Climate change and the Opportunity Cost of Conflict

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A growing empirical literature associates climate anomalies with increased risk of violent conflict. This association has been portrayed as a bellwether of future societal instability as the frequency and intensity of extreme weather events are predicted to increase. This paper investigates the theoretical foundation of this claim. A seminal microeconomic model of opportunity costs – a mechanism often thought to drive climate-conflict relationships – is extended by considering realistic changes in the distribution of climate-dependent agricultural income. Results advise caution in using empirical associations between short-run climate anomalies and conflicts to predict the effect of sustained shifts in climate regimes: Although war occurs in bad years, conflict may decrease if agents expect more frequent bad years. Rather, theory suggests a non-monotonic relation between climate variability and conflict that emerges as agents adapt and adjust their behavior to the new income distribution. We identify three measurable statistics of the income distribution that are each unambiguously associated with conflict likelihood. Jointly, these statistics offer a unique signature to distinguish opportunity costs from competing mechanisms that may relate climate anomalies to conflict.

civil conflict | climate change | water resources | agriculture

Climate change is commonly portrayed as one of the most important potential threats to human, ecosystem, and societal well-being (e.g., 1). Perhaps the most direct of these threats is the purported link between climate anomalies and violent conflicts, a notion that is presently shaping political, military, and popular discourse (2)This attention underscores the need for understanding the institutional, economic, and psychological factors that collectively drive individuals and groups to fight. While there is growing consensus among academics that the relation between climate anomalies and conflicts is robust (3), competing explanations and notable exceptions remain. Interpretation and projection of empirical findings in the context of climate change requires careful theoretical consideration of underlying mechanisms. In this study, we relate hydrologic and microeconomic theory to mechanistically describe how changes in water resource availability might alter the emergence of negative income shocks, a potential driver of conflict that is sensitive to climate change (3).

Why do violent conflicts emerge and persist if they are so destructive? This paradox has long attracted the interest of political scientists and economists. The high cost of violence implies that peace is typically a better (Pareto-improving) alternative, and most grievances are believed to be resolved through bargaining (4). Violence might emerge from a bargaining breakdown that prevents a peaceful redistribution of land or resources (5). Among the suspected causes of bargaining breakdown (see 6) are the absence of institutional or social checks, which creates a disconnect between decision makers and foot soldiers who pay the price for violence; incomplete information, including miscalculations of opponents' strength or strategic withholding of private knowledge; and the inability to commit to a bargain, for example due to fluctuations in resource availability. Our analysis focuses on the last factor, because it is perhaps most directly affected by climate change (3, 7), rather than by historical, cultural, institutional and socioeconomic contexts. A growing empirical literature highlights the link between climate variability and negative income shocks as an important determinant of violence (7, 8): fighting tends to happen during bad years, particularly for non-state level conflicts short of civil war that do not require the levels of funding and mobilization necessary for organized armed rebellion (9).

In a seminal paper, Chassang and Padro-i Miquel (10) use an opportunity cost argument to provide a theoretical underpinning to the empirical relation between income shocks and conflict. The basic idea is that attacking diverts productive resources but yields an offensive advantage. There is little to lose in diverting resources to attack in bad years, but much to be gained from the expected future returns of captured resources. In bad years, the returns from attack outweigh the returns from peace. This prevents peaceful bargaining over resources, and parties go to war. This causal association between anomalously bad weather shocks and conflict occurrence has been robustly documented in the empirical

Significance Statement

There is growing consensus among academics that climate change may amplify the risk of violent conflicts. While underlying mechanisms are poorly understood, negative income shocks associated with climate variability have been long-hypothesized to play an important role. We relate recent hydrologic and microeconomic advances to investigate the theoretical foundation of this claim. Results prescribe caution in interpreting empirical relations between climate variability and conflict in the context of climate change. While fighting preferentially occurs during climate anomalies, more frequent anomalies may not yield more conflicts. By shifting the entire distribution of rainfall, climate change effectively redefines the very notion of climate anomaly. Adaptation to this new normal can have a dominant, and often counterintuitive, effect on conflict probability.

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literature. Motivated by both the theory and the empirical observations, many have argued that opportunity costs may be an important mechanism by which climate change can increase the propensity for conflict (see 3, 7). More extreme weather events and reduced crop productivity (e.g., 11) might increase the frequency and intensity of income shocks during which fighting tends to occur. This possibility is particularly important to consider in institutionally weak and ethnically fragmented regions where climate most directly impacts livelihoods (12–14) – ironically, regions believed to be particularly vulnerable to future climate change (15).

Two important knowledge gaps remain. First, existing studies look at anomalous weather events, which affect the cost but not the benefit of war. They find that parties go to war in 'bad' years. A changed climate, however, alters the *distribution* of annual rainfall. This affects the distribution of income, which in turn affects both the costs and benefits of fighting. Drought years will become more frequent as rainfall variability increases, which raises concerns about higher conflict likelihood. However, captured resources will also become less productive, which lowers the incentives for attack. An internally consistent prediction on the conflict impact of climate change has to account for both of these changes in agents' cost-benefit analysis in a way that, to our knowledge, existing projections do not. Second, competing mechanisms (other than opportunity costs) can explain the observed link between climate anomalies and conflict (see, e.g., 16) and current studies do not conclusively speak to their relative salience. Yet, effective policy design requires an accurate identification of the underlying drivers for conflict.

We address these gaps by linking the opportunity cost model proposed by Chassang and Padro-i Miquel (10) to a parametric distribution of climate-related income that is consistent with the current state of the art in hydrologic and agronomic models (17–19). We perform a comparative statics analysis (20) that accounts for agents' strategic adjustment to a changed environment. Results yield important, and perhaps counter-intuitive, insights on the two identified knowledge gaps. First, one must be cautious in using empirical associations between short-run climate anomalies and conflicts to predict the effect of sustained shifts in climate regimes. If precipitation becomes more variable, as climate models predict, conflicts will not necessarily become more frequent. Rather, conflict likelihood can go either up or down, as agents adapt and adjust their response to the new income distribution. Even shifts in climate *averages* will affect the income *variance*, and therefore conflict, due to non-linear processes that link climate to income. Second, we identify three measurable statistics of the income distribution that individually have an unambiguous effect on conflict and are jointly sufficient to predict the response of conflict to a change in climate. These testable predictions may help distinguish opportunity costs from competing mechanisms relating climate anomalies to conflicts.

It is important to note that the model is not a tool for making quantitative projections of climate-conflict trends in a specific geopolitical context, particularly given the multiple pathways by which societies can respond to climate or economic shocks (see 6, 16). Rather, the primary objective of the model is a careful theoretical treatment of opportunity costs as a mechanism often thought to drive the relationship between climate change and conflict. In doing so we elucidate the rich dynamics, and often counterintuitive outcomes, that emerge even under highly stylized theoretical representations of human behavior and climate (21).

Model overview

Consider two groups of farmers, whose annual income is subject to random rainfall variability, and who might fight for control over limited land and labor resources (22). Each year, the decision to attack is taken by weighing the immediate opportunity costs of fighting against future expected returns from the captured resources. The former is given by the current year's rainfall draw and the latter is jointly determined by the entire distribution of rainfall, by the probability of victory, and by the endogenous risk of conflict occurring in future years (see Materials and Method). Under these conditions, Chassang and Padro-i Miquel (10) show that conflict emerges in 'bad' years, when income falls below a threshold determined by its underlying distribution. Insofar as income is influenced by climate, their model offers a mechanism that can explain the empirical findings that relate climate anomalies to conflicts (16).

We extend the existing model by specifying a rainfall distribution and an income-generating crop function that are analytically tractable and consistent with governing meteorological and hydrological processes (see Materials and Methods). Doing so introduces a nonlinear relation between climate and income, which implications for conflict we discuss in the following section. The parametric distribution of income also allows us to compare predictions of conflict probabilities *across distributions* by altering parameters to emulate the effect of climate change (Figure 1). We initially focus on changes in the relative variability of seasonal rainfall, quantified by its coefficient of variation (CV_W). The focus on CV_W places our study at the intersection of empirical research exploring historic associations between conflict, income, and short-run anomalies of seasonal rainfall (see 7, 8)and climate modeling research predicting an increase in rainfall variability (e.g., 11). By performing a comparative statics exercise (20), we allow agents to adapt to changed costs and benefits by adjusting their fighting threshold. A changed climate affects both the present opportunity cost and the future returns from conflict, to which agents *adapt* by shifting the income threshold below which they will decide to fight. For analytical tractability, we favor this rather narrow definition of climate adaptation over a broader interpretation that would allow agents to endogenously optimize income distribution itself, e.g., through crop, policy and infrastructure selection.

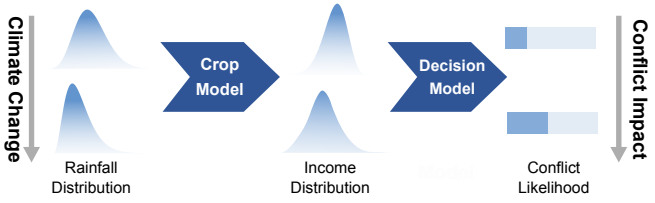

Fig. 1. Schematized relation between climate, crop and conflict models. Moving from left to right, rainfall distributions are related to income distributions via a deterministic model relating seasonal water availability to crop yield, taken as a proxy for income. Income distributions then inform a decision model for conflict. Changes in climate (top to bottom) alter the distribution of water availability, a change that propagates to an altered conflict likelihood.

Mean climate can affect income variance

Crop yields do not generally scale linearly with water supply (e.g., 19), and so changes in *mean* water availability will alter the *variance* of agricultural income. In particular, a crop chosen to be robust to climate variations will have mean water availability map to a flat region of its yield function (dark blue line in Figure 2 top). For such a crop choice, the effect of climate variability on income variability is minimal under existing climate conditions (dark blue line in Figure 2 bottom). However, a systematic decrease in water availability will enhance income variability due to the concave nature of the crop yield curve. This effect is particularly pronounced in the low water availability region (low W) of the crop yield curve, where curvature is maximal. There is a broad consensus in climate predictions that points to an increase in rainfall variability and an increase in mean temperatures (see, e.g., 11). The discussion below focuses on changing drought characteristics caused by an increase in rainfall variability. However, the nonlinearity of the climate-income link implies similar conclusions for sustained increases in mean temperature or for excess precipitation (see *Supporting Information*).

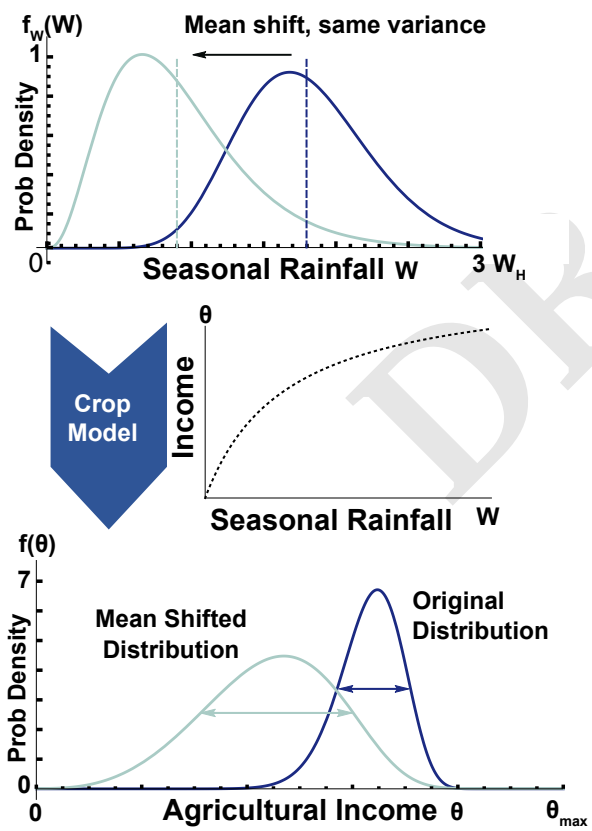

Fig. 2. Changes in mean climate can cause changes in income variability. A decrease in mean rainfall W (with variance conserved, *top*), causes the distribution to map to a more concave region of the crop model (middle), resulting in distributions of income θ with a larger variance σ_θ^2 (*bottom*). This increasing variance compounds the effect of a decreased mean income μ_θ and increases the coefficient of variation $CV_\theta = \sigma_\theta/\mu_\theta$ of income. Model parameters (see Materials and Methods): $W_H = 150$ mm, $\theta_{max} = 3$ currency units, $\sigma_W = 69.6$ mm, $\mu_W = 270$ mm (dark lines) and 135 mm (light lines).

Non-monotonic effect of climate variability on conflict

Despite the stylized nature of the opportunity cost model, changes in the coefficient of variability of water elicit complex nonlinear, and at times non-monotone, effects on the probability of conflict. Figure 3 illustrates how conflict probability increases monotonically with climate variability, captured by the coefficient of variation CV_W of rainfall, for some parameter combinations (red line), but the relationship becomes non-monotonic for others (pink line). Indeed, it is possible that conflict prevalence decreases with climate variability for small enough values of CV_W and a large enough offensive advantage in the odds of victory (see *Supplementary Information*). This behavior suggests that the opportunity cost framework does *not* consistently predict that a more variable climate will give rise to more prevalent conflicts. This insight is important to consider when using the framework to interpret empirical results. For instance, an empirical study finding an insignificant (Figure 3 point A) or negative (Figure 3 point B) relation between climate variability and conflict may not be incompatible with the opportunity cost framework. It also does not dismiss the possibility that a positive relation will emerge as CV_W increases under the effect of climate change (as seen in positive slopes at A' and B' on Figure 3).

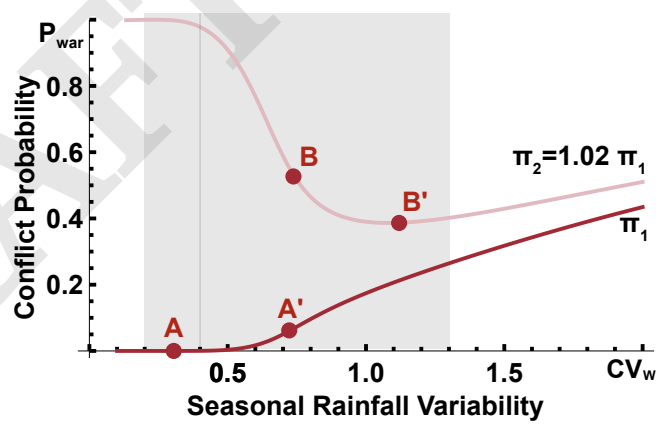

Fig. 3. Subtle changes in economic parameters can substantially alter the qualitative relationship between conflict probability and climate variability. A slight (2%) increase in the probability of first strike victory π (see Materials and Methods) introduces a non-monotone relationship between the coefficient of variation of seasonal rainfall (CV_W) and the predicted probability of conflict (P_{war}): a higher climate variability successively *decreases* and then increases the probability of conflict for a higher value of π (pink line), whereas the relationship remains monotonically increasing for a lower first strike advantage (red line). The shaded area shows the mean (vertical line) and 99% confidence interval of CV_W observed for seasonal (3-monthly) rainfall, constructed from daily observations at 671 locations within the United States (23). Model Parameters (see Materials and Methods): $\pi_1 = 0.5148$ (red), $\pi_2 = 0.5252$ (pink), $c = 0.9$, $\delta = 0.9$, $\mu_W = W_H = 150$ mm, $\theta_{\max} = 3$.

Governing Statistics and Strategic Adaptation

Changes in rainfall variability (CV_W) might cause farmers to alter the income threshold below which they will engage in conflict. This adaptation response can strongly influence the probability of conflict (P_{war}) as farmers weigh the current opportunity costs of attack against expected future profits. Opportunity costs are lower during a negative climate shock due to decreased crop productivity. Attacking then increases potential future profits for two reasons. First, the victor will capture her opponent's resources and permanently increase

Table 1. Qualitative effect of the three governing statistics of income distribution on the predicted probability of conflict

Marginal Change in income Statistic	Direct Effect on P_{war}	Adaptation effect on P_{war}
↑ Income Shock Frequency $F(\tilde{\theta})$	↑	↑
↓ Mean Income $E[\theta]$	-	↓
↓ Conflict destructivity $cE[\theta \mid \theta < \tilde{\theta}]$ (or ↑ income shock intensity)	-	↓

her own agricultural profits. Second, triggering a conflict during an income shock hedges against the possibility of a conflict ever occurring in future periods, when opportunity costs are higher on average. In the stark language of our our simple model, both incentives rely on the assumption that the defeated opponent exits the game forever. However, qualitatively similar incentives emerge if the defeated agent temporarily loses his land and ability to fight back, particularly when agents place a high emphasis on short-term profits.

Consequently, the opportunity cost model points to three fundamental statistics of the income distribution that govern the relationship between climate change, adaptation response and conflict: (i) The frequency of income shocks, defined as the probability $F(\tilde{\theta})$ that income falls below agents' conflict threshold $\tilde{\theta}$, has a direct effect on the probability of conflict. Any change to the income distribution that increases shock frequency will directly increase P_{war}. However, this direct effect also causes war to occur sooner in expectation, thereby reducing the future profits from (current) peace. This gives rise to a second, indirect, effect of an increase in income shock frequency: Because peace becomes less advantageous, farmers respond by increasing the income thresholds below which they attack, an adaptation that further exacerbates P_{war}. (ii) A decrease in mean income $E[\theta]$, for instance associated with a permanent decrease in mean rainfall, makes victory less profitable. Agents adapt to this by adjusting their income threshold for conflict. This causes a decrease in agents' threshold and, all other statistics being held constant, a decrease in P_{war}. (iii) Expected income during conflict-inducing shocks $E[\theta|\theta < \tilde{\theta}]$, as a measure of the intensity of income shocks, is proportional to the destructivity of conflicts and affects agents' incentive to fight through the hedging motive described above. More intense income shocks cause smaller expected losses in income during conflict years. Future conflicts are then less costly on average, which incentivizes agents to postpone fighting. Consequently (and perhaps surprisingly), the anticipation of more intense income shocks has a negative effect on P_{war}.

Changes in the three income statistics discussed above have independent and consistent (either positive or negative) effects on conflict prevalence, as summarized in Table 1. However, the influence of changes in *climate* on all three *income* statistics is complex and driven by the specific shape of the distribution that governs inter-seasonal climate variability. For a realistic distribution of water availability (see *Materials and Methods*), these relations are displayed in Figure 4 (top) and show that changes in water variability (CV_W) elicit different changes in each of the three income statistics, in terms of sign and magnitude. In particular, the income shock frequency response can either be positive or negative, depending on the value of CV_W and the equilibrium threshold for fighting (Figure 4 top, dark blue). In the bottom panel, we decompose the overall changes in conflict probability caused by increased climate variability ($\frac{\partial P_{\text{war}}}{\partial CV_W}$, in red) into its previously described fundamental components (Table 1). Depending on the relative magnitude of the responses, the overall relation between climate variability and conflict may itself be non-monotone (Figure 4 and Figure 3, pink). In particular, the figure shows that the relation can be dominated by agents' response to changes (dashed) in both mean income (gray dashed) and in the intensity of income shocks (i.e. conflict destructivity, light blue dashed). This insight is relevant in the context of recent literature focusing almost exclusively on the effect of changes in the *frequency* of income shocks on conflicts (e.g., 7). Our theoretical results suggest that farmer adaptation to other climate-driven income statistics, such as the *intensity* of income shocks, may be equally important to consider.

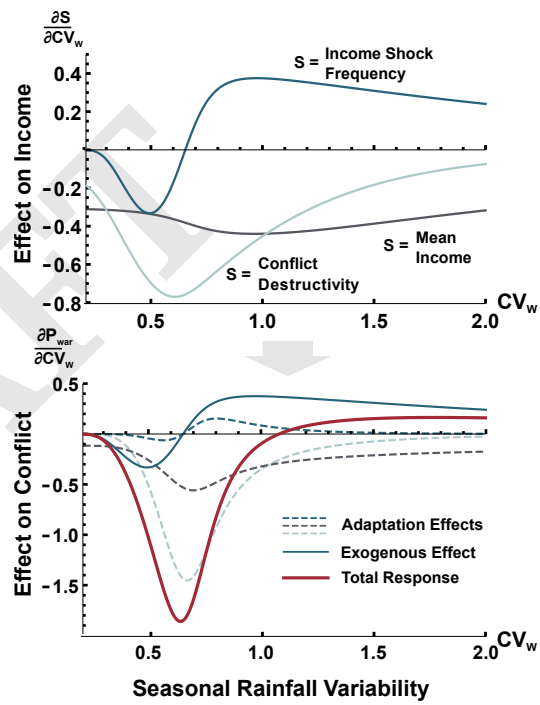

Fig. 4. Components of the climate-income-conflict relationship. *Top*: A marginal increase in rainfall variability affects each of the three governing statistics S of the income distribution: shock frequency $F(\tilde{\theta})$, mean income $E[\theta]$ and conflict destructivity $cE[\theta \mid \theta < \tilde{\theta}]$ (as a measure of shock intensity). The magnitude of each effect is expressed as a partial derivative with respect to CV_W. Variables θ, $\tilde{\theta}$, c and CV_W respectively indicate annual income (a random variable with cumulative density function F), the income threshold for conflict, the opportunity cost parameter and the coefficient of variation of rainfall (see Materials and Method). *Bottom*: Income shock frequency has a direct and axiomatic impact on the probability of conflict $P_{\text{war}} = F(\tilde{\theta})$ (solid blue). However, changes in all three income statistics affect P_{war} because agents adapt by changing their income threshold $\tilde{\theta}$ (dashed lines; see Table 1). The total contribution of these effects determines the non-monotonic response of P_{war} (red), which is also expressed as a partial derivative with respect to CV_W. Parameters (see Materials and Methods): $\pi = 0.523$, $c = 0.9$, $\delta = 0.9$, $\mu_W = W_H = 150$ mm, $\theta_{\max} = 3$.

Relation to Empirical Regularities

Chassang and Padro-i Miquel (10) point to two stylized facts that persistently emerge from the empirical literature on income and conflict: (i) conflicts tend to happen during bad income shocks and (ii) conflicts are more prevalent in low-

income countries. At first sight, these regularities may appear at odds with our theoretical predictions suggesting that more intense income shocks and lower average income both *decrease* the propensity for conflict (Table 1).

At a closer look however, stylized fact (i) is a statement about low individual draws from a *given* distribution (horizontal direction in Figure 1), whereas Table 1 concerns sustained shifts in the *distribution* of income (vertical direction in Figure 1). In line with (10), conflict occurs in our model when income falls below a certain threshold. Table 1 is saying that a sustained shift in the distribution towards more extreme droughts causes agents to lower that threshold. In other words, agents fight in *anomalously* dry years for a given distribution, but they think twice about fighting for a given draw if dry years become the 'new normal'.

Regarding the second stylized fact, it is important to point out that the theoretical results in Table 1 concern *marginal* changes in each income statistic, with the two other statistics held constant. Any non-marginal change in distribution will also change the other two statistics because they are themselves determined by the threshold $\tilde{\theta}$. For instance, scaling annual income by a constant factor affects all three statistics in a way that they exactly cancel out (see *Supplementary Information*). This gives rise to the invariance of P_{war} to income scaling noted by Chassang and Padro-i Miquel (10). Similarly, a constant upward *shift* in income results in a *decrease* in P_{war} under reasonable assumptions, as shown in *Supplementary Information*. The reality may be best captured by a combination of the two: Rich countries have more income, and also less volatile income. The model would then indeed predict a lower probability of war.

Practical Implications

The theoretical arguments in this paper are a strong simplification of reality. The economic incentives we discuss represent a small subset of the social, political and historical processes that together give rise to violent conflicts. Nonetheless, they capture important dynamics through which climate-related income shocks may cause rational agents to be amenable to conflict. Theoretical insights from the model have three important implications that can guide policy and empirical research.

First, it is important to distinguish *climate* from *income* variability when examining their implications for conflicts. The non-linear and highly local effect of climate on agricultural income has been highlighted in several studies (e.g., 24, 25) and has a strong qualitative impact on conflict incentives. It emerges from a combination of natural (timing of rain events (26)), technical (crop choice (27)), economic (agricultural prices (28, 29)) and institutional (insurance and regulation (30)) processes that were often put in place precisely to decouple income from climate variability (31). However, as climate variability begins to exceed historical ranges, these hedging mechanisms may become less effective. For instance, a crop that is adapted to a certain precipitation range will be more susceptible to variation at lower rainfall levels due to the increased curvature of the crop function (see Figure 2). This curvature causes a change in *mean* climate to affect the *variability* of income, which propagates to conflict incentives. This stylized example highlights the necessity of a careful empirical characterization of the climate-income relationship to understand implications for conflicts.

Second, theoretical results may inform empirical research that seeks to disentangle opportunity cost motives from other mechanisms that predict conflict during bad years. Alternative hypotheses (see 16) include weakened government structures (caused by a drop in tax revenue), increased (perceived) inequality, climate-induced migration, as well as cognitive and physiological factors that contribute to aggression. All of these competing mechanisms also predict that current conflict is negatively correlated with current income. However, since none of the alternative explanations are forward-looking, they would predict either none, or perhaps a negative, correlation between current conflict and the income in prior years (see discussion in *Supplementary Information*). Opportunity costs are different: If agents update their belief about future incomes in a Bayesian way (some evidence of it is given in **??**), a sequence of good years leads agents to expect greater gains from attack, and thus render them *more*, not less, aggressive in subsequent years. This is a testable implication that is unique to the opportunity cost argument and can thus serve to empirically assess its explanatory power.

Finally, caution must be exercised in using micro-economic income shock arguments to interpret empirical analyses of historic data and draw extrapolations for climate change. While the model does suggest a positive correlation between weather anomalies and conflict, it does not support the argument that conflicts will always be more prevalent if these anomalies occur more frequently due to climate change. Rather, the theory suggests a complex, and potentially non-monotonic, relation between climate variability and conflict. This complexity emerges both from non-linear climate to income relationships, and from strategic adaptation by agents to a changing income distribution. By affecting the entire distribution of climate, climate change will effectively define a "new normal". Agents strategically adapt to multiple facets of climate change by adjusting their response to income variability. In doing so, they redefine the very notion of climate anomalies and associated negative income shocks as they pertain to climate-related conflicts.

Materials and Methods

Conflict. Two groups of farmers occupy a common territory over an infinite number of periods (growing seasons). Three productive inputs determine crop yields and agricultural income: land, labor and water availability. Land and labor are equitably distributed between the two players (unequal distribution can be resolved through peaceful bargaining (see 10)) and constant across periods. However, rainfall varies randomly across periods, following a known probability distribution and affecting both groups identically. In each period, both groups observe rainfall and either group can unilaterally launch an attack to seize permanent control of the entire territory. If neither group attacks, peace prevails, all labor is put to productive use, and both groups keep control of their own land and labor. If either side attacks, violence prevails, and both groups divert a fixed share c of labor to armed conflict. In a one-sided attack, the attacker has an offensive advantage and wins with probability $\pi > 0.5$. In a simultaneous attack, both groups win with equal probability. The winner controls the entire territory forever, and the loser exits the game.

The decision to attack in each season t relies on weighing the expected future benefits of victory against the current opportunity cost of conflict. Peace will prevail if the expected returns of peace, $E[\mathcal{P}]$, are larger than the expected returns of launching a surprise

attack, $E[\mathcal{W}]$:

$$\underbrace{\overbrace{\theta_t}^{\text{current season}} + \overbrace{\delta V^{\mathcal{P}}}^{\text{future seasons}}}_{\mathrm{E}[\mathcal{P}]} > \underbrace{\overbrace{\pi\, 2\theta_t(1-c)}^{\text{current season}} + \overbrace{\pi\delta V^{V}}^{\text{future seasons}}}_{\mathrm{E}[\mathcal{W}]} \qquad [1]$$

where θ_t is an income sampled from the PDF $f(\theta)$; $V^{\mathcal{P}}$ are the future expected returns of peacefully farming one's own land (discounted by a constant factor, δ); π is the probability of victory in a surprise attack; c is the fractional cost of the present season's production devoted to war; and V^V represents the expected returns of victory (discounted by δ). The factor 2 appears because the victorious farmer obtains both plots of land.

A key characteristic of the model is that the current opportunity cost is driven by an individual draw θ, while the future benefits are affected by the entire probability distribution F of income. Groups go to war when current income falls below a threshold $\tilde{\theta}$, which depends on economic parameters and the distribution F. Chassang and Padro-i Miquel (10) show that $V^V = 2E[\theta]/(1-\delta)$, where $E[\,]$ is the expectation operator. In contrast, $V^{\mathcal{P}}$ is an implicit equation that depends on the attack threshold, $\tilde{\theta}$, defined as the θ at which $E[\mathcal{P}] = E[\mathcal{W}]$ (see *Supplementary Information*). An implicit expression for $\tilde{\theta}$ is found by substituting V^V and $V^{\mathcal{P}}$ into 1, setting $\mathrm{E}[\mathcal{W}] = \mathrm{E}[\mathcal{P}]$, and rearranging:

$$\tilde{\theta} = \frac{\delta}{1-2P(1-c)}\left[(2P-1)\frac{E[\theta]}{1-\delta} + \frac{F(\tilde{\theta})\cdot cE[\theta \mid \theta < \tilde{\theta}]}{1-\delta(1-F(\tilde{\theta}))}\right] \qquad [2]$$

where $F(\tilde{\theta}) = \int_0^{\tilde{\theta}} f(x)\mathrm{d}x$, and $E[\,|\,]$ is the conditional expectation operator. The probability of war in any season is simply $P_{\text{war}} = F(\tilde{\theta})$.

Climate, water availability and crop productivity. We assume that both farmer groups are subject to the same crop productivity (θ_t) governed by seasonal water volume, W [L], normalized by catchment area. We use a model for lumped crop yield potential [M L^{-2}] as a proxy for agricultural income, θ. Water supply is assumed to be the yield-limiting factor (19), allowing us to map $f(\theta)$ directly to the distribution of water supply, $f_W(W)$. Although additional factors such as intraseasonal dry spells are known to affect crop yields , we do not include them in our model since our principal aim is to maintain emphasis on the human decision model, and yields have been shown to be primarily determined by total precipitation . Based on observations reported in (19), we specify a parsimonious boundary function relation for yield, $B(W)$:

$$\theta = \theta_{\max}\cdot\frac{W}{W+W_H}, \qquad [3]$$

where W_H is a half-saturation constant, and $\theta_{\max}$ is the maximum productivity. We assume land to be spatially homogeneous and situated in a watershed sufficiently flat for hydrologic conditions to be driven by vertical rainfall infiltration into the soil layer (32). We assume that water is derived from rainfall, allowing $f_W(W)$ to be approximated using a Gamma distribution (see 18, and *Supplementary Information*). Under these assumptions, an exact expression for $f(\theta)$ is:

$$f(\theta) = \frac{\exp\left(-\frac{\theta}{(\theta_{\max}-\theta)(\mu_W\, W_H^{-1})CV_W^2}\right)\left(\frac{\theta}{(\theta_{\max}-\theta)(\mu_W\, W_H^{-1})CV_W^2}\right)^{\frac{1}{CV_W^2}}}{\frac{\theta}{\theta_{\max}}(\theta_{\max}-\theta)\,\Gamma\left(\frac{1}{CV_W^2}\right)}. \qquad [4]$$

where μ_W [L] and CV_W [–] are the mean and coefficient of variation of $f_W(W)$, respectively, and $\Gamma(-)$ is the Gamma function.

Response of P_{war} to Changing Water Resources. We determine the response of $P_{\text{war}} = F(\tilde{\theta})$ to water variability by numerically differentiating $F(\tilde{\theta})$ with respect to CV_W:

$$\frac{\mathrm{d}P_{\text{war}}}{\mathrm{d}CV_W} = \underbrace{\frac{\partial P_{\text{war}}}{\partial CV_W}}_{\text{mechanistic effect}} + \underbrace{\sum_{n=1}^{3}\frac{\partial P_{\text{war}}}{\partial\tilde{\theta}}\cdot\frac{\partial\tilde{\theta}}{\partial S_n}\cdot\frac{\partial S_n}{\partial CV_W}}_{\text{farmer adaptation}} \qquad [5]$$

where $S \in \{E[\theta], F(\tilde{\theta}), E[\theta \mid \theta < \tilde{\theta}]\}$ are the three fundamental statistics that govern $\tilde{\theta}$ (Equation 2). Total sensitivity of P_{war} is partitioned into direct and adaptation effects (following Burke et al. (7), Eq. 5). Changes in $f_W(W)$ alter the probability of an income shock in a given period (direct effect), thereby changing the probability that farmers will attack, $F(\tilde{\theta})$. The direct change to $f(\theta)$ also alters the expected returns from peace, $V^{\mathcal{P}}$ (see *Supplementary Information*). Farmers therefore adapt $\tilde{\theta}$ to a value that again satisfies 1 with equality (adaptation effect).

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1. W. Neil Adger, Juan M. Pulhin, Jon Barnett, Geoffrey D. Dabelko, Grete K. Hovelsrud, Marc Levy, Ursula Oswald Spring, and Coleen H. Vogel. Human security. In Dokken DJ Mach KJ Mastrandrea MD Bilir TE Chatterjee M Ebi KL Estrada YO Genova RC Girma B et Field CB al., Barros VR, editor, *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 755–791. Cambridge University Press, 2014.
2. Wendy Barnaby. Do nations go to war over water? *Nature*, 458(7236):282, 2009.
3. Katharine J. Mach, Caroline M. Kraan, W. Neil Adger, Halvard Buhaug, Marshall Burke, James D. Fearon, Christopher B. Field, Cullen S. Hendrix, Jean-Francois Maystadt, John O'Loughlin, Philip Roessler, Jörgen Scheffran, Kenneth A. Schultz, and Nina von Uexkull. Climate as a risk factor for armed conflict. *Nature*, June 2019. .
4. James D Fearon and David D Laitin. Explaining interethnic cooperation. *American political science review*, 90(4):715–735, 1996.
5. James D Fearon. Rationalist explanations for war. *International organization*, 49(3):379–414, 1995.
6. Christopher Blattman and Edward Miguel. Civil war. *Journal of Economic literature*, 48(1): 3–57, 2010.
7. Marshall Burke, Solomon M Hsiang, and Edward Miguel. Climate and conflict. *Annu. Rev. Econ.*, 7(1):577–617, 2015.
8. Edward Miguel, Shanker Satyanath, and Ernest Sergenti. Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy*, 112(4):725–753, 2004.
9. Cullen S Hendrix and Idean Salehyan. Climate change, rainfall, and social conflict in africa. *Journal of peace research*, 49(1):35–50, 2012.
10. Sylvain Chassang and Gerard Padro-i Miquel. Economic shocks and civil war. *Quarterly Journal of Political Science*, 4(3):211–228, 2009.
11. J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M. M. Iqbal, D. B. Lobell, and M. I. Travasso. Food security and food production systems. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White, editors, *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*, pages 485–533. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014.
12. Nina Von Uexkull, Mihai Croicu, Hanne Fjelde, and Halvard Buhaug. Civil conflict sensitivity to growing-season drought. *Proceedings of the National Academy of Sciences*, 113(44): 12391–12396, 2016.
13. Carl-Friedrich Schleussner, Jonathan F. Donges, Reik V. Donner, and Hans Joachim Schellnhuber. Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. *Proceedings of the National Academy of Sciences*, 113(33):9216–9221, 2016.
14. Kristine Eck. The law of the land: Communal conflict and legal authority. *Journal of Peace Research*, 51(4):441–454, July 2014. ISSN 0022-3433, 1460-3578. . URL http://journals.sagepub.com/doi/10.1177/0022343314522257.
15. Melissa Dell, Benjamin F Jones, and Benjamin A Olken. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95, 2012.
16. Solomon M Hsiang, Marshall Burke, and Edward Miguel. Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367, 2013.
17. Gianluca Botter, Stefano Basso, Ignacio Rodriguez-Iturbe, and Andrea Rinaldo. Resilience of river flow regimes. *Proceedings of the National Academy of Sciences*, 110(32):12925–12930, 2013.
18. David Dralle, Nathaniel Karst, Marc Müller, Giulia Vico, and Sally E Thompson. Stochastic modelling of inter-annual variation of hydrologic variables. *Geophysical Research Letters*, 2017.

19. Martin K van Ittersum, Kenneth G Cassman, Patricio Grassini, Joost Wolf, Pablo Tittonell, and Zvi Hochman. Yield gap analysis with local to global relevance—a review. *Field Crops Research*, 143:4–17, 2013.
20. Andreu Mas-Colell, Michael Dennis Whinston, and Jerry R Green. *Microeconomic theory*. Oxford university press New York, 1995.
21. Marc F. Müller and Morgan C. Levy. Complementary vantage points: integrating hydrology and economics for sociohydrologic knowledge generation. *Water Resources Research*, 2019.
22. Jampel Dell'Angelo, Paolo D'Odorico, and Maria Cristina Rulli. The neglected costs of water peace. *Wiley Interdisciplinary Reviews: Water*, 5(6):e1316, 2018. . URL https://onlinelibrary.wiley.com/doi/abs/10.1002/wat2.1316.
23. Nans Addor, Andrew J Newman, Naoki Mizukami, and Martyn P Clark. The camels data set: catchment attributes and meteorology for large-sample studies. *Hydrology and Earth System Sciences (HESS)*, 21(10):5293–5313, 2017.
24. Wolfram Schlenker and Michael J Roberts. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598, 2009.
25. Mathieu Couttenier and Raphael Soubeyran. Drought and civil war in sub-saharan africa. *The Economic Journal*, 124(575):201–244, 2013.
26. Giulia Vico and Amilcare Porporato. From rainfed agriculture to stress-avoidance irrigation: I. a generalized irrigation scheme with stochastic soil moisture. *Advances in Water Resources*, 34(2):263 – 271, 2011. ISSN 0309-1708. . URL http://www.sciencedirect.com/science/article/pii/S0309170810002198.
27. Maximilian Auffhammer and Tamma A. Carleton. Regional crop diversity and weather shocks in india. *Asian Development Review*, 35(2):113–130, 2018. . URL https://doi.org/10.1162/adev_a_00116.
28. Eoin McGuirk and Marshall Burke. The economic origins of conflict in africa. Technical report, National Bureau of Economic Research, 2017.
29. Nicolas Berman and Mathieu Couttenier. External shocks, internal shots: the geography of civil conflicts. *Review of Economics and Statistics*, 97(4):758–776, 2015.
30. Salvatore Di Falco, Felice Adinolfi, Martina Bozzola, and Fabian Capitanio. Crop insurance as a strategy for adapting to climate change. *Journal of Agricultural Economics*, 65(2):485–504, 2014.
31. M. Chambwera, G. Heal, C. Dubeux, S. Hallegatte, L. Leclerc, A. Markandya, B. A. McCarl, R. Mechler, and J. E. Neumann. Economics of adaptation. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White, editors, *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*, pages 945–977. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014.
32. Ignacio Rodriguez-Iturbe, A Porporato, L Ridolfi, V Isham, and DR Coxi. Probabilistic modelling of water balance at a point: the role of climate, soil and vegetation. In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, volume 455, pages 3789–3805. The Royal Society, 1999.

Supplementary Information for

Climate Change and the Opportunity Cost of Conflict

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Supplementary text
Figs. S1 to S5
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Supporting Information Text

1. Model description

Conflicts. Two groups of farmers share a given territory. Each group exploits all land units ℓ_i that it controls and generates a profit that is proportional to a productivity factor θ_t, which describes crop yield per unit of land in the growing season of that particular year. In water-limited agricultural regions, θ_t is associated with the availability of water for irrigation, which is itself governed by climate variability (1). Consequently, θ_t is independently sampled every year from a known probability density function (PDF), $f(\theta)$, and drives the annual income of both groups.

Upon observing the current year's productivity, θ_t, each group chooses between two alternatives: either they farm their land in peace (and make a profit $\ell_i\theta_t$), or they attempt to appropriate the other group's land through violence. Labor is limited, so attacking comes with an opportunity cost expressed as a reduced profit $(1-c)\,\ell_i\theta_t$ with $c \in [0,1]$. However, choosing to attack also comes with a first-strike advantage expressed as a (known) probability of victory $\pi \in (0.5, 1]$. If either group attacks, the other group will defend itself, resulting in war. In war, both groups endure a reduced profit $(1-c)\,\ell_i\theta_t$. The victorious group occupies all land and reaps all profits for the present and all future years. Future profits are discounted by a factor $\delta \in [0,1]$. The loser exits the game.

Chassang and Padro-i Miquel (2) show that, under these conditions, unequal access to resources can be resolved by bargaining. War ensues in a model with bargaining and unequal landholdings if and only if it ensues in the model with equal landholdings and no bargaining. We therefore set $\ell_i = 1$ for each farmer and abstract away from the bargaining phase without loss of generality.

Intuitively, each party will attack if expected profits from attacking exceed the opportunity costs. The probability of attack is unaffected if the income distribution $f(\theta)$ is scaled by a constant factor, since both the opportunity cost of conflict (foregone crop profit $c\theta_t$) and the expected spoils of victory change proportionally (3). On the other hand, groups will fight if income drops temporarily (e.g., a drought year), due to low (current) opportunity costs and potentially large future rewards.

Formally, the decision to attack in each production period t is based rationally on the expected returns (i.e., profits) from victory in the current and all future periods. Peace will prevail if the returns of peace, $E[\mathcal{P}]$, are larger than the expected returns of launching a surprise attack, $E[\mathcal{W}]$:

$$\underbrace{\overbrace{\theta_t}^{\text{current}} + \overbrace{\delta V^{\mathcal{P}}}^{\text{future}}}_{\text{Expected returns from peace, } E[\mathcal{P}]} > \underbrace{\overbrace{\pi\, 2\theta_t(1-c)}^{\text{current}} + \overbrace{\pi\delta V^V}^{\text{future}}}_{\text{Expected returns from war, } E[\mathcal{W}]} \qquad \text{[S-1]}$$

where θ_t is the current period production sampled from $f(\theta)$, and $\delta V^{\mathcal{P}}$ are the future expected returns of peacefully farming one's own land (discounted by factor δ). The first term on the right hand side (RHS) represents the current expected returns from choosing war, which is the expected returns from victory weighted by π. The factor 2 appears because the victorious farmer obtains both plots of land. The last RHS term $\pi\delta V^V$ represents the expected future returns of victory (discounted by δ).

The returns of victory, V^V, are the future (discounted) production of all resources:

$$V^V = E\left[\sum_{t=0}^{\infty} \delta^t 2\theta_t\right] = \frac{2E[\theta]}{1-\delta} \qquad \text{[S-2]}$$

where $E[\cdot]$ is the expectation operator. Returns of not attacking, $V^{\mathcal{P}}$, depend on the probability that war emerges in any future period. Chassang and Padro-i Miquel (2) show that the dominant strategy for the stage game is for both farmers to attack as soon as $E[\mathcal{W}] > E[\mathcal{P}]$, which occurs for all θ_t below a threshold $\tilde{\theta}$. Expected returns of peace are expressed as:

$$V^{\mathcal{P}}(\tilde{\theta}) = F(\tilde{\theta}) \cdot \underbrace{\frac{1}{2} \cdot \left(2E[\theta \mid \theta < \tilde{\theta}](1-c) + \delta V^V\right)}_{\text{Expected returns if war arises}} + (1 - F(\tilde{\theta})) \cdot \underbrace{\left(E[\theta \mid \theta > \tilde{\theta}] + \delta V^{\mathcal{P}}(\tilde{\theta})\right)}_{\text{Expected returns if no war arises}}$$

where $F(\theta)$ is the cumulative distribution function (CDF) for income, $F(\theta) = \int_0^\theta f(x)\mathrm{d}x$, and $E[\cdot|\cdot]$ is the conditional expectation operator. The first right hand term represents expected returns if a conflict arises (i.e. if $\theta < \tilde{\theta}$). These returns are weighted by $1/2$ because both farmers simultaneously choose to attack, resulting in a symmetric war with equal probability of victory. Terms in the parentheses represent expected returns for the winning group during the current period (in the event a conflict arises), and expected returns during all future periods. The second right hand term represents expected returns if no conflict arises. An expression for $V^{\mathcal{P}}$ is found by employing the Law of Total Expectation, $E[\theta] = F(\tilde{\theta})E[\theta \mid \theta < \tilde{\theta}] + (1 - F(\tilde{\theta}))E[\theta \mid \theta > \tilde{\theta}]$, and then rearranging terms:

$$V^{\mathcal{P}}(\tilde{\theta}) = \frac{E[\theta]}{1-\delta} - \frac{F(\tilde{\theta})}{1-\delta(1-F(\tilde{\theta}))} \cdot cE[\theta \mid \theta < \tilde{\theta}]. \qquad \text{[S-3]}$$

Equation S-3 represents the difference between each group's expected returns of playing peace forever (first RHS term), and the expected cost of a symmetric war occurring at a time in the future. The value of playing peace decreases with increasing $\tilde{\theta}$ due to the increasing probability that conflict will occur in any given period, i.e., increasing $\tilde{\theta}$ increases $F(\tilde{\theta})$ (all else being

equal). This increases the loss term in $V^{\mathcal{P}}$ for two reasons: (1) war occurs sooner in expectation, so expected costs are less discounted ($\frac{F(\tilde{\theta})}{1-\delta(1-F(\tilde{\theta}))}$ increases); and (2) the amount of resources expected to be lost to war increases since war cannot be prevented for higher levels of income ($cE[\theta \mid \theta < \tilde{\theta}]$ increases). Chassang and Padro-i Miquel (2) substitute Equations S-2 and S-3 into S-1 to determine an implicit expression for the threshold probability for attack, which is the $\tilde{\theta}$ for which E[$\mathcal{P}$]=E[$\mathcal{W}$]:

$$\tilde{\theta} = \frac{\delta}{1-2\pi(1-c)}\left[(2\pi-1)\frac{E[\theta]}{1-\delta} + \frac{F(\tilde{\theta})}{1-\delta(1-F(\tilde{\theta}))}\cdot cE[\theta \mid \theta < \tilde{\theta}]\right] \quad \text{[S-4]}$$

The probability of war in any given period is simply

$$P_{\text{war}} = P\{\theta \leq \tilde{\theta}\} = F(\tilde{\theta})$$

and is a monotonically increasing function of $\tilde{\theta}$ (all other parameters assumed constant). A direct relation between P_{war} and climate change within this framework requires that the income distribution $f(\theta)$ is physically linked to temperature and precipitation. We build this linkage in the following sections by introducing a well-known water resource model that is used to represent water availability (as seasonal rainfall or streamflow). We map these models to a model of agricultural income based on crop yields.

Climate. Daily rainfall is described as a stationary marked Poisson process with rate λ_p [d^{-1}] and exponentially-distributed event depths α_p [mm] (e.g., 4, 5), which aggregates to Gamma-distributed PDF of seasonal rainfall volumes:

$$W \sim \Gamma\left(\frac{1}{CV_W^2}, \mu_W\, CV_W^2\right) \quad \text{[S-5]}$$

with mean $\mu_W = \lambda_p \alpha_p$ and coefficient of variation $CV_W = \sqrt{\frac{2}{L\,\lambda_p}}$, where L [d] is the length of a season.

Average seasonal temperatures during the growing season is assumed normally distributed (6).

Crop yields. In this section, we consider various models for lumped crop yield potential [M L^{-2}] as a proxy for agricultural income, θ.

Droughts. In the main text, seasonal water volume is assumed to be the yield-limiting factor, thus capturing the effect of meteorological droughts on crop production. This allows (gamma-distributed) seasonal water volumes W to be mapped directly to to seasonal crop yield potential. We match observation patterns presented in (7) and specify a saturation-type yield function $B(W)$:

$$\theta = B(W) = \theta_{\max} \cdot \frac{W}{W + W_H}, \quad \text{[S-6]}$$

where W_H is a half-saturation constant, and $\theta_{\max}$ is the maximum productivity. Although additional factors such as intraseasonal dry spells are known to affect crop yields (e.g., 8), we do not include these factors in Equation S-6 since our principal aim is to maintain emphasis on the human decision model, and yields have been shown to be primarily determined by total precipitation (9). We assume that both farmer groups are subject to the same crop productivity (θ_t) governed by water availability W that year (as rainfall or as streamflow). Annual water supply is drawn from a Gamma PDF, $f(W)$, with mean μ_W and coefficient of variation CV_W (see Climate section above). We use the corresponding CDF of annual water supply, $F(W)$, to invert Equation S-6, which yields the CDF for income, $F(\theta)$,

$$F(\theta) = \frac{\gamma\left(\frac{1}{CV_W^2}, B^{-1}(\theta)\cdot\frac{1}{\mu_W CV_W^2}\right)}{\Gamma\left(\frac{1}{CV_W^2}\right)}, \quad \text{[S-7]}$$

where $B^{-1}(\theta) = \frac{\theta \cdot W_h}{\theta_{\max}-\theta}$.

By taking the derivative, we obtain the probability density function for income θ,

$$f(\theta) = \frac{\exp\left(-\frac{\theta}{(\theta_{\max}-\theta)(\mu_W\, W_H^{-1})CV_W^2}\right)\left(\frac{\theta}{(\theta_{\max}-\theta)(\mu_W\, W_H^{-1})CV_W^2}\right)^{\frac{1}{CV_W^2}}}{\frac{\theta}{\theta_{\max}}(\theta_{\max}-\theta)\,\Gamma\left(\frac{1}{CV_W^2}\right)}. \quad \text{[S-8]}$$

Equation S-8 is the desired probability density function of seasonal land productivity, which we assume is proportional to income. This distribution is derived from a physically-based distribution of seasonal water availability. It is controlled directly by precipitation due to its explicit dependence on the stochastic rainfall signal. It is controlled indirectly by mean temperature when income is derived from streamflow, due to the functional dependence of runoff frequency on evapotranspiration (see 10). The shape of $f(\theta)$ is primarily controlled by the shape of the Gamma rainfall distribution. It exhibits similar behavior as it crosses the threshold $CV_W = 1$, at which point rainfall switches from a persistent to an erratic regime where the distribution mode is at $W = 0$ (11). It differs from a pure Gamma distribution in that an erratic water supply does not necessarily correspond to a monotonically decreasing $f(\theta)$ (Figure S1 bottom, red line).

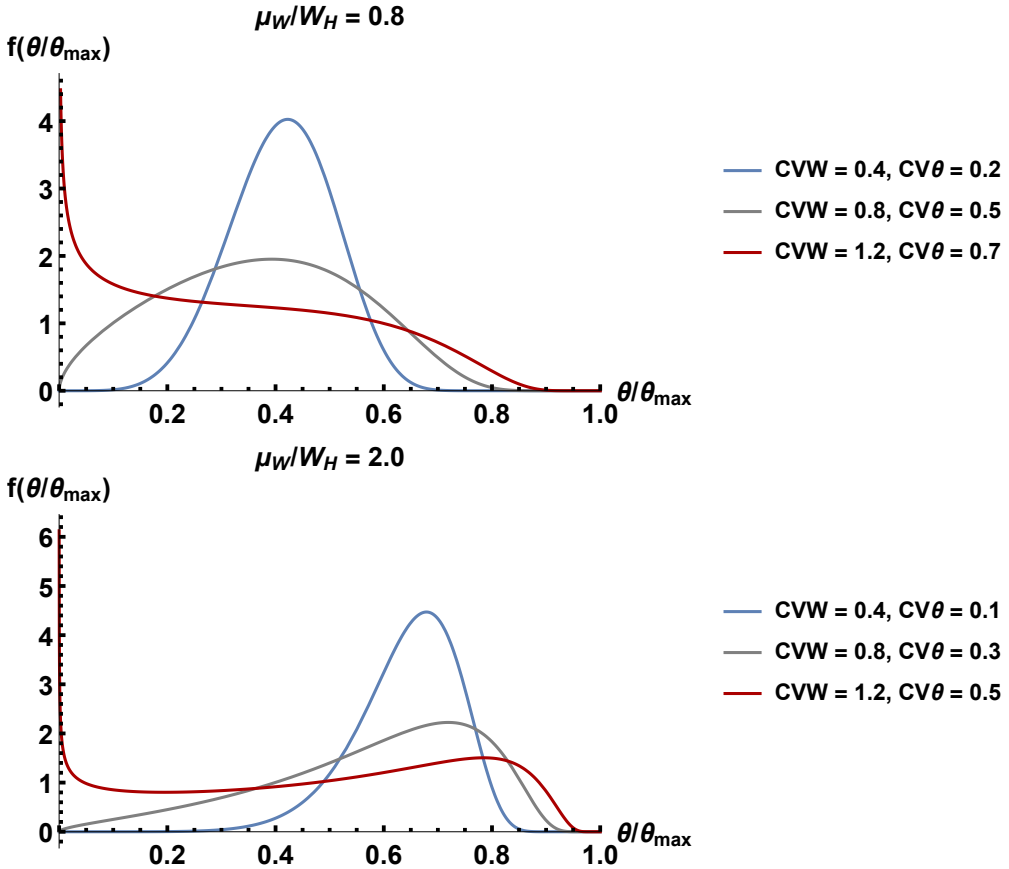

Fig. S1. Example income distributions (Equation S-8), non-dimensionalized by the half-saturation constant, W_H, and the maximum income, $\theta_{\max}$, specified by the crop function (Equation S-6). Income distribution $f(\theta)$ is controlled by mean water availability, μ_W, and by the coefficient of variation, CV_W, of the distribution of $f(W)$.

Excess Rain. The monotonously increasing water-yield relation described in the previous section neglects the damaging impact of excessive seasonal rainfall on crop yields. We assess the sensitivity of our results to this effect by specifying an alternative, 4-parameter (θ_{max},W_{peak},m,k), water-yield function depicted in the middle left panel of Figure S2,

$$\theta(W) = \begin{cases} \theta_{max} \sin[W \frac{\pi}{2W_{peak}}] & \text{if } W < W_{peak} \\ N \frac{1}{\Gamma(k)m^k} W^{k-1} e^{-W/m}, & \text{otherwise} \end{cases} \quad \text{[S-9]}$$

where $W \geq 0$ is seasonal water volume and $N = \frac{\theta_{max}}{\Gamma(k)m^k} W_{peak}^{k-1} e^{-W_{peak}/m}$ a normalizing constant. This alternative water-yield function is composed of a sinusoidal function ($W < W_{peak}$) appended to a gamma probability density function ($W \geq W_{peak}$). This emulates the inverted U-shape relationship observed in empirical studies (12–14), while the sinusoid section of the function for low water volumes preserves the concave curvature of saturation-type function assumed for droughts in the main text. The water-yield function is inverted and the corresponding probability density function of crop yield (depicted in the bottom left panel of Figure S2) is obtained numerically.

Temperature. Crop yields can be constrained by temperature in regions where water availability is not a limiting factor. For example, Schlenker and Lobell (15) show that temperatures exceeding $\sim 29°$ C sharply reduces yields for multiple U.S. crops. We assess the sensitivity of our results to temperature constraints by specifying an alternate crop function where yields are determined by mean seasonal temperature T,

$$\theta(T) = \begin{cases} e^{-\frac{(T-T_{peak})^2}{2\sigma_{low}^2}} (\theta_{max} - \theta_{min}) + \theta_{min} & \text{if } T < T_{peak} \\ e^{-\frac{(T-T_{peak})^2}{2\sigma_{high}^2}} (\theta_{max} - \theta_{min}) + \theta_{min}, & \text{otherwise} \end{cases} \quad \text{[S-10]}$$

where T_{peak},θ_{min}, θ_{max} and $\sigma_{low} \ll \sigma_{high}$ are model parameters. This temperature-yield function is composed of adjoined normal probability density functions with different standard deviation values on either side of T_{peak}, as depicted in the middle right panel of Figure S2. This emulates qualitatively the non-symmetric inverted U-shaped relation between mean seasonal temperature and crop yields that can be constructed from the daily-scale relations reported in (12). The temperature-yield function is inverted and the corresponding probability density function of crop yield (depicted in the bottom right panel of Figure S2) is obtained numerically.

2. Equilibrium Analysis

Existence, stability and selection of model solutions. We use a comparative statics approach to determine equilibrium solutions to the full model (16). By comparing equilibrium states, we invoke a timescale separation that assumes agents adjust their attack thresholds far more quickly than the distribution of the relevant climate statistic (rainfall or temperature) changes. The full model is solved by first specifying the mean and coefficient of variation of the relevant climate variable (W or T). The distribution of this random variable is then used directly to parameterize $f(\theta)$ (using Equation S-8 for droughts, or numerically for floods and temperature), which is subsequently used to determine the three relevant income statistics in Equation S-4. Finally, the full equation is solved for the threshold income for conflict, $\tilde{\theta}$, and conflict probability, $P_{\text{war}} = F(\tilde{\theta})$. We solve the model numerically using Mathematica v11.3 (Wolfram Research Inc., Champaign, IL, USA).

The model was analyzed using fixed values of $c = 0.9, \delta = 0.9$ and varying values of π. We single out the importance of the first-strike advantage because we believe it is an intuitively simple parameter that allows comparisons across different war technologies. The takeaway message would, however, be the same if we instead modified one of the other socioeconomic parameters c or δ. It is merely for expositional clarity that we keep two parameters fixed and modify the third one.

Chassang and Padro-i Miquel (2) show that, for an equivalent model with no income variability (i.e., $CV_W \to 0$), war is inevitable when:

$$\pi > \pi^D = \frac{1}{2(1 - c(1 - \delta))}.$$

This condition indeed leads to war for all parameters used in this analysis, and we thus use values $\pi \in (0.5, \pi^D)$. For values of π that fall in this range, there exists a range of CV_W with two stable solutions: an upper solution that limits to $P_{\text{war}} = 1$ as $CV_W \to 0$, and a lower solution that limits to $P_{\text{war}} = 0$ as $CV_W \to 0$ (Figure S3 left column). This result is a consequence of there existing two stable roots, $\tilde{\theta}$, to Equation S-4 (recalling that $P_{\text{war}} = F(\tilde{\theta})$). Roots for specific income distributions are shown in plots of $E[\mathcal{P}] - E[\mathcal{W}]$ vs. θ (Figures S3 right column). Values of $\tilde{\theta}$ corresponding to locally stable equilibria are those where $E[\mathcal{P}] = E[\mathcal{W}]$, and a slight increase in θ causes $E[\mathcal{P}] > E[\mathcal{W}]$ (i.e., upward crossings of the x-axis on SIfig:PwarRoots). One root disappears as CV_W increases beyond a threshold value, resulting in a bifurcation in the corresponding plots of P_{war} vs. CV_W (Figure S3 left column).

We focus on the root that changes continuously over the entire range of CV_W. We believe this is justified because agents would transition away from the other stable root for sufficiently large perturbations in CV_W. This approach is different from Chassang and Padro-i Miquel (2), who instead focus on the lowest $\tilde{\theta}$ on the grounds that it represents the most efficient equilibrium. Since our focus is on adaptations to changes in income distribution, we believe that our equilibrium selection procedure is more robust in our context. If the first strike advantage is low, $\pi \in (0.5, \pi^{\text{crit}})$ (Figure S3a), our criteria overlap.

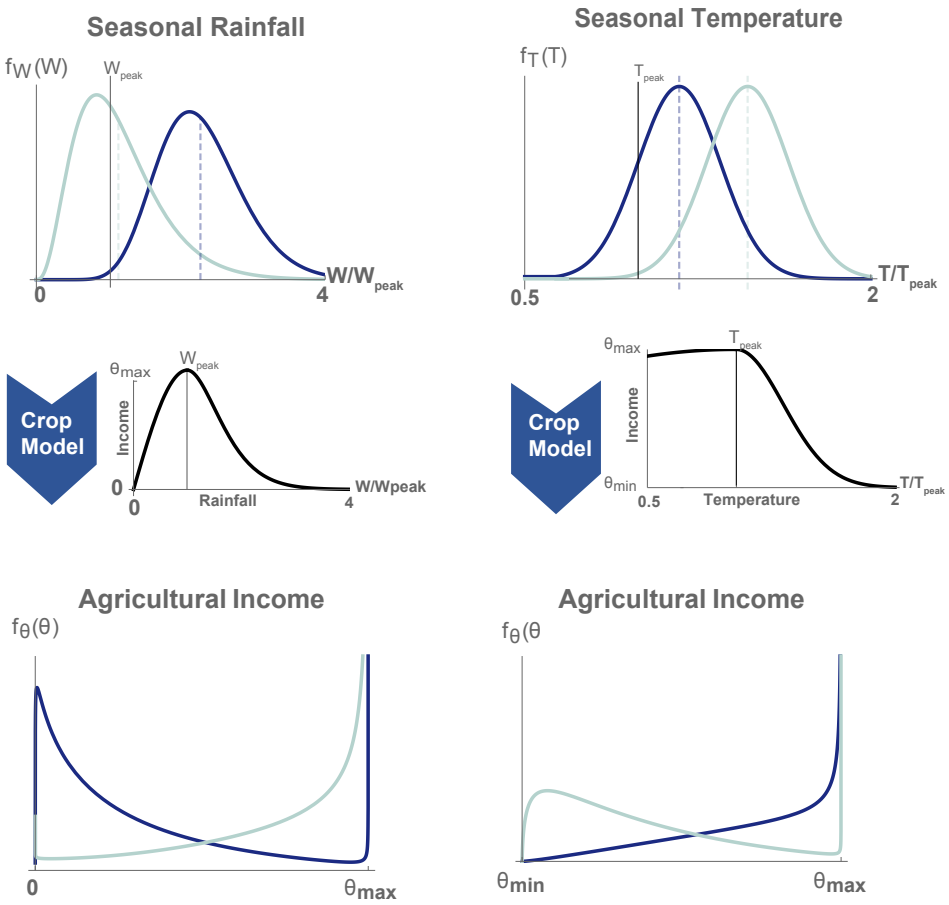

Fig. S2. Climate and income distributions for alternative climate-yield specifications. *Left* Crop yields are constrained by both excess and deficiency in seasonal rainfall. *Right* Crop yields are constrained by mean seasonal temperature. *Top*: Gamma-distributed seasonal rainfall and normally distributed seasonal temperatures. Graphs portray shifts in mean seasonal values (decreased mean rainfall and increased mean temperature: dark blue to light blue) with variances being held constant. *Middle*: Climate-yield relations from Equations S-9 (Rainfall) and S-10 (Temperature). *Bottom*: Income distributions obtained by mapping the stochastic climate variable (*Top*) to the yield curve (*middle*). For both temperature and rainfall shifting the seasonal mean climate variable affects the variability of income due to the non-linear nature of the yield curve.

The variable π^{crit} denotes the particular value of first strike advantage, where there exist two stable roots when $CV_W < CV_W^{\text{crit}}$ and a pitchfork bifurcation at $CV_W = CV_W^{\text{crit}}$. Peaceful play is then nearly certain when variability is low (i.e., $CV_W \to 0$), due to the diminishing probability that an income shock will occur. If the first strike advantage is high, $\pi > \pi^{\text{crit}}$ (Figure S3c), we instead focus on the larger stable root. Now, our model predicts certain war in the limit where variability disappears. In other words, the threshold for peace $\tilde{\theta}$ is high relative to the increasingly concentrated income distribution. This generates a nonmonotonic response to variability: Small increases in variability increase the probability that incomes will exceed this high threshold, which reduces P_{war} and the threshold $\tilde{\theta}$. At some point, the threshold moves from the right to the left tail. Further increases in CV_W then, instead, increase the frequency of negative income shocks, and CV_W becomes (again) positively associated with increasing variability.

Sensitivity of conflict probability to income statistics and climate. As $f(\theta)$ changes, farmers adjust their thresholds for attack according to Equation S-4, above. This implicit equation is determined by three fundamental statistics S of the income distribution: $S \in \{E[\theta], F(\tilde{\theta}), E[\theta \mid \theta < \tilde{\theta}]\}$. The sensitivity of each statistic to water resource variability is investigated by taking its partial derivative with respect to CV_W, as specified in main text Equation 4 and reproduced here:

$$\frac{\mathrm{d}P_{\text{war}}}{\mathrm{d}CV_W} = \underbrace{\frac{\partial P_{\text{war}}}{\partial CV_W}}_{\text{mechanistic effect}} + \underbrace{\sum_{n=1}^{3} \frac{\partial P_{\text{war}}}{\partial \tilde{\theta}} \cdot \frac{\partial \tilde{\theta}}{\partial S_n} \cdot \frac{\partial S_n}{\partial CV_W}}_{\text{farmer adaptation}} \qquad \text{[S-11]}$$

Scaling and mean shifts of the income distribution. Consider two countries, $i \in \{1, 2\}$, that differ only in their income distribution $F_i(\theta)$. Country 1 is richer on average richer than country 2. The empirical literature (see 2) overwhelmingly suggests that this would lead to a *lower* probability of conflict in country 1 (the richer country). We wish to determine the conditions (if any), under which our theoretical model will predict this outcome.

Chassang and Padro-i Miquel (2) explain that if income in the rich country is obtained by simply scaling the income of the poor country by a positive constant $\phi > 1$, the opportunity cost argument implies that war occurs with the same probability in both countries. Formally, if $F_1(\phi\theta) = F_2(\theta)$, then $P_{\text{war},1} = P_{\text{war},2}$. As a placebo test, we here demonstrate that this property holds for all CV_W by determining the response of P_{war} to a marginal scaling of θ, decomposed into the three fundamental statistics S that determine agent response. Response to scaling is defined as a derivative with respect to ϕ:

$$\frac{\mathrm{d}P_{\text{war}}}{\mathrm{d}\phi} = \frac{\partial P_{\text{war}}}{\partial \phi} + \sum_{n=1}^{3} \frac{\partial P_{\text{war}}}{\partial \tilde{\theta}} \cdot \frac{\partial \tilde{\theta}}{\partial S_n} \cdot \frac{\partial S_n}{\partial \phi} \qquad \text{[S-12]}$$

Although all three statistics respond to a marginal increase in ϕ (e.g., Figure S4 top), the total effect of scaling on P_{war} is zero for any choice of model parameters (e.g., Figure S4 bottom, red line). In other words, scaling of income affects all three statistics in Table 1, but in a way that their impact on P_{war} exactly cancels out. Figure S4 makes it clear that this overall scaling invariance does not, in fact, contradict our theoretical predictions in Table 1: the positive marginal effect of changes in $E[\theta]$ on P_{war} (Table 1) is simply compensated by opposing marginal effects of changes in the two other statistics.

A perhaps more realistic assumption, however, is that economic development does not only scale income up, but also reduces its temporal variability. For instance, economic growth might become less dependant on climatic variability as countries industrialize and are less reliant on the agricultural sector (see, e.g., 17). Consider the situation where income in the rich country is obtained as an upward shift of income in the poor country:

$$F_1(\theta + s) = F_2(\theta)\, \forall \theta$$

for some $s > 0$. Let $\tilde{\theta}$ be an income threshold below which conflict will arise. According to Equation S-4, income $\tilde{\theta}$ is a stable threshold under distribution F if and only if

$$0 = G(\tilde{\theta} \mid F) = \tilde{\theta} - \frac{\delta}{1 - 2\pi(1-c)} \left[(2\pi - 1)\frac{E_F[\theta]}{1-\delta} + \frac{F(\tilde{\theta})}{1 - \delta(1 - F(\tilde{\theta}))} \cdot cE_F[\theta \mid \theta < \tilde{\theta}] \right]$$

and $G'(\tilde{\theta} \mid F) > 0$. Let $\tilde{\theta}_2$ denote the threshold in country 2 (the poorer country), and consider $G(\tilde{\theta}_2 + s \mid F_1)$. Note that $F_1(\tilde{\theta}_2 + s) = F_2(\tilde{\theta}_2)$, $E_{F_1}[\theta] = E_{F_2}[\theta] + s$ and $E_{F_1}[\theta \mid \theta < \tilde{\theta} + s] = E_{F_2}[\theta \mid \theta < \tilde{\theta}] + s$. Using some algebra, it therefore follows that

$$G(\tilde{\theta}_2 + s \mid F_1) > 0 \qquad \Longleftrightarrow \qquad F_2(\tilde{\theta}_2) < \frac{1-\delta}{\delta} \frac{1 - 2\pi(1 - c(1-\delta))}{(2\pi - 1)(1 - c(1-\delta))}.$$

If the above condition holds, the stable threshold $\tilde{\theta}_1$ for (rich) country 1 must be smaller than $\tilde{\theta}_2 + s$. It follows that (rich) country 1 will be more peaceful than (poor) country 2. In other words, when the likelihood of war, $F_2(\tilde{\theta}_2)$, is not too high, then a marginal upward shift in income will lower the probability of war. For the parameters considered in our analysis ($\pi = 0.523, c = 0.9, \delta = 0.9$), this happens when $P_{\text{war}} < 10.86\%$.

In other words, our model predicts that richer countries will fight less if they also have a lower income variability (as CV) and if war is not too frequent to begin with. All these conditions are in general agreement with the empirical literature.

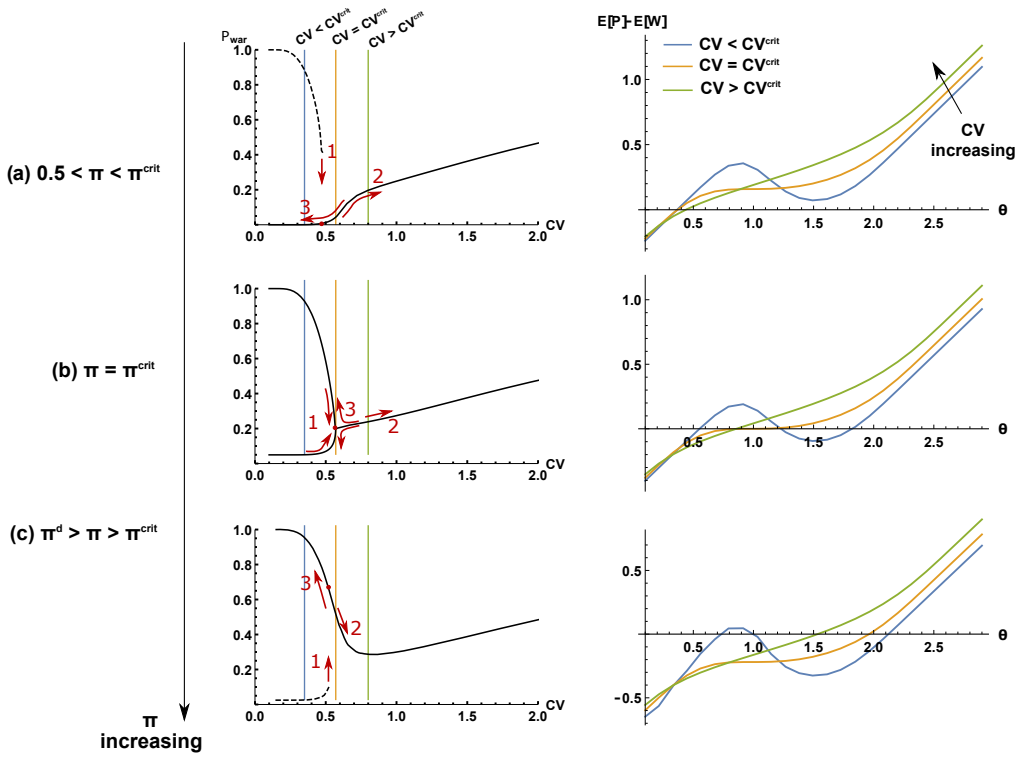

Fig. S3. Model outputs for different values of first strike advantages (π) and water variability (CV). *Left*: The relation between CV and the modeled conflict probability (P_{war}) exhibits different qualitative features for different values of π. The discontinuity in the CV-P_{war} relation transitions from concerning the higher solution for P_{war} to the lower solution as π increases. In this paper, we focus on the stable root that is continuous over all CV_W (left-hand plots, solid black lines). This corresponds to the lowest stable root when $\pi < \pi^{\text{crit}}$, and to the highest stable root when $\pi > \pi^{\text{crit}}$. The value $\pi = \pi^{\text{crit}}$ denotes a special case where there exist two stable roots when $CV_W < CV_W^{\text{crit}}$ and a pitchfork bifurcation at $CV_W = CV_W^{\text{crit}}$. *Right*: The income threshold $\tilde{\theta}$ below which farmers will fight, and the associated probabilities of conflict $P_{\text{war}} = F(\tilde{\theta})$, are determined by finding the roots to Equation S-4. Roots are visualized as upward crossings of the x-axis in plots of $E[\mathcal{P}] - E[\mathcal{W}]$ vs. θ for specific values of CV. Line colors in right-hand plots correspond to a CV_W of the same colored vertical line in left-hand plots. For all plots, $\delta = 0.9, c = 0.9, \mu_W = W_H = 500\text{mm}$.

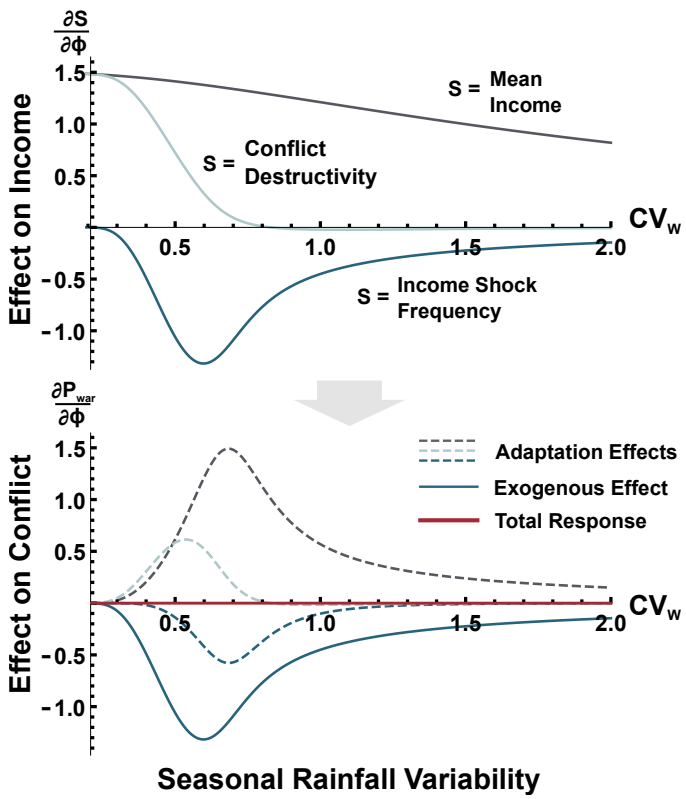

Fig. S4. Invariance to Scaling. *Top*: Income statistics respond differently to a linear scaling of the income distribution, $f(\theta)$. *Bottom*: These changes to individual statistics alter the probability of conflict due to exogenous (climate-driven) changes to the frequency of income shocks, as well as to agent adaptation to the changing income distribution. However, the aggregate effect of these changes is zero, and P_{war} is thus unaffected by scaling of $f(\theta)$.

3. Results for excess rain and temperature

Similar results to Figures 3 and 4 of the main text are shown in Figure S5 for seasonal rainfall (*left*) and seasonal temperature (*right*). Unlike in the main text, where the water-yield relation only accounts for the effect of insufficient seasonal rainfall (droughts), results presented for seasonal rainfall account for both insufficient and excessive rainfall using the yield curve displayed in Figure S2. For rainfall, we consider the effect of changes in relative variability at the seasonal scale (CV_W), as in the main text. For temperature, we consider the effect of changes in *mean* seasonal temperature, which causes an increase in the relative variability of income (CV_θ) because of the non-linear nature of the yield curve (see Figure S2 and discussion in the main text). We focus on these two trends (increase in CV_W and increase in μ_T), because they are consistantly predicted to occur in future climates (e.g., 18).

Results exhibit similar characteristics as in the main text, namely two solutions for the modeled probability of conflict (P_{war}), the higher of which varies non-monotonically with the considered climate variable (CV_W or μ_T). Partial derivatives displayed in Figure S5 show that the climate variables also have similar qualitative effects as in the main text, both in terms of the three fundamental income statistics that drive incentives for conflict (Figure S5 *middle* and discussion in main text), and on the components of the conflict response (*bottom*). This suggests that insights from the stylized case presented in the main text are robust to alternative specifications of the climate-income relationship.

4. Possible Empirical Implications

Identifying the impact of changes in income distribution on conflict ('vertical direction' in Figure 1 in the main text) with empirical data is non-trivial and, to the best of our knowledge, an outstanding gap in the empirical literature. It requires simultaneous observation of income and conflicts at the micro level, over a period long enough to reliably estimate the three income statistics, and in a setting that allows to properly identify their effect. Assuming such data is available, the following thought experiment is perhaps enlightening when considering the empirical relations to look for.

If agents are Bayesian, then they will update their prior distribution F_θ^t after each observation and adjust their (unobservable) cutoff $\tilde{\theta}^t$ accordingly. Thus, income θ_t in year t would both determine whether the agents go to war on year t (conflict occurring whenever $\theta_t < \tilde{\theta}^t$) and affect the agents' prior for the subsequent year, F_θ^{t+1}. Qualitatively, our theoretical results (Table 1 in main document) would predict that the threshold moves up ($\tilde{\theta}^{t+1} > \tilde{\theta}^t$) after (a) good draws θ_t (via a raised estimate for $E[\theta]$), (b) good draws during conflict years (via a raised estimate for $E[\theta \mid \theta < \tilde{\theta}]$) and (c) conflict years (via a raised estimate for $F(\tilde{\theta})$). The increase in the threshold makes countries more belligerent in subsequent years. At a specific income level, they would thus be more likely to go to war following years that satisfy criteria (a)-(c). Thus one expects to observe, for example, both a *negative* relation between current income and conflict (which emerges from opportunity costs – horizontal direction in Figure 1 of the main document) and a *positive* relation between historic income and current conflict (which emerges from agent adaptation to changed benefits – vertical direction in Figure 1 of the main document).

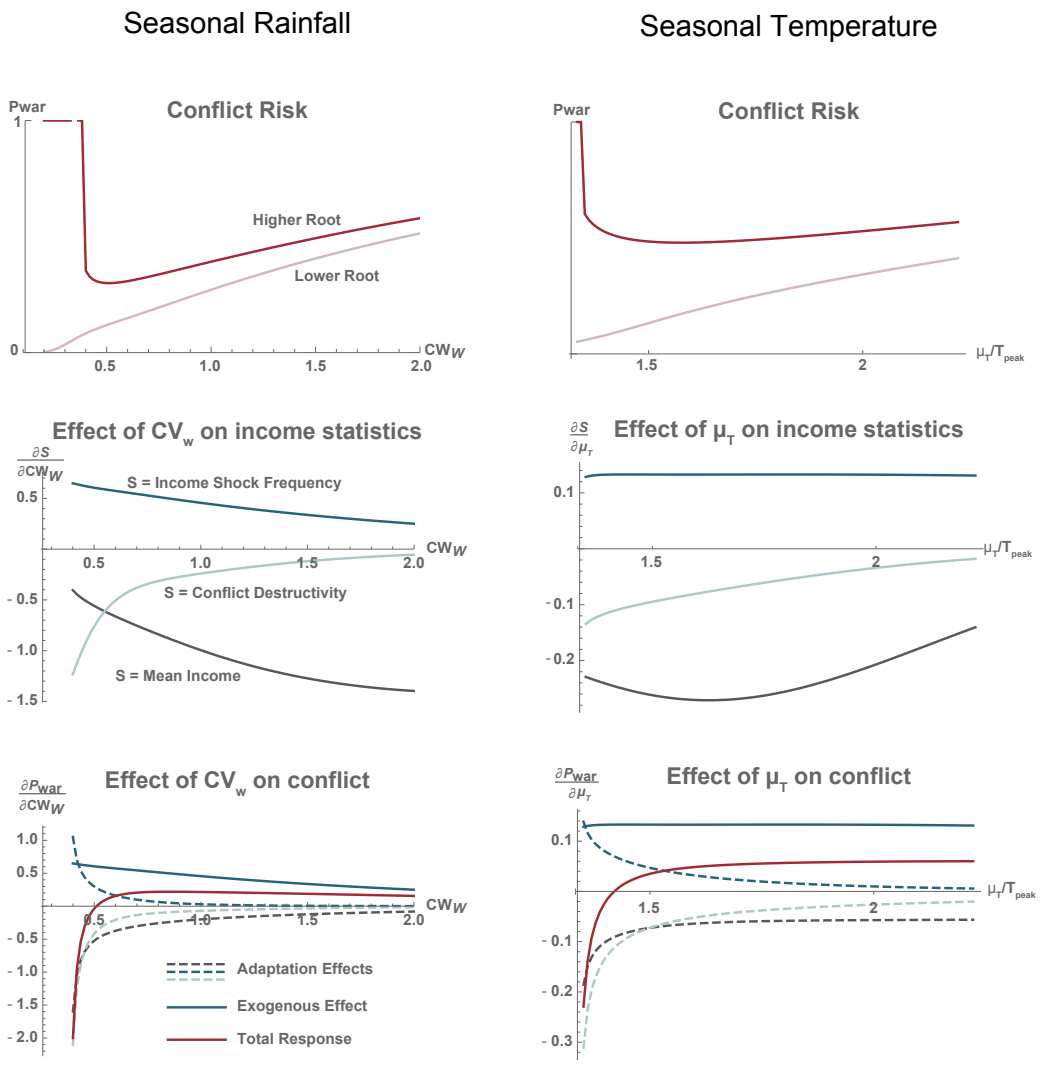

Fig. S5. Insights from the main text are robust to alternate specifications of the climate-crop yield relationship. *Left*: Crop yields are constrained by both deficiency and excess in seasonal rainfall. *Right*: Crop yields are constrained by mean seasonal temperature. *Top*: Modeled conflict probability for increased rainfall variability and seasonal mean temperature. *Middle*: Effect of rainfall variability and mean temperature on the three income statistics driving conflict incentives. *Bottom*: Effect of rainfall variability and mean temperature on the components of the conflict response. All graphs use the same economic parameters as in the main text, and reproduce the qualitative features highlighted in the main analysis.

References

1. Marshall Burke, Solomon M Hsiang, and Edward Miguel. Climate and conflict. *Annu. Rev. Econ.*, 7(1):577–617, 2015.
2. Sylvain Chassang and Gerard Padro-i Miquel. Economic shocks and civil war. *Quarterly Journal of Political Science*, 4(3): 211–228, 2009.
3. James Fearon. Economic development, insurgency, and civil war. *Institutions and economic performance*, 292:328, 2008.
4. Ignacio Rodriguez-Iturbe, A Porporato, L Ridolfi, V Isham, and DR Coxi. Probabilistic modelling of water balance at a point: the role of climate, soil and vegetation. In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, volume 455, pages 3789–3805. The Royal Society, 1999.
5. David Dralle, Nathaniel Karst, Marc Müller, Giulia Vico, and Sally E Thompson. Stochastic modelling of inter-annual variation of hydrologic variables. *Geophysical Research Letters*, 2017.
6. Clarence W Richardson. Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water resources research*, 17(1):182–190, 1981.
7. Martin K van Ittersum, Kenneth G Cassman, Patricio Grassini, Joost Wolf, Pablo Tittonell, and Zvi Hochman. Yield gap analysis with local to global relevance—a review. *Field Crops Research*, 143:4–17, 2013.
8. Giulia Vico and Amilcare Porporato. From rainfed agriculture to stress-avoidance irrigation: I. a generalized irrigation scheme with stochastic soil moisture. *Advances in Water Resources*, 34(2):263 – 271, 2011. ISSN 0309-1708. . URL http://www.sciencedirect.com/science/article/pii/S0309170810002198.
9. Kaiyu Guan, Benjamin Sultan, Michela Biasutti, Christian Baron, and David B. Lobell. What aspects of future rainfall changes matter for crop yields in west africa? *Geophysical Research Letters*, 42(19):8001–8010, 2017. . URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015GL063877.
10. Gianluca Botter, A Porporato, I Rodriguez-Iturbe, and A Rinaldo. Basin-scale soil moisture dynamics and the probabilistic characterization of carrier hydrologic flows: Slow, leaching-prone components of the hydrologic response. *Water resources research*, 43(2), 2007.
11. Gianluca Botter, Stefano Basso, Ignacio Rodriguez-Iturbe, and Andrea Rinaldo. Resilience of river flow regimes. *Proceedings of the National Academy of Sciences*, 110(32):12925–12930, 2013.
12. Wolfram Schlenker and Michael J Roberts. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598, 2009.
13. László Márton, MP Pereda, and SG Mohinder. Long-term studies of crop yields with changing rainfall and fertilization. *Agricultural Engineering Research*, 13:37–47, 2007.
14. Cynthia Rosenzweig, Francesco N Tubiello, Richard Goldberg, Evan Mills, and Janine Bloomfield. Increased crop damage in the us from excess precipitation under climate change. *Global Environmental Change*, 12(3):197–202, 2002.
15. Wolfram Schlenker and David B Lobell. Robust negative impacts of climate change on african agriculture. *Environmental Research Letters*, 5(1):014010, 2010.
16. Andreu Mas-Colell, Michael Dennis Whinston, and Jerry R Green. *Microeconomic theory.* Oxford university press New York, 1995.
17. Edward Miguel and Shanker Satyanath. Re-examining economic shocks and civil conflict. *American Economic Journal: Applied Economics*, 3(4):228–32, 2011.
18. J. R. Porter, L. Xie, A. J. Challinor, K. Cochrane, S. M. Howden, M. M. Iqbal, D. B. Lobell, and M. I. Travasso. Food security and food production systems. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, and L. L. White, editors, *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*, pages 485–533. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014.