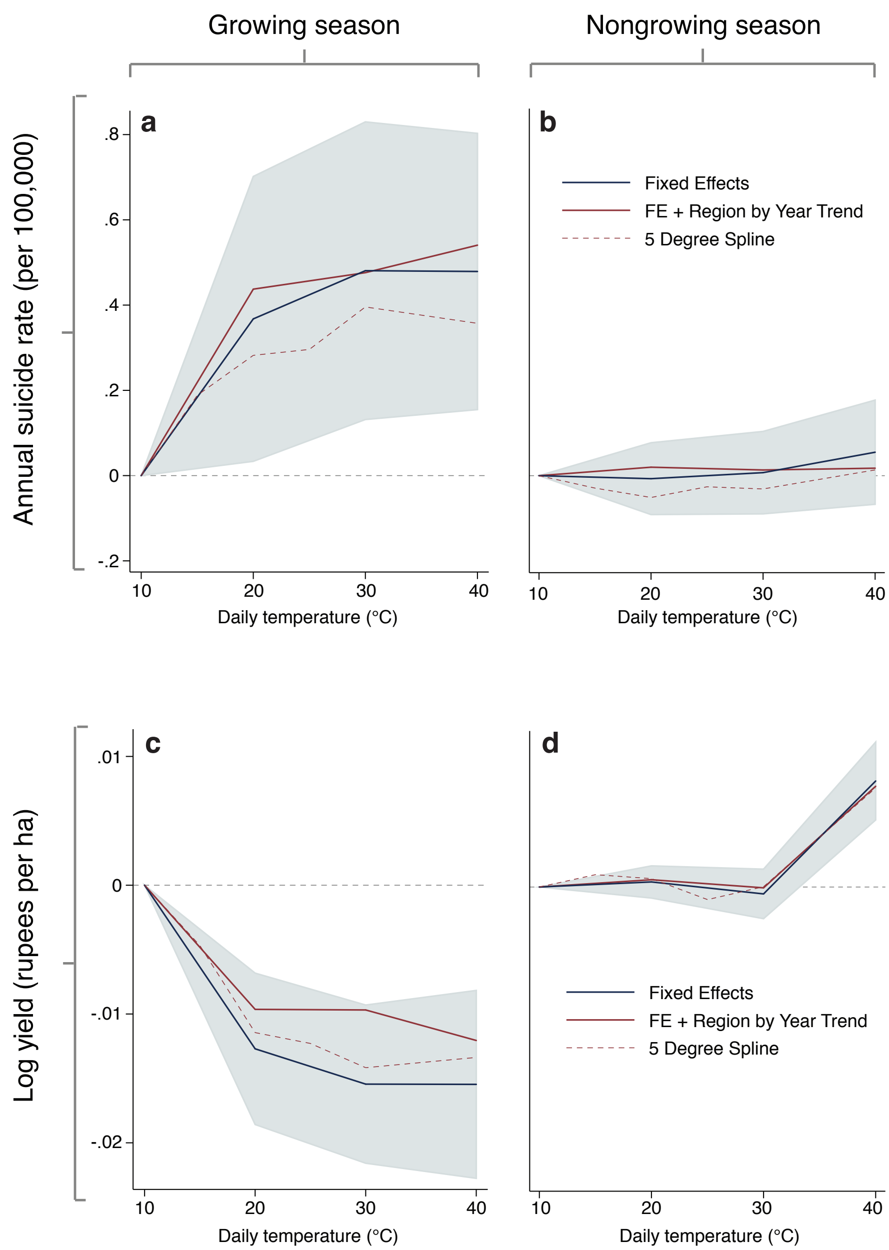

Figure S6: Nonlinear relationship between temperature and suicide rates, and between temperature and yield. **a** and **b** show the response of annual suicides per 100,000 people to growing season (June through September) and nongrowing season (all other months) temperatures, respectively. Panels **c** and **d** show the response of annual log yield, valued in rupees per hectare, to growing season (June through September) and nongrowing season (all other months) temperatures, respectively. The fixed effects regression includes year fixed effects, while the FE + Region by Year Trend regression includes year fixed effects and linear regional time trends. The 5 Degree Spline model estimates a linear spline with knots at every 5°C interval. All graphs are centered at zero.

3.3 Monthly estimation of temperature and precipitation effects

With my main specification, I am unable to reject that rainfall has no effect on suicide rates. This result may be due to my need to characterize monsoon rainfall at the state level, as there can be important within-state differences in monsoon arrival and withdrawal [4]. The higher-resolution district-level agricultural data, in contrast, suffer far less from this problem. Figure S7 suggests measurement error may be at play: this plot of *monthly* rainfall effects illustrates a consistently negative, yet often insignificant, impact of rainfall on suicide rates during the main growing season months.

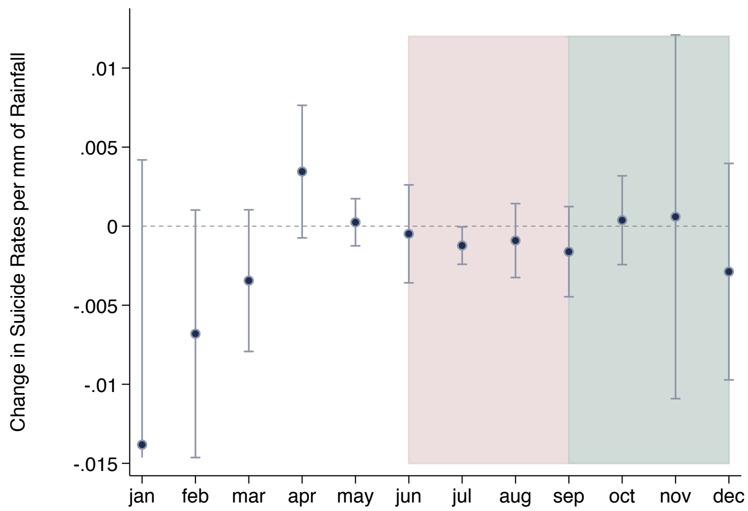

Figure S7: Points represent the marginal effect of one mm of rainfall in each month on suicide deaths per 100,000 people. Shaded pink areas represent the growing season months and shaded green areas represent the harvesting season months, although some states continue to grow crops through October and November.

3.4 Lagged effects

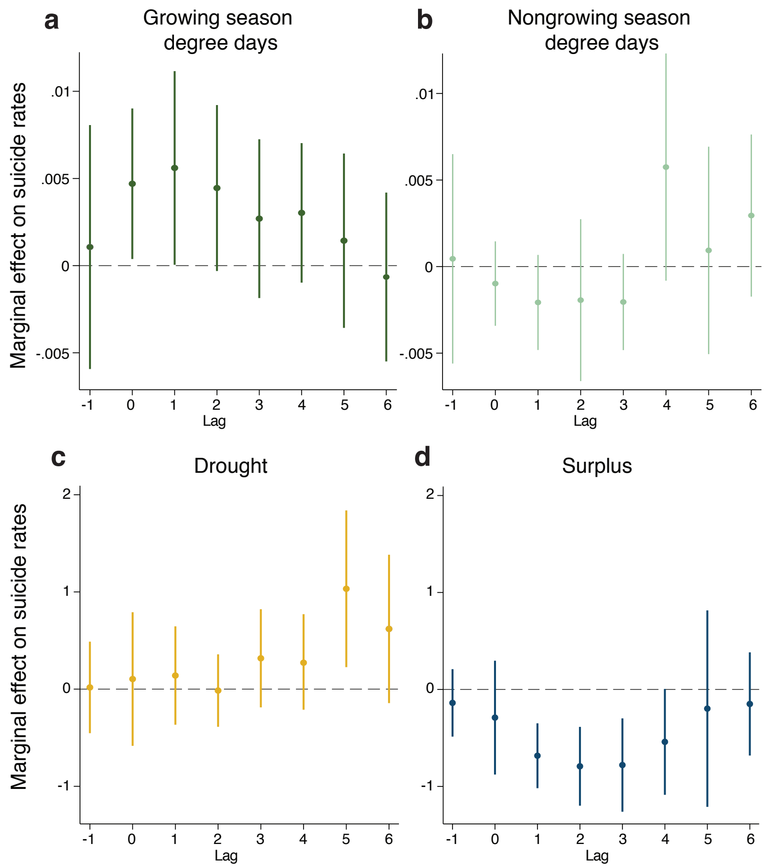

Figure S8: Points represent the marginal effect of degree days (panels **a** and **b**), an indicator for drought (panel **c**), or an indicator for surplus rainfall (panel **d**) on the annual number of suicides per 100,000 people. The x-axis corresponds to the number of annual lags. All coefficients shown in panels **a** and **b** were estimated jointly in a degree days model with a cutoff of 20°C and a cubic polynomial in precipitation; all coefficients shown in panels **c** and **d** were estimated jointly in a degree days model with a cutoff of 20°C where indicators for drought (annual rainfall below state-specific 20^{th} percentile) and surplus (annual rainfall above state-specific 80^{th} percentile) were used instead of continuous rainfall. Standard errors are clustered at the state level, and 95% confidence intervals are shown around each coefficient.

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