Climate change and the Opportunity Cost of Conflict

Kevin R. Roche, Michèle C. Müller-Itten, David Dralle, Diogo Bolster, and Marc F. Müller

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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 semianalytical 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.](http://example.com/fig1.png)
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).

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 Supporting 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).

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 their opponent’s resources and permanently increase...
Table 1. Qualitative effect of the three governing statistics of income distribution on the predicted probability of conflict

<table>
<thead>
<tr>
<th>Marginal Change in Income Statistic</th>
<th>Direct Effect on $P_{\text{war}}$</th>
<th>Adaptation Effect on $P_{\text{war}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>↑ Income Shock Frequency $F(\theta)$</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>↓ Mean Income $E[\theta]$</td>
<td>↓</td>
<td>↓</td>
</tr>
<tr>
<td>↓ Conflict destructivity $cE[\theta</td>
<td>\theta &lt; \tilde{\theta}]$</td>
<td>↓</td>
</tr>
<tr>
<td>(or ↑ income shock intensity)</td>
<td></td>
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</tr>
</tbody>
</table>

- in conflict probability caused by increased climate variability ($\partial P_{\text{war}}/\partial CV_W$, 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 $F(\theta)$, mean income $E[\theta]$ and conflict destructivity $cE[\theta | \theta < \tilde{\theta}]$ (as a measure of shock intensity). The magnitude of each effect is expressed as a partial derivative with respect to $CV_W$. Variables $\theta$, $\tilde{\theta}$, $c$ 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 Methods). Bottom: Income shock frequency has a direct and axiomatic impact on the probability of conflict $P_{\text{war}} = F(\theta)$ (solid blue). However, changes in all three income statistics affect $P_{\text{war}}$ 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 $P_{\text{war}}$ (red), which is also expressed as a partial derivative with respect to $CV_W$. Parameters (see Materials and Methods): $\pi = 0.523$, $c = 0.9$, $\delta = 0.9$, $\mu = W_H = 150 \text{ mm}$, $\theta_{\text{max}} = 3$.](image)

**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-

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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Note: The document excerpt contains numerous references to specific pages and lines, which are not transcribed here due to the nature of the task. These references are likely placeholders for actual page numbers and line references.
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 $P_{\text{war}}$ to income scaling noted by Chassang and Padro-i Miquel (10). Similarly, a constant upward shift in income results in a decrease in $P_{\text{war}}$ 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 are 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 avert losses 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 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, $E[P]$, are larger than the expected returns of launching a surprise...
where \( \theta_t \) is an income sampled from the PDF \( f(\theta) \); \( V^p \) are the future expected returns of peacefully farming one's own land (discounted by a constant factor, \( \delta \)); \( \pi \) 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 \( \delta \)). 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 \( \theta \), where 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, \( V^p \) is an implicit equation that depends on the attack threshold, \( \tilde{\theta} \), defined as the \( \theta \) at which \( E[P^e] = E[V^v] \) (see Supplementary Information). An implicit expression for \( \tilde{\theta} \) is found by substituting \( V^v \) and \( V^p \) into 1, setting \( E[W] = E[P^e] \), and rearranging:

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

where \( F(\tilde{\theta}) = \int_{\tilde{\theta}}^{\infty} f(x)dx, \) and \( E[] \) is the conditional expectation operator. The probability of war in any season is simply \( P_{war} = F(\tilde{\theta}) \).

Climate, water availability and crop productivity. We assume that both farmer groups are subject to the same crop productivity (\( \theta_t \)) 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, \( \theta \). 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, \( E(W) \).

\[
\theta = \theta_{\text{max}} \frac{W}{W + W_H},
\]

where \( W_H \) is a half-saturation constant, and \( \theta_{\text{max}} \) 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:

\[
f(\theta) = \frac{\theta}{\Gamma(\theta_{max} - \theta)} \left( \mu \nu W_H^{-\theta_{max}} C V_W^{\theta_{max} - \theta} \right) \frac{\theta_{max} - \theta}{\theta_{max} - \Gamma} \left( \frac{1}{CV_W} \right),
\]

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

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

\[
\frac{dP_{war}}{dCV_W} = \frac{n \cdot \theta_{\text{max}} - \theta}{\theta_{\text{max}} - \Gamma} \left( \frac{1}{CV_W^2} \right)
\]

where \( S \in \{E[\theta], F(\tilde{\theta}), E[\theta | \theta < \tilde{\theta}]\} \) are the three fundamental statistics that govern \( \theta \) (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 \( f(\tilde{\theta}) \) also alters the expected returns from peace, \( V^p \) (see Supplementary Information). Farmers therefore adapt \( \tilde{\theta} \) to a value that again satisfies 1 with equality (adaptation effect).

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Supplementary Information for
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This PDF file includes:
- Supplementary text
- Figs. S1 to S5
- References for SI reference citations
Supporting Information Text

1. Model description

Conflicts. Two groups of farmers share a given territory. Each group exploits all land units \( \ell_i \) that it controls and generates a profit that is proportional to a productivity factor \( \theta_i \), which describes crop yield per unit of land in the growing season of that particular year. In water-limited agricultural regions, \( \theta_i \) is associated with the availability of water for irrigation, which is itself governed by climate variability (1). Consequently, \( \theta_i \) 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, \( \theta_i \), each group chooses between two alternatives: either they farm their land in peace (and make a profit \( \ell_i \theta_i \)), 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 \( (1 - c) \ell_i \theta_i \) 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 \( (1 - c) \ell_i \theta_i \). 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.

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

where \( \theta_i \) is the current period production sampled from \( f(\theta) \), and \( \delta V^P \) are the future expected returns of peacefully farming one’s own land (discounted by factor \( \delta \)). The first term on the right hand side (RHS) represents the current expected returns of choosing war, which is the expected returns from victory weighted by \( \pi \). 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 \( \delta \)).

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

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

where \( E[\cdot] \) is the expectation operator. Returns of not attacking, \( V^P \), 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 \( E[W] > E[P] \), which occurs for all \( \theta_i \) below a threshold \( \tilde{\theta} \). Expected returns of peace are expressed as:

\[
V^P(\tilde{\theta}) = F(\tilde{\theta}) \left( \frac{1}{2} \cdot (2E[\theta < \tilde{\theta}] (1 - c) + \delta V^V) + (1 - F(\tilde{\theta})) \cdot (E[\theta > \tilde{\theta}] + \delta V^P(\tilde{\theta})) \right)
\]

where \( F(\theta) \) is the cumulative distribution function (CDF) for income, \( F(\theta) = \int_{0}^{\theta} f(x) dx \), and \( E[\cdot] \) 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 \( V^P \) is found by employing the Law of Total Expectation, \( E[\theta] = F(\tilde{\theta}) E[\theta < \tilde{\theta}] + (1 - F(\tilde{\theta})) E[\theta > \tilde{\theta}] \), and then rearranging terms:

\[
V^P(\tilde{\theta}) = \frac{E[\theta]}{1 - \delta} - \frac{F(\tilde{\theta})}{1 - \delta (1 - F(\tilde{\theta}))} \cdot c E[\theta > \tilde{\theta}] \cdot \left( 1 - \delta (1 - F(\tilde{\theta})) \right)
\]

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 \( \delta \) due to the increasing probability that conflict will occur in any given period, i.e., increasing \( \delta \) increases \( F(\delta) \) (all else being
We assume that both farmer groups are subject to the same crop productivity ($B$ with mean $\mu_B$), with the maximum productivity. Although additional factors such as intraseasonal dry spells are known to affect crop yields (e.g., $\delta$), we do not include these factors in Equation S-6 since our principal aim is to prevent for higher levels of income ($cE[\theta | \theta < \tilde{\theta}]$ 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 $E[P] = E[W]$:

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

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 $P_{\text{war}}$ 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 $\lambda_p$ [d$^{-1}$] and exponentially-distributed event depths $\alpha_p$ [mm] (e.g., 4, 5), which aggregates to Gamma-distributed PDF of seasonal rainfall volumes:

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

with mean $\mu_W = \lambda_p \alpha_p$ and coefficient of variation $CV_W = \sqrt{\frac{\mu_W}{\lambda_p \alpha_p}}$, 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, $\theta$.

**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 seasonal crop yield potential. We match observation patterns presented in (7) and specify a saturation-type yield function $B(W)$:

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

where $W_H$ is a half-saturation constant, and $\theta_{\text{max}}$ 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 ($\theta_i$) 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 $\mu_W$ 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, $F(\theta)$,

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

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

By taking the derivative, we obtain the probability density function for income $\theta$,

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

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, $\theta_{\text{max}}$, specified by the crop function (Equation S-6). Income distribution $f(\theta)$ is controlled by mean water availability, $\mu_W$, and by the coefficient of variation, $CV_W$, of the distribution of $f(W)$. 
We assess the sensitivity of our results to temperature constraints by specifying an alternate crop function where yields are

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

where \( W \geq 0 \) is seasonal water volume and \( N = \frac{\theta_{\text{max}}}{\Gamma(k, m)} W_{\text{peak}}^{k-1} e^{-W_{\text{peak}}/m} \) a normalizing constant. This alternative water-yield function is composed of a sinusoidal relation (\( W < W_{\text{peak}} \)) appended to a gamma probability density function (\( W \geq W_{\text{peak}} \)). 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.

**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 alternate, 4-parameter \((\theta_{\text{max}}, W_{\text{peak}}, m, k)\), water-yield function depicted in the middle left panel of Figure S2,

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

where \( W \geq 0 \) is seasonal water volume and \( N = \frac{\theta_{\text{max}}}{\Gamma(k, m)} W_{\text{peak}}^{k-1} e^{-W_{\text{peak}}/m} \) a normalizing constant. This alternative water-yield function is composed of a sinusoidal relation (\( W < W_{\text{peak}} \)) appended to a gamma probability density function (\( W \geq W_{\text{peak}} \)).

We solve the full model numerically using Mathematica v11.3 (Wolfram Research Inc., Champaign, IL, USA).

**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 \( \sim 29^\circ C \) 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 \( T \),

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

where \( T_{\text{peak}}, \theta_{\text{min}}, \theta_{\text{max}} \) and \( \sigma_{\text{low}} < \sigma_{\text{high}} \) are model parameters. This temperature-yield function is composed of adjoined normal probability density functions with different standard deviation values on either side of \( T_{\text{peak}} \), 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, \( \bar{\theta} \), and conflict probability, \( \bar{P}_{\text{war}} = F(\bar{\theta}) \). We solve the model numerically using Mathematica v1.1.3 (Wolfram Research Inc., Champaign, IL, USA).

The model was analyzed using fixed values of \( c = 0.9, \delta = 0.9 \) and varying values of \( \pi \). 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 \( \delta \). 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 \( \pi \) 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, \( \theta_* \), to Equation S-4 (recalling that \( P_{\text{war}} = F(\bar{\theta}) \)). Roots for specific income distributions are shown in plots of \( E[P] - E[\theta] \) vs. \( \theta \) (Figures S3 right column). Values of \( \theta \) corresponding to locally stable equilibria are those where \( E[P] = E[\theta] \), and a slight increase in \( \theta \) causes \( E[P] > E[\theta] \) (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 \( P_{\text{war}} \) 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 \( \theta \) 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, \( \pi \in (0.5, \pi^D) \) (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 $\pi^{\text{crit}}$ 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 $\hat{\theta}$ 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 $P_{\text{war}}$ and the threshold $\hat{\theta}$. 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: $S \in \{E[\theta], F(\theta), E[\theta | \theta < \bar{\theta}]\}$. 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:

$$\frac{dP_{\text{war}}}{dCV_W} = \frac{\partial P_{\text{war}}}{\partial CV_W} \text{mechanistic effect} + \sum_{n=1}^{3} \frac{\partial P_{\text{war}}}{\partial \theta_n} \frac{\partial \theta_n}{\partial CV_W} \text{farmer adaptation}$$

**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 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 $P_{\text{war}}$ to a marginal scaling of $\theta$, decomposed into the three fundamental statistics $S$ that determine agent response. Response to scaling is defined as a derivative with respect to $\phi$:

$$\frac{dP_{\text{war}}}{d\phi} = \frac{\partial P_{\text{war}}}{\partial \phi} + \sum_{n=1}^{3} \frac{\partial P_{\text{war}}}{\partial \theta_n} \frac{\partial \theta_n}{\partial \phi}$$

Although all three statistics respond to a marginal increase in $\phi$ (e.g., Figure S4 top), the total effect of scaling on $P_{\text{war}}$ 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 $P_{\text{war}}$ exactly cancels out. Figure S4 makes it clear that this overall scaling invariance does not hold, in fact, contradict our theoretical predictions in Table 1: the positive marginal effect of changes in $E[\theta]$ on $P_{\text{war}}$ (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

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

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

$$G(\tilde{\theta}_2 + s | F_1) > 0 \iff F_2(\tilde{\theta}_2) < \frac{1 - \delta}{\delta} \left[ \frac{1 - 2\pi(1-c)(1-\delta)}{(2\pi - 1)(1-c)} \right]$$

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 ($\pi = 0.523, c = 0.9, \delta = 0.0$), 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 (left-hand plots, solid black lines). This corresponds to the lowest stable root when π < π^{crit}, and to the highest stable root when π > π^{crit}. The value π = π^{crit} denotes a special case where there exist two stable roots when CV_{W} < CV_{crit} and a pitchfork bifurcation at CV_{W} = CV_{crit}. Right: The income threshold ˜θ below which farmers will fight, and the associated probabilities of conflict P_{war} = F(˜θ), are determined by finding the roots to Equation S-4. Roots are visualized as upward crossings of the x-axis in plots of E[P] - E[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, δ = 0.9, v = 0.9, µ_{W} = W_{H} = 500mm.
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 $f(\theta)$. 

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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 ($CV_\theta$) 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 $\mu_T$), because they are consistently 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 $\mu_T$). 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 $F_\theta^t$ after each observation and adjust their (unobservable) cutoff $\tilde{\theta}_t$ accordingly. Thus, income $\theta_t$ 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, $F_\theta^{t+1}$. Qualitatively, our theoretical results (Table 1 in main document) would predict that the threshold moves up ($\tilde{\theta}_t^{t+1} > \tilde{\theta}_t^t$) after (a) good draws $\theta_t$ (via a raised estimate for $E[\theta]$), (b) good draws during conflict years (via a raised estimate for $E[\theta | \theta < \tilde{\theta}_t^t]$) 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