Supplementary Information,
Forecasting Civil Conflict along the Shared Socioeconomic Pathways

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S1 Overview

This Supplementary Information provides a summary of the storylines embedded in the Shared Socioeconomic Pathways or SSPs (Section S2), the statistical model underlying the simulations (S3), the simulation procedure generating the forecasts (S4), documentation of the out-of-sample evaluation (S5), a review of the core predictors in the model as operationalized in each SSP (S6), additional simulation results (S7), and a set of adjustments done to the historical and projected data used (S8).

Replication files, instructions to reproduce all results, data, and further documentation are available at http://havardhegre.net/forecasting/ and https://www.prio.org/data/.

S2 The Shared Socioeconomic Pathways

The Shared Socioeconomic Pathways (SSPs) are intended to represent five potential future pathways of development, as points of departure for assessing possible futures with various implications for climate change [1,2]. The SSPs replace the previous scenarios developed by the climate change research community, known as SRES, from the Special Report on Emissions Scenarios [3]. The SSPs are developed as narratives and require formulation as projections for specific variables in order to be operable. The operationalization of the SSPs are documented in Section S4.2 and presented visually in S6.

Unlike the SRES, these reference SSP pathways do not include explicit projections of emissions. Rather, modeling teams will employ the socioeconomic and demographic information contained in the SSPs to estimate emissions and end-of-century implications for global and regional climatic changes using a range of integrated assessment models (IAMs). , Climate policies can be then be modeled for each of these pathways with mitigation and adaption costs expected to differ across the SSPs.

Capturing alternative plausible but divergent pathways, the SSPs comprise the following scenarios: “Sustainability” (SSP1), “Middle of the Road” (SSP2), “Fragmentation” (SSP3), “Inequality” (SSP4), and “Conventional Development” (SSP5). These five scenarios are classified according to the challenges for the mitigation of the corresponding greenhouse gas (GHG) emissions and challenges for adaptation to the impacts of climate change. For example, both SSP1 and SSP5 have stabilizing populations and economic convergence across countries, but differ in the structure of the economy and fossil-fuel dependency. With a greater reliance on fossil fuel, the SSP5 pathway was designed to constitute larger challenges to GHG emissions mitigation than SSP1, which has lower energy-service demand and more use of renewable energy technologies. Both SSP1 and SSP5 pathways, however, are likely to allow for relatively easy adaptation to the impacts of climate change. By contrast, a SSP3 pathway with significant growth in population but lower economic growth would render both mitigation and adaptation more challenging. Complementing the assumptions of climate change adaptation and mitigation, each SSP has specific quantitative drivers, notably population, GDP, and education. These storylines also have qualitative descriptions of other drivers, such as technological development and agricultural yield growth rates. Assumptions about institutional characteristics (e.g., land use change regulations) are incorporated in these storylines, although political institutions are not explicitly modeled.

S2.1 Sustainability (SSP1)

In SSP1, the world is making good progress towards sustainable development with strong international governance and local institutions. Importantly, this pathway assumes that the Millennium Development Goals (MDG) are achieved early (i.e., within the next one to two decades) for all countries [4]. This implies rapid development of low-income countries, high levels of environmentalism, and planned urbanization. The economy is assumed to be open and globalized. Economic inequality both between and within countries will decrease. Consumption is oriented towards low material growth and energy intensity. Traditional fossil fuels experience a quick phase-out, driven by policies and technological development. Large investments are made in education. Due to economic growth, higher education, and family planning, the world population peaks mid-century and declines to 7.2 billion in 2100 [5].

S2.2 Middle of the Road (SSP 2)

SSP2 is designed to be a middle-of-the-road pathway. There is some progress to achieving the MDGs. Reductions in resource and energy intensity happens at historic rates, with a slowly diminishing fossil-fuel dependency.

S2.3 Fragmentation (SSP3)

In SSP3, the world experiences rapid population growth coupled with slow economic growth. Specifically, it fails to achieve the MDGs. The international system is characterized by weak international governance and local institutions. Countries organize into regional blocks with little coordination between them. International trade is severely restricted. There is high resource intensity in the economy, high levels of fossil fuel dependency, low levels of investments in technology development, and unplanned settlements. There is also little investment in education. As a result of both low education and low economic development, the global population reaches 14.1 billion in 2100, although growth varies by country, with the majority of the population growth occurring in Africa.

S2.4 Inequality (SSP4)

This pathway envisions a world with persistent and increasing levels of inequality within and across countries. Governance is centralized and controlled by a small number of rich global elites. This leads to a world where only a small elite is responsible for GHG emissions, as the poor majority contributes little in that regard. Investments in new energy technologies are made by global energy corporations. Most societies are shaped by limited access to higher education and basic services. The population reaches 11.8 billion in 2100, with most of the growth occurring in poor regions (i.e., roughly half of the global population in 2100 is in Africa).

S2.5 Conventional Development (SSP5)

In SSP5, economic growth is seen as the solution to socioeconomic concerns; thus, the world pursues rapid economic development, however, using more conventional measures. Specifically, energy systems continue to be dominated by fossil fuels with a focus on consumerism. The MDGs are mostly achieved with the eradication of extreme poverty and universal access to education and basic services. Large investments in technology development lead to highly engineered infrastructure and ecosystems. Education and technology development, coupled with an open global economic system, lead to a rapid convergence and a global population that peaks mid-century before declining to 7.7 billion in 2100.

S3 The statistical model underlying the simulations

The unit of analysis in the study is the independent country, observed once every year for all years, 1960–2013 (historical period) and 2014–2100 (simulation period). The sample is consistent with the Gleditsch and Ward historical list of independent states [6] and assumes no changes in the existence or delineation of states throughout the simulation period.

We apply a mixed-effects multinomial logistic regression model that estimates the transition probabilities between peace and two intensity levels of armed conflict, 1960–2013. The specification of this model reflects the state-of-the-art of quantitative civil war research[7]. The 'no conflict' outcome is set as the reference outcome such that we estimate one equation for the minor conflict and one for the major conflict outcome, including the same independent variables in each equation. Sections 3.1 and 3.2 detail the data used to estimate the model. Tables S1 and S2 report descriptive statistics for the data used in the estimation. In section S4.2, we account for the projections up to 2100 for the predictors. We made a number of adjustments to several of these datasets in order to obtain maximum coverage of cases and to link the historical series to the projections. This is detailed in Section S8.

S3.1 Dependent variable

Our conflict data are from the 2014 update of the UCDP/PRIO Armed Conflict Dataset [8,9], the industry standard for quantitative conflict research. This dataset records conflicts at two severity levels with annual statistics, 1946–2013. Minor conflicts are those that pass the 25 annual battle-related deaths threshold, but have less than 1,000 deaths in a calendar year. Major conflicts are those conflicts that generate at least 1,000 annual deaths. We only look at civil conflicts, i.e., those that involve military battles between a state government and one or more organized non-state actors. This is by far the dominant form of armed conflict today. Following convention, we only consider the countries whose governments are included in the primary conflict dyad as hosting a civil conflict (i.e., countries that intervene in an ongoing civil conflict in another state are not coded as part of the conflict). In our historical sample, around 16% of the observations hosted a civil conflict (Table S1).

Table S1. Descriptive statistics for the conflict data, 1960–2013

Indicator	Outcome	N
Conflict incidence	No conflict	6,528
	Minor conflict	886
	Major conflict	395
Neighboring conflict	No conflict	4,273
	Conflict	3,536

S3.2 Independent variables

Countries with previous conflicts are more likely to see renewed conflict [10,11]. We include information on conflict status (no conflict, minor, or major conflict) at *t*–1, the year before the year of observation. This is coded as two dummy variables, **c1** and **c2,** for minor and major conflicts, respectively. In addition, to account for the legacy of a longer conflict history, we include a variable capturing the number of years in peace in a country up to (but not including) the year before the year of the observation. The variable is log-transformed to reflect that an additional year of peace changes the risk of conflict more in the first year after the conflict than a couple of decades later. In the tables below (as well as in the replication dataset), this variable is called **ltsc0**.

Newly established states are also more fragile than states that have been around for some time [7,12,13]. To capture this, we code for each country the time since the state was established in its current form or since the year 1700 if the state became independent before then [6]. The count is log-transformed since it is reasonable to assume that the uncertainty surrounding a new statehood decays over time. The variable is named **ltimeindep**.

Adverse impacts of armed conflict often extend beyond the boundaries of the host state [7,14]. We capture the conflict situation in neighboring countries with two variables. The first is a dummy for whether any land-contiguous neighboring country had a minor or a major conflict during the year prior to the year of observation. This variable is called **nc**. 45% of all observations had at least one conflict in a neighboring country (Table S1). The other variable captures the long-term conflict history in the neighborhood, given as the (log) number of years since the most recent neighboring conflict, up to (but not including) the year before the year of observation. The variable is referred to as **ltsnc**.

Unobserved global time-specific shifts in armed conflict propensity are captured through decade dummies for the **1960s**, **1970s**, **1980s**, and **1990s**, with 2000–13 as the reference category.

The three main predictors representing the SSPs are **Population**, **GDP/capita**, and **YMHEP** (share of males age 20–24 that have attained at least upper secondary education). All variables are lagged one year. Population, derived from the UN World Population Prospects 2012 Revision [15], are given in (log) thousands. GDP/capita is given in (log) purchasing power parity (PPP) adjusted 2005 US dollars. The primary source for the empirical GDP data is the World Development Indicators [16], using the variable NY.GDP.PCAP.PP.KD. When this series had missing observations, we resorted to either NY.GDP.PCAP.KD from the same source, Penn World Table [17] or Maddison [18]. YMHEP is based on age group-specific education data from IIASA [19] for the period 1970–2010 and backdated to 1960 using linear interpolation. Table S2 presents the descriptives for these indicators.

Table S2. Descriptive statistics for independent variables, 1960–2013

Indicator	25^{th} percentile	Median	75^{th} percentile
Population	3,114,014	8,117,742	22,671,134
GDP/capita	1,337	3,983	11,408
YMHEP (education)	0.16	0.33	0.58
ltsc0 (log time since conflict)	1.10	2.71	3.71
ltsnc (log time since conflict, neighbors)	1.39	2.49	3.22
ltimeindep (log time since independence)	3.09	3.83	4.93
N (country years)			7,809
N (listwise deletion)			97
N (valid sample)			7,712
N (countries)			166

Note: Population and GDP statistics reflect values before transformation.

S3.3 The multinomial logistic regression model

Since the dependent variable contains three outcomes (no conflict, minor conflict, major conflict), the multinomial logit model is appropriate. In order to model unobserved differences in armed conflict propensities between countries, we estimate time-invariant country-specific intercepts. We include separate sets of intercepts in each of the minor and major conflict equations, estimated as random effects in two multilevel mixed-effects logistic regressions (`melogit` in Stata) with the same control variables as in the main model. To account for the uncertainty in the magnitude of the country-specific intercepts, the simulation alters between 15 different draws from the probability distributions of these country-specific effects.

We estimate two alternative models in parallel. The first (and main) model includes all variables presented above whereas the second model excludes the YMHEP education indicator. The results from these estimations are reported in Table S3. Due to space constraints we only report the results for the first model in the article.

When we include YMHEP in the model, much of the effect of log(GDP/capita) is absorbed by the education variable. In effect, the model with YMHEP imposes an upper limit to the effect of socioeconomic development since the education indicator by definition is bounded at 100% attainment. Moreover, the education level is assumed to remain virtually constant at present levels in two of the SSP scenarios (see Fig. S4 below) whereas GDP per capita continues to grow across all scenarios. Thus, the socioeconomic development envisaged for YMHEP is much more pessimistic than what we see for GDP/capita. Since we are unable to separate the effect of education and productivity on armed conflict, we interpret both YMHEP and GDP/capita as proxies for different dimensions of socioeconomic development.

A comparison of the two models reveals that broad socioeconomic development, as represented by universal education, is more important for conflict risk reduction than the narrower conceptualization of development usually represented by average income statistics. Overall, Model 1 has a lower AIC score than the simpler Model 2 and also performs slightly worse in terms of out-of-sample prediction (see Table S7).

The simulation procedure takes the joint effect of all these parameters into account, but a brief discussion of the substantial impact of the various terms is useful. The discussion below refers to the minor and major conflict equations in Model 1, but the effects are roughly similar in Model 2. The discussion is in terms of the effect of odds of conflict. Since the baseline probability of armed conflict is relatively low, the effect on odds of conflict is roughly similar to the effect on the probability of conflict.

The estimates for log population indicate that the odds of both minor and major conflict increase by 39% when population is increased by a factor of $e \approx 2.7$ – more populous countries have more frequent conflicts, but considerably less conflict per capita than smaller ones.

Table S3. Estimation results of civil conflict incidence, 1960–2013

	Group	(Model 1)				(Model 2)			
		Minor		Major		Minor		Major	
		β	*z*-stat.	β	*z*-stat.	β	*z*-stat.	β	*z*-stat.
(Intercept)		**-6.058**	(-8.33)	**-6.841**	(-5.42)	**-4.143**	(-6.52)	**-6.427**	(-5.38)
Log(Population t-1)	1	**0.327**	-7.11	**0.327**	-4.46	**0.277**	-6.13	**0.366**	-4.94
Log(GDP/capita t-1)	2	0.053	-0.66	-0.232	(-1.85)	**-0.27**	(-4.17)	**-0.403**	(-3.74)
Log(GDP/capita t-1)*c1	2	**0.12**	-4.76	0.057	-1.17	**0.122**	-4.84	0.06	-1.24
Log(GDP/capita t-1)*c2	2	**0.126**	-3.25	**0.123**	-2.22	**0.129**	-3.39	**0.125**	-2.27
Log(GDP/capita t-1)*ltsc0	2, 4	-0.018	(-1.63)	-0.04	(-1.89)	-0.019	(-1.76)	-0.041	(-1.91)
YMHEP(education) t-1	3	**-2.141**	(-5.66)	-0.802	(-1.41)				
c1 (minor conflict at t-1)		**2.885**	-9.57	**3.519**	-4.69	**2.866**	-9.62	**3.72**	-4.83
c2 (major conflict at t-1)		**2.277**	-4.88	**5.379**	-6.73	**2.374**	-5.09	**5.676**	-6.97
ltsc0 (log time since conflict)	4	-0.178	(-1.69)	-0.022	(-0.09)	-0.179	(-1.71)	-0.055	(-0.22)
Ltimeindep (log time since independence)	5	0.072	-1.1	0.04	-0.39	**0.19**	-3.02	0.073	-0.74
nc (neighbor in conflict)	6	0.335	-1.15	0.398	-0.48	0.315	-1.08	0.509	-0.6
ltsnc (log time since conflict, neighbors)	6	0.009	-0.18	0.015	-0.18	-0.067	(-0.58)	0.183	-0.56
nc*c1	6	-0.293	(-0.83)	-0.115	(-0.13)	-0.233	(-0.66)	-0.302	(-0.34)
nc*c2	6	0.28	-0.5	0.519	-0.55	0.147	-0.26	0.209	-0.22
ncts0 (neighbor in conflict*ltsc0)	4, 6	-0.04	(-0.34)	0.13	-0.41	-0.044	(-0.81)	0.025	-0.3
1960s	7	-0.173	(-0.82)	0.505	-1.5	0.093	-0.46	**0.822**	-2.52
1970s	7	0.023	-0.12	**0.655**	-2.17	0.224	-1.23	**0.789**	-2.66
1980s	7	0.197	-1.11	**0.91**	-3.43	**0.336**	-1.9	**1.052**	-3.98
1990s	7	0.128	-0.8	0.32	-1.25	0.156	-0.97	0.37	-1.43
Country-effect minor conflict	8	**1.065**	-9.83	**0.684**	-3.78	**1.005**	-8.83	0.263	-1.48
Country-effect major conflict	8	0.176	-1.87	**1.135**	-6.84	**0.242**	-2.36	**1.078**	-6.58
N		7,553				7,553			
AIC		3,447.20				3,473.60			
Log-likelihood		-1,679.60				-1,694.80			

Note: Mixed-effects multinomial logit coefficients with z-scores in parenthesis. Coefficients significant at the 0.05 level are set in boldface. Model 1 is the complete historical model; Model 2 is without the education indicator. To assess the joint significance of parameters across equations and interaction terms, we assigned the variables in Model 1 to eight variable groups (as indicated with group numbers in Column 2 of the table). We then reran Model 1 omitting these variables in turn and calculated likelihood ratio tests. All groups of variables were significant at the 0.05 level except for group 6 (neighborhood variables).

Because of the multiple interaction terms involving ln GDP per capita, the direct effect of income is less straightforward to interpret from the estimates (the simulation procedure takes the joint effect of all the terms into account, though). Among countries currently at peace, increasing GDP per capita from e.g. USD 1,000 to USD 2,700 decreases the odds of major conflict by 20%. The interaction term with ltsc0 (log number of years since conflict up to t-2) indicates that this effect is even stronger for countries that have been peaceful for some time – after 20 years of peace, this increase in GDP per capita reduces risk of major conflict by 30%. In countries that already have a conflict, GDP per capita has a much weaker effect (this is driven by the long conflicts in relatively rich countries such as the UK and Israel/Palestine).

Controlling for the effect of GDP per capita, increasing YMHEP education by 0.1 (e.g., changing the proportion of the male population between 20 and 24 years from 30 to 40%) further reduces the odds of conflict by 20%.

The estimates for lagged conflict (c1, c2) must be interpreted taking the interaction with GDP per capita into account. A low-income country with GDP per capita at USD 1,100 (i.e., 7 in log form) has an estimated odds of minor conflict more than 20 times higher than a similar country at peace, whereas the odds of major conflict is 500 times higher than that of a peaceful country. This 'conflict trap' effect is a powerful contributor to the simulation results shown in Fig. 3.

The term ltsc0 reflecting the log of consecutive years in peace up to t-2 adds to the conflict trap effect. A country that has been at peace for 20 years up to t-1 has an estimated odds of minor conflict 40% lower than for a country where peace broke out at t-1.

A number of terms for conflict in the neighborhood complement the model of the conflict trap. Most importantly, the nc term implies that a country with a neighboring country in conflict is 40–50% more likely to be in conflict than one that is located in a peaceful neighborhood.

Table S4 shows the correlation between the dependent variable and predictors in Model 1. Correlations are always substantial between multiplicative interaction terms as well as the terms constituting categorical variables. In addition, the correlation between log GDP per capita and our education measure is considerable, at r=0.69.

The direct interpretation of the parameter estimates is interesting in itself, but the coefficients' main function is to provide a basis for calculating the probabilities of no conflict, minor conflict, and major conflict as a function of the values for the predictors as described below. The procedure handles multicollinearity problems by construction, since the simulation draws realizations of the coefficients reported in Table S3 while simultaneously taking into account both the standard errors of the estimates and the correlation between them as estimated in the variance-covariance matrix. The variance-covariance matrix for Model 1 is reported (in correlation form) in Table S5.

Table S4. Matrix of correlation between predictors

	conflict	c1	c2	ltsc0	nc	ncc1	ncc2	ltsnc	ncts0	lpop	lGDPcap	lGDPcap_c1	l_GDPcap_c2	lGDPcap_ltsc0	YMHEP	ltimeindep	1960s	1970s	1980s	1990s	random_1	ramdom_2
conflict	1.00																					
c1	0.47	1.00																				
c2	0.64	-0.08	1.00																			
ltsc0	-0.57	-0.55	-0.35	1.00																		
nc	0.18	0.13	0.12	-0.26	1.00																	
ncc1	0.37	0.78	-0.06	-0.43	0.31	1.00																
ncc2	0.55	-0.07	0.84	-0.30	0.21	-0.05	1.00															
ltsnc	-0.01	-0.02	0.00	0.22	-0.07	0.02	0.01	1.00														
ncts0	-0.33	-0.30	-0.20	0.65	-0.77	-0.24	-0.16	0.22	1.00													
lpop	0.24	0.21	0.13	-0.12	0.19	0.18	0.11	0.16	-0.15	1.00												
lGDPcap	-0.23	-0.13	-0.18	0.47	-0.28	-0.14	-0.17	0.22	0.44	-0.03	1.00											
lGDPcap_c1	0.46	0.99	-0.08	-0.54	0.12	0.75	-0.07	-0.02	-0.30	0.21	-0.09	1.00										
lGDPcap_c2	0.63	-0.08	0.99	-0.35	0.11	-0.06	0.81	0.00	-0.19	0.13	-0.15	-0.08	1.00									
lGDPcap_lt~0	-0.52	-0.49	-0.32	0.97	-0.28	-0.38	-0.27	0.25	0.69	-0.10	0.62	-0.49	-0.32	1.00								
YMHEP	-0.16	-0.12	-0.10	0.36	-0.19	-0.11	-0.09	0.21	0.36	0.17	0.69	-0.09	-0.08	0.48	1.00							
ltimeindep	0.01	0.06	-0.03	0.36	-0.07	0.04	-0.03	0.36	0.27	0.40	0.38	0.08	-0.02	0.41	0.24	1.00						
1960s	-0.04	-0.05	-0.02	-0.02	-0.08	-0.05	-0.02	-0.20	0.04	-0.03	-0.12	-0.05	-0.02	-0.04	-0.16	-0.14	1.00					
1970s	-0.02	-0.02	-0.02	0.00	-0.06	-0.06	-0.02	-0.06	0.03	-0.06	-0.05	-0.02	-0.02	-0.02	-0.12	-0.08	-0.18	1.00				
1980s	0.06	0.02	0.06	0.01	0.03	0.01	0.05	0.06	-0.02	-0.02	-0.02	0.02	0.06	0.00	-0.06	0.03	-0.19	-0.22	1.00			
1990s	0.04	0.05	0.02	-0.06	0.07	0.06	0.02	-0.03	-0.07	0.01	0.00	0.04	0.02	-0.05	0.07	0.00	-0.20	-0.23	-0.24	1.00		
random_1	0.19	0.30	0.01	-0.22	0.03	0.19	0.00	-0.07	-0.12	-0.01	0.04	0.31	0.02	-0.19	0.05	0.00	0.00	-0.01	-0.01	0.00	1.00	
random_2	0.18	0.02	0.20	-0.08	0.03	0.03	0.16	-0.02	-0.05	0.00	-0.12	0.01	0.20	-0.08	-0.04	-0.05	0.00	-0.01	-0.01	0.00	-0.03	1.00

Table S5. Matrix of correlation between estimates, model 1

1 (minor conf)	c1	c2	ltsc0	nc	ncc1	ncc2	ltsnc	ncts0	llpop	llGDPcap	llGDPc~1	llGDPc~2	llGDPc~0	lYMHEP	ltimei~p	1960s	1970s	1980s	1990s	random_1	random_2	_cons
1																						
c1	1.00																					
c2	0.46	1.00																				
ltsc0	0.19	0.11	1.00																			
nc	0.63	0.41	-0.31	1.00																		
ncc1	-0.77	-0.34	0.26	-0.82	1.00																	
ncc2	-0.34	-0.74	0.15	-0.52	0.43	1.00																
ltsnc	0.02	0.02	0.03	-0.03	-0.02	-0.02	1.00															
ncts0	0.53	0.34	-0.39	0.82	-0.68	-0.43	-0.04	1.00														
llpop	-0.02	-0.03	-0.05	-0.05	0.01	0.03	-0.03	0.05	1.00													
llGDPcap	0.09	0.09	0.10	0.08	-0.02	-0.02	0.03	0.04	0.21	1.00												
llGDPcap_c1	-0.19	-0.12	-0.05	-0.04	0.02	0.01	-0.01	-0.06	-0.01	-0.23	1.00											
llGDPcap_c2	-0.12	-0.31	-0.05	-0.01	0.01	0.03	-0.03	-0.03	-0.01	-0.13	0.48	1.00										
llGDPcap_l~0	-0.31	-0.20	-0.62	-0.06	0.03	0.03	-0.04	-0.08	0.09	-0.28	0.52	0.35	1.00									
lYMHEP	-0.06	-0.07	-0.02	-0.05	0.05	0.04	-0.07	-0.07	-0.31	-0.57	-0.02	-0.04	-0.02	1.00								
ltimeindep	-0.02	-0.01	-0.02	0.03	0.01	0.01	-0.20	0.01	-0.39	-0.34	-0.15	-0.07	-0.12	0.20	1.00							
1960s	0.01	0.01	0.02	0.03	0.02	0.00	0.16	0.00	-0.07	-0.05	-0.01	-0.03	-0.07	0.20	0.13	1.00						
1970s	-0.03	-0.02	-0.01	0.02	0.05	0.01	0.10	0.01	-0.03	-0.09	-0.04	-0.02	-0.05	0.19	0.13	0.40	1.00					
1980s	-0.05	-0.04	-0.06	0.00	0.04	0.02	0.03	0.03	0.04	-0.08	-0.05	-0.07	-0.03	0.14	0.09	0.36	0.41	1.00				
1990s	-0.01	0.00	0.01	0.01	0.01	0.00	0.06	0.02	0.07	0.01	-0.02	-0.04	-0.03	0.01	0.04	0.37	0.41	0.42	1.00			
random_1	-0.05	0.01	-0.03	0.02	0.01	-0.01	0.10	-0.01	0.15	-0.09	-0.06	0.03	0.12	-0.14	0.03	-0.04	-0.01	0.03	0.01	1.00		
random_2	-0.01	-0.05	-0.03	0.01	-0.02	0.01	0.04	0.00	0.10	0.07	-0.02	-0.10	0.02	-0.03	0.03	0.04	0.05	0.10	0.06	0.07	1.00	
_cons	-0.28	-0.19	-0.07	-0.30	0.21	0.12	-0.10	-0.26	-0.60	-0.76	0.15	0.07	0.20	0.49	0.19	-0.11	-0.09	-0.09	-0.18	-0.07	-0.14	1.00
2																						
c1	0.14	0.03	0.04	0.03	-0.10	-0.02	0.00	0.02	0.00	0.01	-0.05	-0.01	-0.07	0.00	-0.02	0.01	0.00	-0.01	-0.01	-0.03	0.02	-0.01
c2	0.05	0.32	0.04	0.03	-0.02	-0.24	0.00	0.02	-0.01	0.03	-0.04	-0.11	-0.06	-0.02	-0.02	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.01
ltsc0	0.04	0.05	0.12	-0.02	0.02	-0.01	0.01	-0.02	-0.01	0.03	-0.01	-0.01	-0.12	0.00	-0.01	0.01	0.00	-0.02	0.00	-0.01	0.00	-0.02
nc	0.02	0.02	-0.01	0.05	-0.04	-0.03	-0.01	0.03	-0.01	0.02	-0.01	0.00	-0.01	-0.01	0.00	0.01	0.00	-0.01	0.00	0.00	0.01	-0.01
ncc1	-0.10	-0.01	0.01	-0.04	0.13	0.02	0.00	-0.03	0.00	0.00	0.00	-0.01	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.01	-0.01	0.00
ncc2	-0.03	-0.23	0.01	-0.04	0.03	0.34	0.00	-0.03	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.02	0.01	0.00	0.00	-0.01
ltsnc	0.01	-0.01	0.01	-0.02	-0.01	0.02	0.44	-0.02	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.10	0.06	0.04	0.01	0.04	0.03	0.02	-0.04
ncts0	0.02	0.02	-0.01	0.04	-0.03	-0.02	-0.01	0.04	0.01	0.01	-0.01	0.00	-0.01	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01
llpop	0.00	0.02	-0.01	-0.02	0.00	0.02	0.01	0.02	0.40	0.08	0.00	0.01	0.03	-0.12	-0.18	-0.03	-0.01	0.02	0.03	0.05	0.01	-0.23
llGDPcap	0.03	0.03	0.04	0.03	-0.01	0.00	0.01	0.01	0.09	0.41	-0.06	-0.02	-0.10	-0.23	-0.12	-0.01	-0.03	-0.02	0.01	-0.03	0.04	-0.32
llGDPcap_c1	-0.03	-0.01	0.02	-0.01	0.00	0.01	0.00	-0.01	0.00	-0.05	0.28	0.08	0.10	0.00	-0.06	0.00	-0.01	-0.01	-0.01	-0.03	0.01	0.03
llGDPcap_c2	-0.02	-0.13	0.00	0.00	0.00	0.02	-0.01	-0.01	0.00	-0.03	0.14	0.45	0.09	-0.02	-0.04	-0.01	-0.01	-0.03	-0.02	0.01	-0.04	0.02
llGDPcap_l~0	-0.07	-0.08	-0.13	-0.01	0.00	0.03	-0.01	-0.01	0.02	-0.08	0.11	0.08	0.21	-0.01	-0.05	-0.02	-0.01	-0.01	-0.01	0.04	-0.01	0.06
lYMHEP	-0.03	-0.05	-0.01	-0.02	0.01	0.00	-0.02	-0.03	-0.13	-0.23	-0.01	-0.01	-0.01	0.38	0.09	0.07	0.07	0.05	-0.01	-0.05	-0.02	0.19
ltimeindep	-0.01	-0.02	-0.01	0.02	0.01	0.03	-0.11	0.00	-0.18	-0.13	-0.07	-0.03	-0.06	0.09	0.41	0.05	0.05	0.03	0.02	0.01	0.03	0.08
1960s	0.00	-0.03	0.01	0.01	0.01	0.01	0.06	0.00	-0.03	0.00	0.00	-0.01	-0.03	0.07	0.04	0.36	0.17	0.16	0.16	-0.02	0.01	-0.05
1970s	-0.01	-0.01	-0.01	0.01	0.02	0.00	0.03	0.00	-0.01	-0.02	-0.01	-0.01	-0.02	0.06	0.04	0.16	0.39	0.17	0.17	-0.01	0.01	-0.04
1980s	-0.02	-0.02	-0.03	0.00	0.02	0.01	0.01	0.01	0.02	-0.02	-0.02	-0.03	-0.01	0.05	0.03	0.16	0.18	0.46	0.20	0.02	0.04	-0.05
1990s	0.00	-0.01	0.01	0.00	0.01	0.01	0.03	0.01	0.03	0.01	-0.01	-0.01	-0.01	0.00	0.01	0.16	0.18	0.18	0.44	0.01	0.03	-0.08
random_1	-0.01	0.05	-0.01	0.01	0.01	-0.01	0.03	0.00	0.06	-0.04	-0.02	0.02	0.04	-0.05	0.01	-0.02	0.00	0.02	0.01	0.36	0.01	-0.02
random_2	0.00	0.00	-0.01	0.01	-0.01	0.00	0.02	0.00	0.00	0.04	-0.01	-0.04	0.00	-0.02	0.02	0.01	0.01	0.03	0.03	0.00	0.37	-0.04
_cons	-0.03	-0.03	-0.03	-0.03	0.01	-0.01	-0.04	-0.03	-0.22	-0.28	0.05	0.00	0.08	0.16	0.09	-0.05	-0.04	-0.04	-0.07	-0.01	-0.06	0.33

2 (major conf)	c1	c2	ltsc0	nc	ncc1	ncc2	ltsnc	ncts0	llpop	llGDPcap	llGDPc~1	llGDPc~2	llGDPc~0	lYMHEP	ltimei~p	1960s	1970s	1980s	1990s	random_1	random_2	_cons
2|																						
c1	1.00																					
c2	0.84	1.00																				
ltsc0	0.13	0.14	1.00																			
nc	0.73	0.68	-0.39	1.00																		
ncc1	-0.78	-0.64	0.37	-0.94	1.00																	
ncc2	-0.65	-0.76	0.33	-0.88	0.83	1.00																
ltsnc	0.00	0.00	0.01	-0.02	0.00	0.00	1.00															
ncts0	0.60	0.57	-0.51	0.85	-0.80	-0.76	-0.03	1.00														
llpop	-0.03	-0.02	-0.02	-0.04	0.02	0.04	-0.07	0.03	1.00													
llGDPcap	0.09	0.10	0.09	0.04	-0.02	-0.01	0.07	0.03	0.17	1.00												
llGDPcap_c1	-0.23	-0.23	-0.16	-0.05	0.03	0.04	-0.04	-0.07	-0.04	-0.33	1.00											
llGDPcap_c2	-0.18	-0.30	-0.16	-0.03	0.02	0.03	-0.05	-0.05	-0.04	-0.27	0.71	1.00										
llGDPcap_l~0	-0.27	-0.29	-0.50	-0.05	0.03	0.06	-0.02	-0.09	0.04	-0.30	0.62	0.56	1.00									
lYMHEP	-0.02	-0.04	0.01	-0.01	0.03	0.02	-0.10	-0.05	-0.27	-0.50	-0.01	-0.01	-0.04	1.00								
ltimeindep	-0.02	-0.03	-0.02	0.00	0.01	0.02	-0.17	0.01	-0.33	-0.28	-0.15	-0.10	-0.13	0.16	1.00							
1960s	0.02	0.01	0.03	0.01	0.01	0.01	0.14	-0.02	0.00	-0.03	-0.03	-0.04	-0.08	0.19	0.18	1.00						
1970s	0.00	0.01	0.00	0.01	0.03	0.01	0.09	-0.01	0.00	-0.06	-0.08	-0.04	-0.08	0.22	0.17	0.44	1.00					
1980s	-0.03	-0.03	-0.04	-0.02	0.04	0.04	0.03	0.00	0.08	-0.07	-0.08	-0.09	-0.06	0.18	0.10	0.44	0.48	1.00				
1990s	-0.02	-0.02	-0.01	-0.02	0.02	0.02	0.07	0.00	0.09	0.03	-0.04	-0.05	-0.03	-0.01	0.10	0.41	0.44	0.49	1.00			
random_1	-0.06	-0.01	-0.01	0.00	0.02	0.00	0.16	-0.01	0.10	-0.10	-0.06	0.02	0.09	-0.12	-0.03	0.02	0.00	-0.01	-0.02	1.00		
random_2	-0.01	-0.01	0.00	0.01	0.01	0.00	0.00	-0.01	0.20	-0.02	0.00	-0.07	0.02	-0.01	-0.04	0.06	0.06	0.12	0.04	0.20	1.00	
_cons	-0.49	-0.47	-0.07	-0.42	0.38	0.34	-0.08	-0.36	-0.55	-0.66	0.23	0.19	0.23	0.35	0.12	-0.17	-0.14	-0.13	-0.20	0.00	-0.13	1.00

S4 Simulation procedure and data projections

S4.1 Simulation procedure

The general setup of the simulation procedure is summarized below. We use the methodology developed in earlier work [13]. The model is dynamic, allowing us to capture how a simulated conflict in one country at any point in time affects the future conflict risk of the same country as well as of its neighbors. At the core is the matrix of transition probabilities. The transition probabilities (i.e., relative frequencies) observed for the 1960–2013 period are given in Table S6. Among the 6,385 country years that had no conflict at *t*–1, 6,176 (96.7%) remained at peace at *t*, 184 (2.9%) transitioned into minor conflict, and 25 (0.4%) transitioned into major conflict. The statistical model described above allows formulating these transition probabilities as functions of the predictors for use in the simulation.

Table S6. Transition probability matrix, 1960–2013

	No conflict at *t*	Minor conflict at *t*	Major conflict at *t*	Total
No conflict at *t*-1	6,176 (0.967)	184 (0.029)	25 (0.004)	6,385 (1.000)
Minor conflict at *t*-1	172 (0.198)	613 (0.705)	84 (0.097)	869 (1.000)
Major conflict at *t*-1	27 (0.069)	80 (0.206)	282 (0.725)	389 (1.000)
Total	6,375 (0.834)	877 (0.115)	391 (0.051)	7,643 (1.000)

Note: Observed number of transitions from state at *t*–1 (rows) to state at *t* (columns), with relative transition frequencies expressed as proportions in parentheses.

The procedure consists of a series of steps outlined below and depicted in Fig. S1 (an extended version of Fig. 4 in the article):

1. Specify and estimate the underlying statistical model.
2. Make assumptions about the distribution of values for all exogenous predictor variables for the first year of simulation and about future changes. In this paper, we base the simulations for the predictor variables on the SSPs, described in Section S2.
3. Draw a realization of the country-fixed effects based on the estimate from the multilevel mixed-effects logistic model.
4. Draw a realization of the coefficients of the multinomial logit model based on the estimated coefficients and the variance-covariance matrix for the estimates.
5. Start simulation in first year. The first simulated year is 2014, using starting values from 2013.
6. Calculate the probabilities of transition between conflict levels (as illustrated in Table S6) for all countries for the first year, based on the realized coefficients and the projected values for the predictor variables.
7. Randomly draw whether a country experiences minor or major conflict, based on the estimated transition probabilities.
8. Update the values for the explanatory variables. A number of these variables, most notably those measuring historical experience of conflict and the neighborhood conflict variables, are contingent upon the outcome of step 7.
9. Repeat (5) – (7) for each year in the forecast period, e.g., for 2014–2100, based on predictor values updated based on the outcome of (7), and record the simulated

outcomes. Repeat forty times to even out the impact of individual realizations of the transition probabilities.

10. Repeat (4) – (9) fifteen times to even out the impact of individual realizations of the multinomial logit coefficients.
11. Repeat (3) – (10) fifteen times to even out the impact of individual realizations of the country-specific intercepts.

In total, we get 40 × 15 × 15 = 9,000 simulated outcomes for each year for each country.

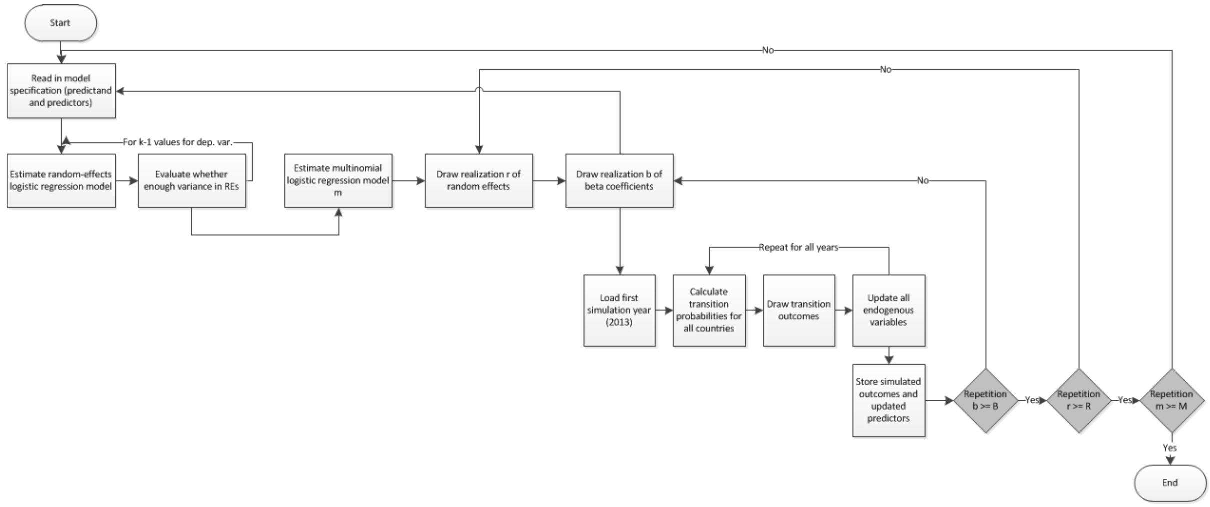

Figure S1. Flow chart of the simulation procedure.

Fig. S1 shows the structure of the general simulation procedure we use. The program reads in the model specification (the multinomial regression model shown in Table S3), estimates separate random-effects models for the *k*-1=2 conflict levels, and estimates the multinomial regression model. The procedure draws *R* realizations of the random effects and *B* realizations of beta coefficients. For each *r*b* combination of realizations, it runs a number of simulations from the first year (2013) to the last (2100), as described above. The procedure allows for running and averaging over *M* different models, but model averaging is not applied in this project.

The simulation procedure has many methodological advantages. Most importantly, it allows modeling the dynamic nature of armed conflicts: If a new conflict is simulated to break out in country *i* in year *t*, the procedure accounts for the fact that this increases the risk of future conflict in that country and its neighbors for decades afterwards. The procedure draws multiple realizations of the model parameters as given by the vector of coefficients (reported in Table S3) and the variance-covariance matrix (Table S5). This allows representing the uncertainty in the statistical estimates underlying the simulations. This uncertainty and the uncertainty originating in drawing outcomes from the estimated transition probability matrix (as illustrated in Table S6) are reflected in the gradually widening prediction intervals shown in Figs. 3 and S10.

Another major advantage is that the procedure allows interpreting the estimated model parameters jointly taking problems with multicollinearity into account. Step 4 in the list above is very close to the procedure in the Clarify software (Tomz et al. 2003) [20], which was designed to handle similar problems.

S4.2 Projections used in the simulation stage

All conflict variables are treated as endogenous variables, and their values are updated in the course of each simulation. This applies to the conflict history dummies (c1, c2), time since the previous conflict (ltsc0), and the neighborhood conflict indicators (nc, ltsnc). Time since independence (ltimeindep) is updated by running a new calculation every year before log transforming. Unlike the historical regression models (Table S3), the simulations do not include any decade dummies but instead assume that the intercept in the future will be similar to the 2000–13 reference category.

The GDP per capita projections were developed by a team at the OECD [21]. The OECD ENV-Growth model is an augmented Solow growth model that takes into account human capital and income from fossil fuels. The model ignores institutional factors that may affect growth performance (beyond time-invariant country effects). We make a few adjustments to the projections as documented in Section S8.

We use version 1.0 of the population projections from IIASA [22]. A newer version 1.1 has been published [23], but the authors recommend using version 1.0 together with the OECD model because the version 1.0 data also is used as input to the OECD-ENV model. We make a few adjustments to the projections as documented in Section S8.

For the education (YMHEP) variable, we use data from the Wittgenstein Centre for Demography and Global Human Capital [23]. We use version 1.1 of this dataset to facilitate matching to the historical data. Details regarding the matching procedure as well as documentation of a few adjustments are given in Section S8.

S5 Out-of-sample evaluation

Table S7 shows the results from an out-of-sample evaluation of the predictive performance of the model as compared to a set of alternative models. We estimated the model corresponding to Model 1 reported in Table S3 for all countries over the 1960–2000 period and ran the simulations as described above for the 2001–13 period (again, for all countries). We then compared the proportion of simulated conflicts (minor or major) for every country for every year 2010, 2011, 2012, and 2013 with the actual occurrence of conflict in these countries. These results are reported as `model 1' in Table S4. The evaluation of Model 2, Table S3 is reported in row 2, and those of nine other models in the remaining rows.

For the evaluation, we construct three dichotomous outcome variables: No conflict vs. conflict, minor conflict vs. not minor conflict, and major conflict vs. minor or no conflict. For each of these outcomes, we report Brier and AUC scores. Models that predict well out of sample obtain low Brier scores and high AUC scores (see [24, 25] for an introduction to these measures). Brier scores cannot be less than 0 and AUC scores cannot be larger than 1. It is, however, somewhat misleading to claim that the AUC scores of 0.90 we obtain constitute very good predictions since they to some extent reflect that any model could do well by simply predicting 'no conflict'. For similar reasons, the scores are comparable across models within the same predicted outcome (no conflict, minor conflict major conflict), but not across different outcomes, since the metrics depend on the distribution of the outcome variables. We report how the 11 models are ranked for each of the six metrics. In order to provide a rough summary of them, we also calculate the sum of ranks in the right-most column of Table S7.

Models 3–11 deviate from Model 1 in various ways. In Model 3, we removed GDP per capita (but left education/YMHEP in). In Model 4, we removed both GDP per capita and and YMHEP. In Model 5, we retained GDP per capita as a main term but removed the interactions and the YMHEP variable. In Model 6, we retained GDP per capita and education as main terms but removed the interactions. Model 7 is Model 1 without log population. Model 8 is Model 1 without decade dummies, and Model 9 is without Time since independence. In Model 10 we removed several terms. Lastly, in Model 11 we added to Model 1 a variable that records the annual deviation from each country's average temperature for the 1970–2000 period, based on data generated through PRIO-GRID [26]. The temperature term was not statistically significant in either equation in the multinomial model, and the out-of-sample predictive performance of Model 11 is uniformly worse than Model 1 across all outcomes and metrics.

Table S7. Out-of-sample evaluation of predictive performance, 2001–2013

Model	Description	No conflict		Minor conflict		Major conflict		Sum of ranks
		Brier	AUC	Brier	AUC	Brier	AUC	
1	Final Model (FM) (Model 1)	.08445 (3)	.90116 (2)	.07911 (4)	.8799 (2)	.03386 (6)	.8516 (3)	20
2	FM without education (Model 2)	.08190 (1)	.9014 (1)	.07711 (1)	.8821 (1)	.03540 (10)	.8502 (4)	18
3	FM without GDP per capita	.08473 (6)	.8936 (7)	.08080 (8)	.8662 (6)	.03297 (3)	.8490 (5)	35
4	FM without GDP per capita and education	.08399 (2)	.8974 (4)	.07956 (5)	.8666 (4)	.03353 (5)	.8343 (10)	30
5	FM without education and GDP per capita interactions	.08449 (5)	.8937 (6)	.07888 (3)	.8665 (5)	.03195 (1)	.8425 (9)	29
6	FM without GDP per capita interactions	.08577 (8)	.8964 (5)	.08216 (11)	.8621 (9)	.03248 (2)	.8482 (7)	42
7	FM without population	.08943 (9)	.8836 (11)	.07960 (6)	.8667 (3)	.03333 (4)	.8336 (11)	44
8	FM without decade dummies	.09143 (11)	.8912 (9)	.08191 (10)	.8596 (10)	.03604 (11)	.8524 (2)	52
9	FM without time since independence	.08446 (4)	.8922 (8)	.07862 (2)	.8634 (8)	.03449 (8)	.8460 (8)	38
10	FM without interactions, time since independence, decade dummies	.09000 (10)	.8884 (10)	.08121 (9)	.8544 (11)	.03495 (9)	.8580 (1)	50
11	FM with temperature deviation	.08500 (7)	.8977 (3)	.08052 (7)	.8634 (7)	.03429 (7)	.8483 (6)	37

Note: Area under the ROC curve (AUC) and Brier scores for the model used in simulations compared with a set of alternative models. Ranks are given in parentheses. Models were trained for 1960–2000 period and evaluated against 2001–2013.

Overall, our two preferred models do better than the others across the various metrics. Model 2 produces the best predictions for no conflict and minor conflict according to both the Brier and AUC scores. Model 1's Brier score for major conflict is among the worst, however. The fact that Model 1 performs poorly for major conflict should be seen in light of the low number of major conflicts in the evaluation period, so the score is quite uncertain. Model 1 never obtains the best score, but does well across all outcomes.

Removing terms from the model clearly hurts predictive performance. The models without decade dummies perform the worst, and removing the population term also hurts prediction.

In [13] we explore a larger set of terms that were not included here. Most important among these are variables denoting oil dependence and the ethnic composition of the country. Since we only have time-invariant data for these predictors, the country-specific random effects included here account for such variation between countries.

S6 Review of the predictors under each of the SSPs

Fig. S2 shows observed population, 1970–2013, and projected population, 2014–2100, for each SSP and for each of nine regions. The definitions of the regions are given in Table S12 below. Global population growth is highest in the Fragmentation (SSP3) and Inequality (SSP4) pathways, and lowest in the Sustainability (SSP1) and Conventional Development (SSP5) pathways. The difference is particularly marked in Central and South Asia and in Africa. SSP 2 is an intermediate scenario.

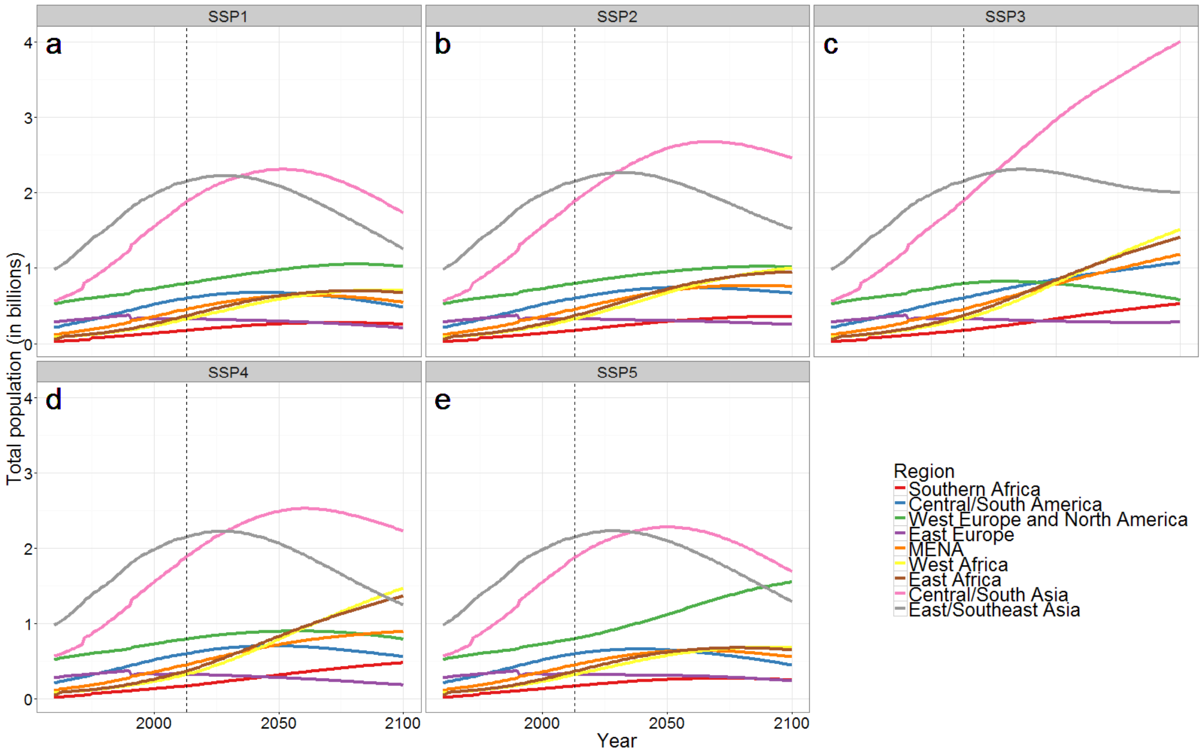

Figure S2. Total population by region and SSP.

Fig. S3 shows observed and projected GDP per capita broken down by region and SSP. GDP per capita growth is highest in SSP5; in 2100, the OECD-ENV model projects all regions to have considerably higher average GDP per capita than current levels in Western Europe and North America. This is also the case for SSP1, although growth is markedly lower. SSP3 has the slowest growth in global average GDP per capita. In SSP4, some regions grow as fast as in SSP1, but regions that are currently poor grow at rates similar to those in SSP3. The Middle-of-the-Road scenario (SSP2) has growth rates only slightly lower than SSP1 and similar to historical trajectories.

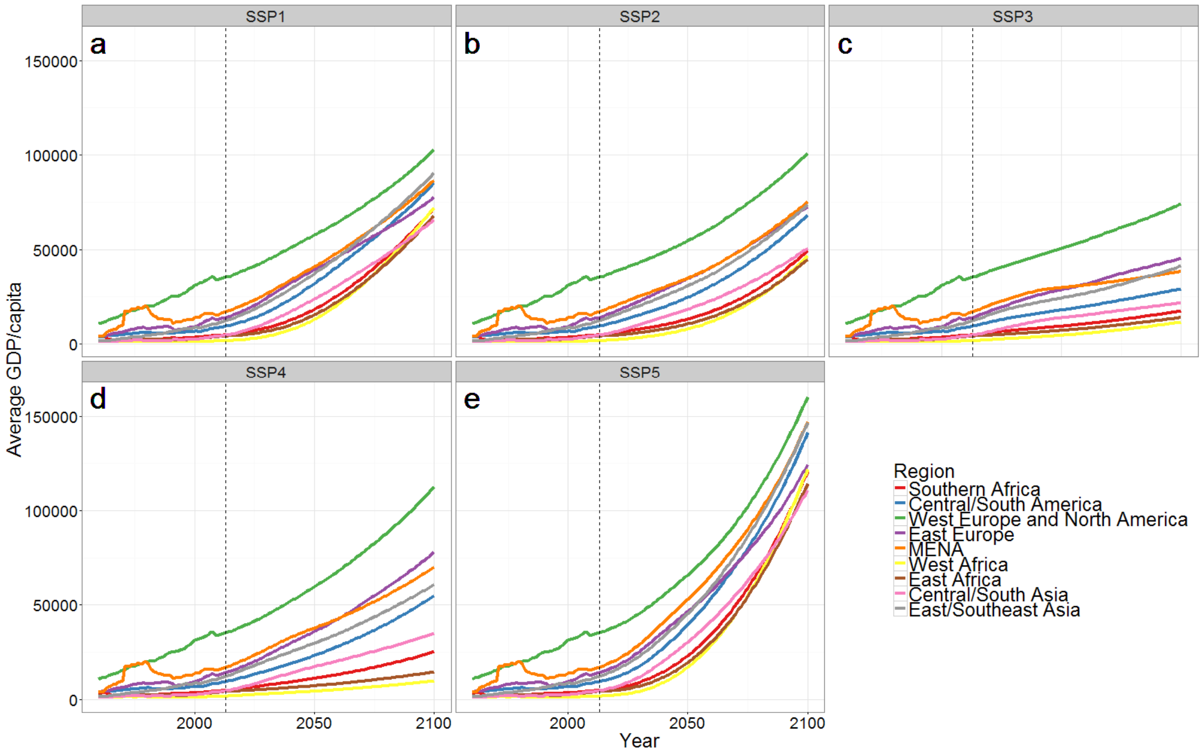

Figure S3. Country average GDP per capita (2005 USD PPP) by region and SSP.

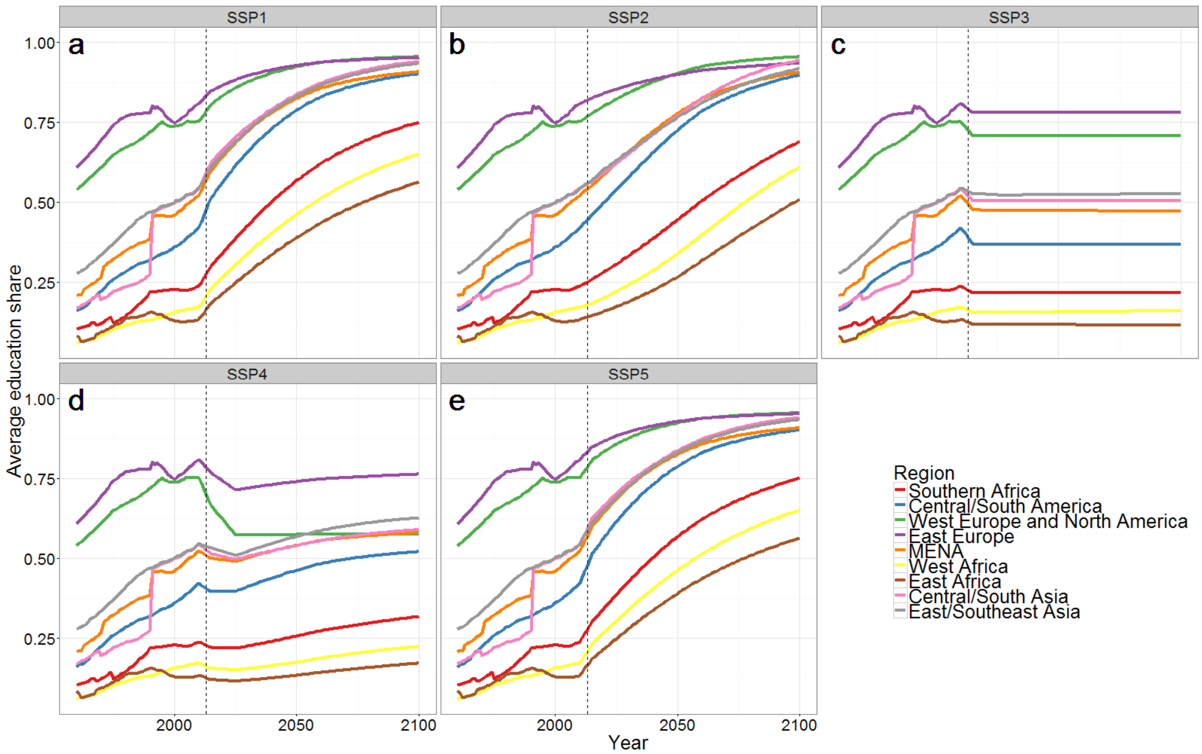

Figure S4. Share of males, age 20-24, with secondary education or higher by region and SSP.

Fig. S4 shows the corresponding observed and projected data for secondary education attainment. In SSP1, SSP2, and SSP5, all regions make substantial progress toward universal secondary education. In SSP3 and SSP4, however, education attainment rates are held virtually constant at levels observed several years period to the beginning of the simulation, hence the notable drop in education attainment in the initial simulation years for these scenarios. Moreover, in SSP4 the extent of this backdating depends on prior levels of education attainment, where more developed countries experience a relatively larger drop. See [27] for a complete description.

S7 Additional simulation results

In this section, we present simulation results broken down at the country level. Figures S5–S9 and S12–S16 display projected risk in the form of maps for each SSP for Models 1 and 2, respectively. All maps were generated using R and ggplot2, while the maps come from the cshapes-package [28,29]. Tables S8 and S9 report the mean point estimates for the probabilities underlying these maps.

S7.1 Model 1 (including education)

This section reports projected conflict risks based on the model that includes both GDP per capita and education attainment (Model 1 in Table S3, the same model as reported in the article).

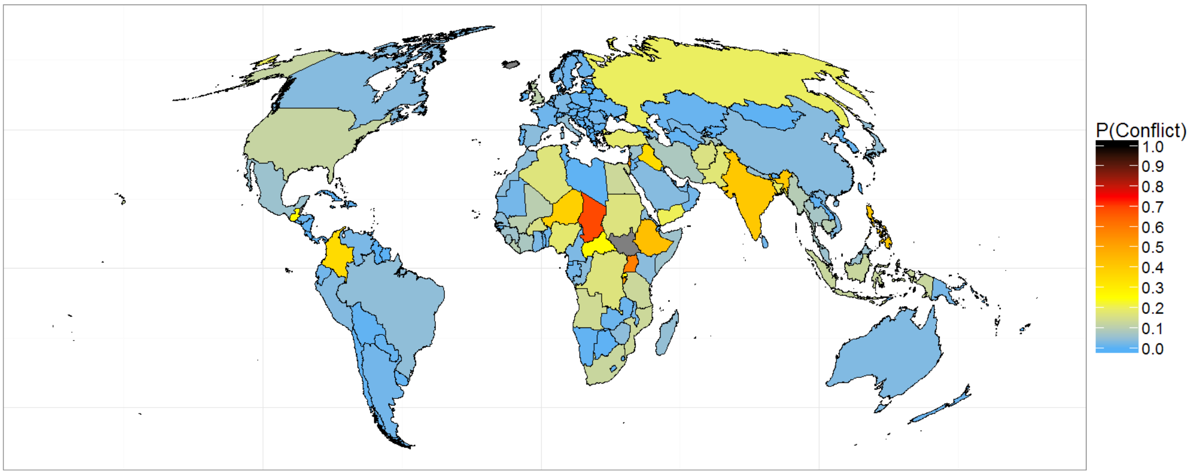

Figure S5. Projected probability of conflict in 2100, SSP1, Model 1.

Figure S5 shows country-level projected risk of minor or major armed conflict at the end of the century given the SSP1 pathway. Most countries have moderate projected conflict risks, including several African countries such as Somalia, Senegal, DR Congo, and Madagascar. The exceptions are a few landlocked or high-population countries, all of them with very violent conflict histories up to 2013, such as Niger, Chad, Ethiopia, India, and Israel, all of which have conflict in 2100 in more than a third of the simulations.

Fig. S6 shows that the corresponding projected probabilities of conflict for SSP2 are slightly higher than for SSP1, but with about the same global distribution.

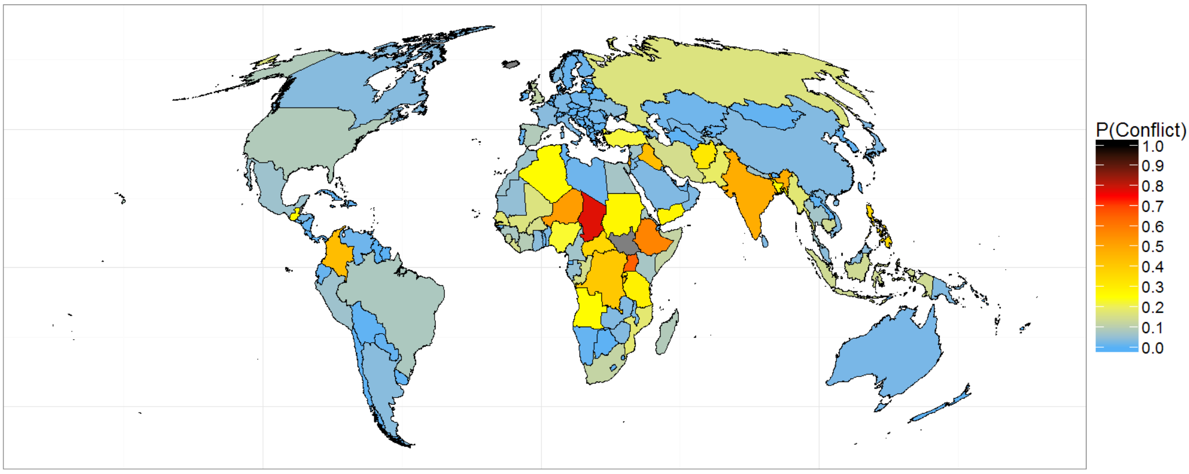

Figure S 6. Projected probability of conflict in 2100, SSP2, Model 1.

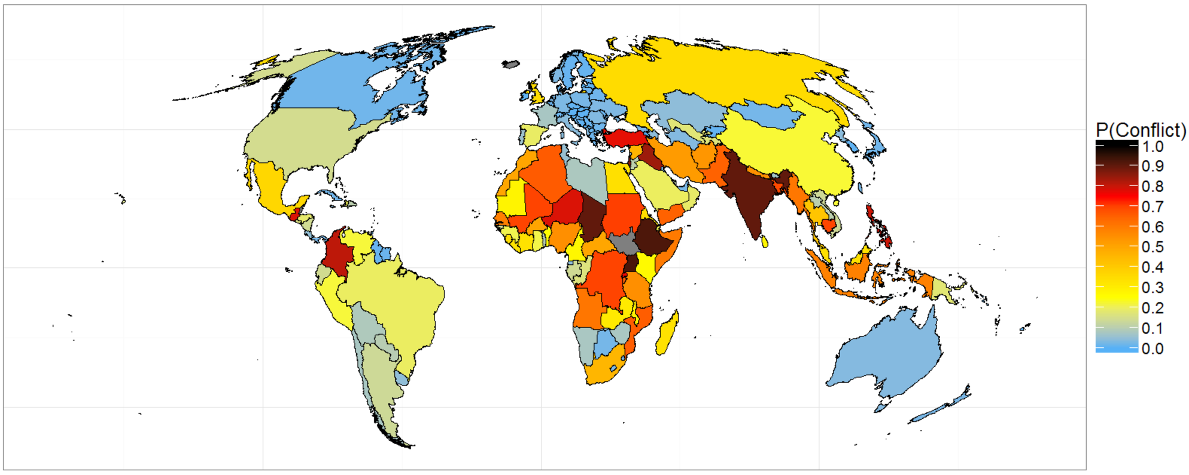

Figure S7. Projected probability of conflict in 2100, SSP3, Model 1.

Fig. S7 reports the projected probabilities given the Fragmentation pathway (SSP3). Here, the projected incidence of conflict is much higher in the developing world than in the previous two SSPs. Conflict propensities are extremely high (i.e., conflict in more than two-thirds of the simulations) in several countries, e.g., Chad, Sudan, Uganda, Ethiopia, and India. Conflict is also likely in many other countries, including Brazil, Russia, Iran, and China. We project a low risk of conflict in North Korea for this SSP as well as all the others. North Korea is a small country in a stable neighborhood with no recent armed conflict. In addition, the data and projections for the country are highly uncertain and possibly overestimate its level of socioeconomic development.

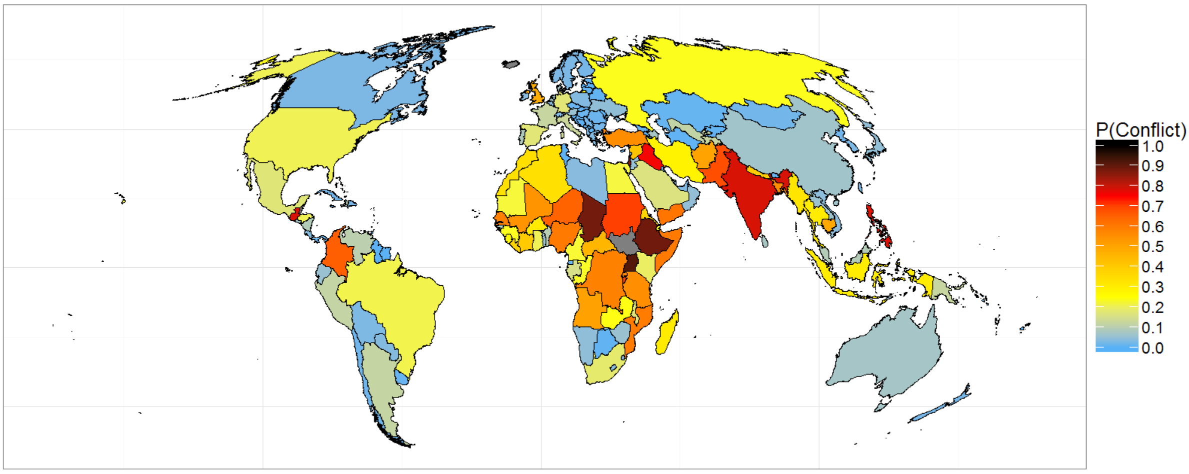

Figure S8. Projected probability of conflict in 2100, SSP4, Model 1.

Fig. S8 shows end-of-century conflict risk for the Inequality pathway (SSP4). In this scenario, projected risks are extremely high for many of the countries that are considered at some risk in other scenarios, such as Chad, Sudan, Uganda, Ethiopia, and India. Because of the more favorable growth trajectories projected for countries that are currently becoming firmly embedded in the global economy, other countries have lower risks of conflict. The lower conflict risk compared to SSP3 is particularly marked for Mexico, South Africa, Vietnam, and China.

Fig. S9 shows projected conflict risks for the Conventional Development pathway. Conflict risks in 2100 are very low in most countries. Main exceptions are countries that have had atypically high levels of conflict up to 2013. Since we include country-specific intercepts in the model, countries such as Chad, Ethiopia, Iraq, Israel, and the Philippines continue to have a relatively high likelihood of armed conflict.

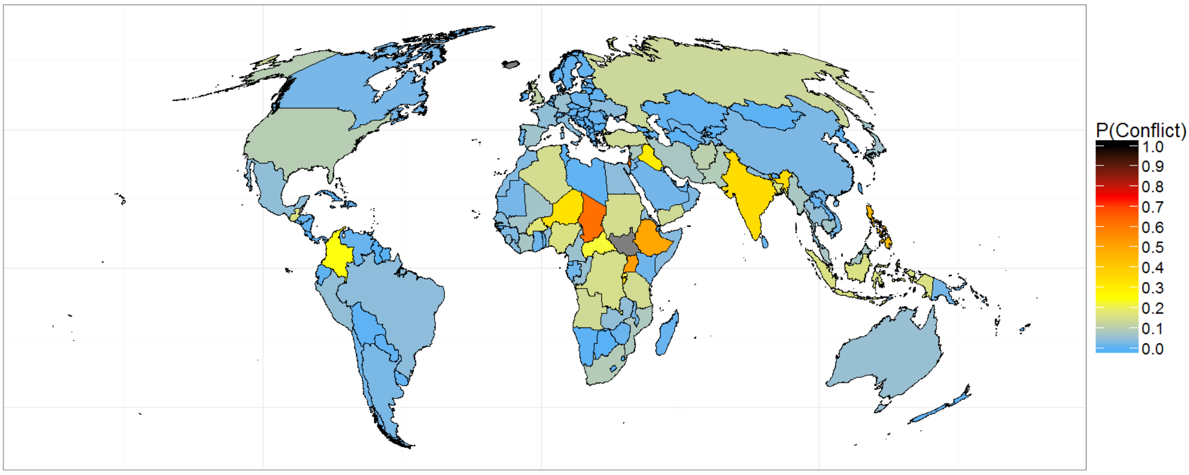

Figure S9. Projected probability of conflict in 2100, SSP5, Model 1.

Table S8 gives a complete list of simulated conflict risk in 2100 for all sample countries, sorted alphabetically. For several countries, the gap in estimated probability between the best (typically SSP5) and the worst (most often SSP3) scenario exceeds an order of magnitude (e.g., Nepal and Senegal).

Table S8. Projected probability of armed conflict in 2100 by country and SSP, Model 1

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Afghanistan	11.8	24.8	46.3	43.1	7.2
Albania	0.6	1.2	2.9	2.8	0.6
Algeria	14.3	24.9	65.2	33.8	12.2
Angola	14.8	28.1	65.0	54.3	14.6
Argentina	1.8	3.9	13.6	11.5	2.4
Armenia	0.3	0.5	0.4	0.7	0.2
Australia	2.7	1.9	3.2	6.1	4.9
Austria	0.9	0.4	0.4	5.4	0.8
Azerbaijan	2.6	2.3	3.7	6.7	1.4
Bahrain	1.1	0.6	5.0	0.8	0.5
Bangladesh	17.0	23.4	68.5	55.5	14.0
Belarus	0.6	0.5	1.6	0.6	0.9
Belgium	1.6	0.3	1.3	3.5	0.7
Benin	1.6	2.8	24.6	10.2	4.5
Bhutan	0.5	0.4	5.8	1.0	0.4
Bolivia	0.6	0.6	7.7	3.1	0.5
Bosnia and Herz.	0.4	0.3	0.6	0.5	0.4
Botswana	0.4	0.5	2.0	0.6	0.2
Brazil	4.0	7.4	19.5	21.5	3.6
Bulgaria	0.7	0.8	1.7	1.9	0.4
Burkina Faso	16.4	15.5	49.2	30.9	17.4
Burundi	51.2	42.6	64.9	70.3	33.2
Cambodia	8.8	12.6	68.0	48.3	6.3
Cameroon	2.5	6.3	26.8	22.9	5.4
Canada	3.1	2.8	1.8	2.3	2.1
Cape Verde	0.4	0.3	1.9	0.8	0.2
Central Afr.Rep.	23.9	33.5	44.7	42.1	21.1
Chad	65.2	75.3	88.9	86.9	58.7
Chile	0.6	0.5	6.8	1.5	1.5
China	3.4	3.3	22.7	6.3	2.4
Colombia	30.1	39.6	79.2	61.8	21.3
Comoros	2.1	3.7	12.5	9.5	2.1
Congo	3.8	15.0	15.7	23.9	5.1
Congo, DRC	13.6	35.0	64.9	51.9	12.4
Costa Rica	0.3	0.7	4.1	2.9	0.4
Cote d'Ivoire	7.9	9.4	33.6	40.0	7.3
Croatia	1.5	2.1	1.8	0.9	0.7
Cuba	0.5	0.8	1.6	2.0	0.4
Cyprus	0.3	0.4	0.8	0.3	0.4
Czech Republic	0.8	0.9	0.7	0.9	0.6
Denmark	0.8	0.7	1.7	6.9	1.4
Djibouti	2.1	2.0	19.9	22.6	1.9
Dominican Republic	0.7	0.9	8.9	2.2	0.8
Ecuador	1.5	1.0	13.7	5.3	0.6
Egypt	12.4	6.5	32.8	22.5	3.9
El Salvador	0.9	1.3	15.0	6.2	0.8
Equatorial Guinea	0.4	0.4	4.1	1.5	0.3
Eritrea	3.9	7.2	35.6	38.2	4.3
Estonia	0.4	0.4	0.8	0.9	0.5
Ethiopia	35.7	51.6	90.5	87.0	41.7
Fiji	0.2	0.3	0.9	0.4	0.2

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Finland	1.3	1.4	0.8	1.9	0.8
France	1.6	3.7	7.0	11.8	4.3
Gabon	2.1	4.9	13.7	14.9	1.8
Georgia	0.4	1.0	2.5	1.0	0.7
Germany	2.5	2.4	2.4	16.2	5.3
Ghana	2.6	4.1	22.8	22.3	1.6
Greece	0.5	0.9	1.4	3.2	1.2
Guatemala	23.8	25.8	77.6	78.5	14.3
Guinea	6.5	7.4	21.4	25.3	2.7
Guinea-Bissau	0.4	1.1	12.9	8.7	0.4
Guyana	0.1	0.2	1.0	0.4	0.1
Haiti	3.7	4.4	21.3	10.1	1.5
Honduras	1.5	2.8	18.6	21.0	1.1
Hungary	0.5	0.8	0.5	1.3	1.2
India	35.4	44.4	88.8	76.3	30.1
Indonesia	13.8	15.4	62.6	32.9	16.4
Iran	6.7	13.1	50.7	26.8	5.9
Iraq	30.9	40.2	83.2	73.4	26.3
Ireland	0.6	0.6	0.6	3.6	0.3
Israel	53.8	47.9	86.8	86.3	61.9
Italy	4.0	2.6	4.0	11.5	3.2
Jamaica	0.3	0.4	3.8	0.6	0.3
Japan	4.2	2.3	1.5	4.1	5.5
Jordan	1.1	2.5	10.1	4.8	2.2
Kazakhstan	1.1	1.4	4.5	1.1	0.9
Kenya	3.4	6.7	25.6	19.5	1.6
Kosovo	0.4	0.3	0.5	0.4	0.3
Kuwait	0.7	0.7	2.2	1.5	0.4
Kyrgyzstan	0.5	1.0	0.8	0.8	0.5
Laos	0.5	0.6	9.5	5.6	0.9
Latvia	0.3	0.6	0.6	0.3	0.8
Lebanon	1.0	0.8	7.3	3.3	1.0
Lesotho	0.7	0.7	2.4	3.7	0.4
Liberia	9.0	13.0	29.4	33.6	3.5
Libya	0.5	1.2	6.6	3.2	0.6
Lithuania	0.3	0.3	1.6	0.7	0.3
Luxembourg	0.4	0.2	0.6	1.4	0.2
Macedonia	0.3	0.8	1.1	0.6	0.6
Madagascar	4.6	8.4	31.6	29.0	1.1
Malawi	2.1	2.6	28.7	16.4	2.0
Malaysia	3.7	2.9	27.4	6.6	4.9
Mali	8.1	13.5	66.1	51.0	5.4
Mauritania	1.7	4.3	25.8	21.5	2.0
Mauritius	0.3	0.2	2.3	1.3	0.3
Mexico	5.3	6.1	36.1	17.3	4.1
Moldova	0.4	0.3	1.2	0.6	0.3
Mongolia	0.5	0.8	2.0	1.8	0.5
Montenegro	0.2	0.3	0.4	0.5	0.5
Morocco	4.3	6.2	51.1	35.6	3.3
Mozambique	10.5	15.7	62.0	55.2	6.3
Myanmar	6.9	13.4	54.4	27.8	5.4

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Namibia	0.6	0.9	8.0	4.5	0.4
Nepal	5.0	5.7	52.4	37.0	4.0
Netherlands	1.9	0.6	2.3	6.2	1.3
New Zealand	0.9	0.3	2.1	1.8	0.4
Nicaragua	0.8	1.1	14.9	10.0	0.7
Niger	36.6	49.9	77.2	62.4	32.5
Nigeria	16.1	20.4	52.5	56.0	13.9
North Korea	0.6	0.9	3.7	1.7	0.5
Norway	2.2	3.1	2.7	2.7	0.8
Oman	1.8	2.8	17.8	4.2	2.8
Pakistan	15.9	17.5	63.1	66.9	7.5
Panama	0.8	0.8	2.3	1.5	0.8
Papua New Guinea	2.1	3.2	17.9	12.3	2.0
Paraguay	1.0	0.8	9.3	3.3	0.6
Peru	2.7	5.2	17.8	9.0	4.0
Philippines	44.9	41.0	81.6	80.5	48.0
Poland	0.9	1.7	2.3	3.0	1.6
Portugal	0.9	0.8	5.1	7.5	1.4
Qatar	0.4	0.4	9.9	3.2	0.4
Romania	1.8	1.3	2.9	1.2	1.0
Russia	19.4	15.9	31.6	22.4	12.0
Rwanda	24.2	30.3	74.9	56.8	20.3
Saudi Arabia	3.0	2.8	19.6	15.5	1.7
Senegal	4.1	17.2	58.9	59.6	3.7
Serbia	1.1	1.1	1.2	1.9	0.6
Sierra Leone	7.2	12.8	35.1	28.9	4.3
Singapore	0.4	0.4	0.6	0.4	0.4
Slovakia	0.6	0.9	0.5	0.8	1.1
Slovenia	0.2	1.6	0.4	0.4	0.4
Solomon Is.	0.2	0.3	1.8	1.3	0.3
Somalia	4.3	8.3	53.0	53.8	2.4
South Africa	9.6	9.8	43.3	17.2	7.4
South Korea	0.9	0.8	0.6	2.2	1.1
Spain	4.1	9.3	20.8	18.7	6.8

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Sri Lanka	2.6	4.3	31.8	8.4	2.1
Sudan	15.2	26.2	68.7	68.2	13.4
Suriname	0.3	0.3	1.3	0.3	0.3
Swaziland	0.6	0.4	2.3	4.0	0.4
Sweden	1.4	1.0	0.9	2.6	1.0
Switzerland	0.5	0.7	1.1	2.6	1.0
Syria	5.1	5.3	40.3	37.0	6.4
Taiwan	0.6	0.6	2.0	2.2	0.7
Tajikistan	7.0	5.5	14.7	10.9	2.3
Tanzania	12.9	29.1	54.7	54.4	13.9
Thailand	5.0	4.8	35.3	24.6	3.5
The Gambia	0.4	0.6	9.3	6.4	0.5
Timor Leste	0.4	0.4	4.0	5.2	0.3
Togo	0.9	1.4	9.4	6.5	0.9
Trinidad and Tobago	0.2	0.2	1.3	0.4	0.2
Tunisia	0.9	0.9	5.7	0.7	0.4
Turkey	14.7	18.6	73.2	49.9	10.1
Turkmenistan	0.7	0.5	3.0	0.7	0.4
Uganda	53.7	61.2	91.2	90.2	46.9
Ukraine	0.9	3.8	2.9	4.1	4.0
United Arab Emirates	2.2	1.1	1.8	2.6	1.0
United Kingdom	12.1	12.9	39.2	50.8	12.4
United States	11.0	8.4	14.0	20.5	9.4
Uruguay	0.7	0.5	4.3	1.0	0.7
Uzbekistan	2.3	2.5	16.0	10.9	1.5
Venezuela	2.3	1.2	22.0	9.8	1.1
Vietnam	3.3	3.3	13.0	4.0	1.7
Yemen	20.5	26.1	62.4	58.3	13.9
Zambia	1.3	3.1	30.3	24.6	4.5
Zimbabwe	4.4	2.9	7.2	5.3	1.1

S7.2 Model 2 (excluding education)

Fig. S10 visualizes the aggregate global results from the simulation without education (Model 2) and is analogous to Fig. 2 in the article that is based on Model 1. Overall, the projected risks are lower since GDP per capita, which is assumed to grow monotonically across all scenarios, has a much larger estimated effect in the absence of education. This is especially clear for SSP3 and SSP4, which have very pessimistic expectations for education levels.

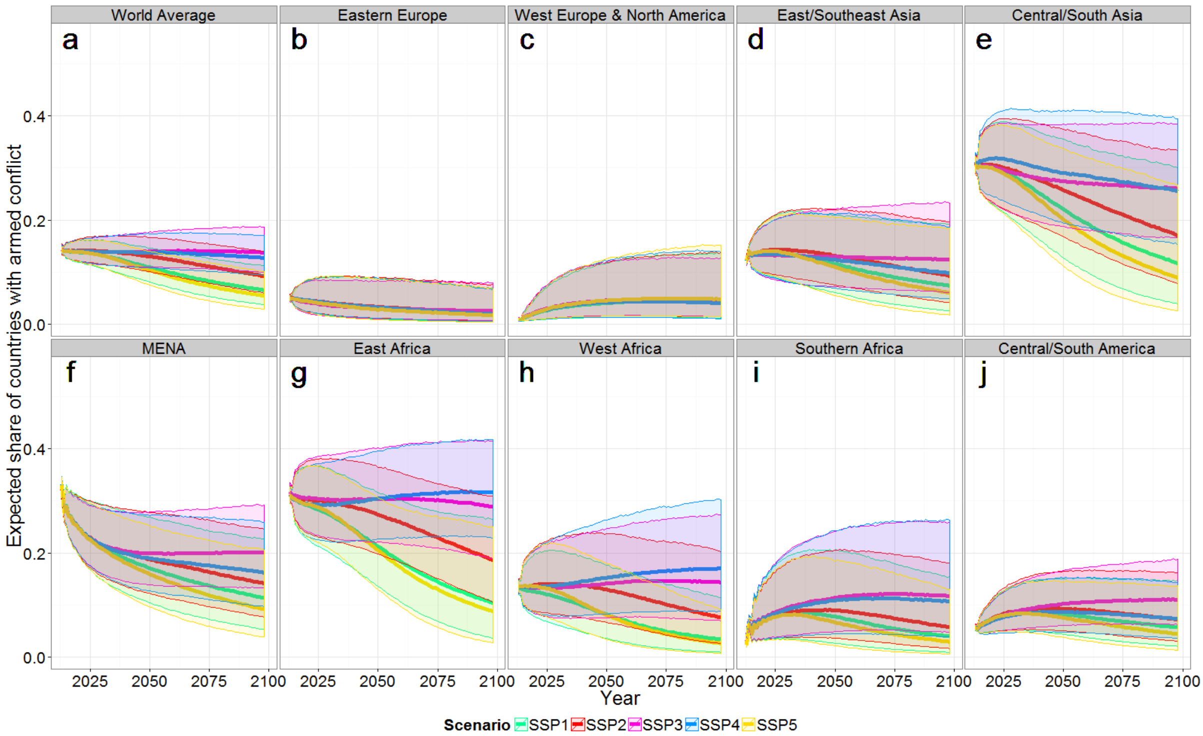

Figure S10. Projected proportion of countries in armed conflict by scenario and year, 2014–2100, Model 2. Panel **a** shows the world average results; panels **b–j** show regionally disaggregated estimates. Shaded areas represent the 50% prediction intervals.

Fig. S11 shows the difference in estimated end-of-century conflict risk between SSP3 and SSP1. The figure is comparable to Fig. 3 in the main article, but is based on Model 2 without education. Since the average incidence of conflict is lower, Fig. S11 indicates a more modest difference between the two pathways. Given this model, the countries that benefit the most from the more optimistic Sustainability pathway are those that currently have very low levels of GDP per capita and recent conflict histories (e.g., Chad, Ethiopia, and Iraq).

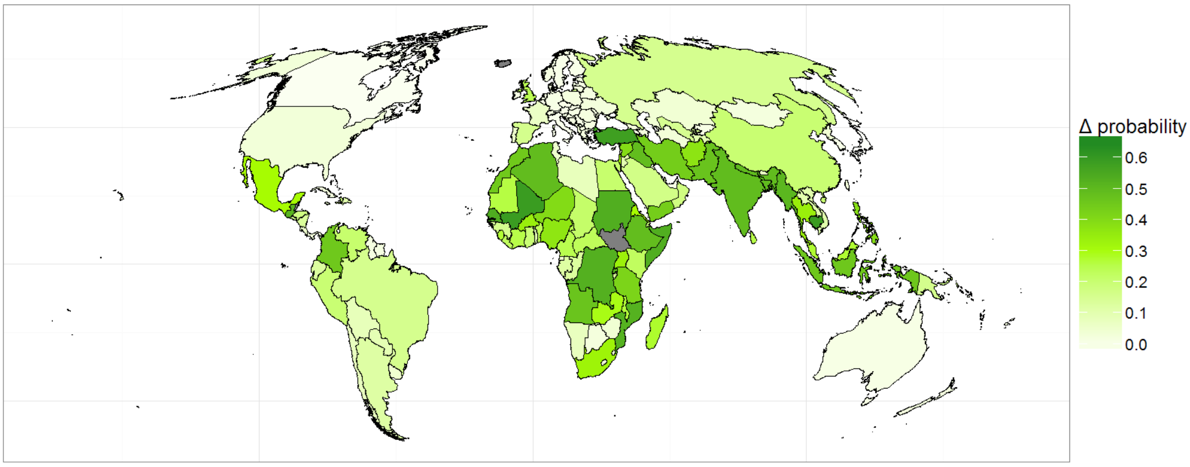

Figure S11. Map of country-specific differences in estimated conflict risk between SSP1 and SSP3 in 2100, Model 2. Darker shades indicate larger benefits in terms of reduced conflict risk by shifting from the adverse regional Fragmentation scenario (SSP3) to a sustainable growth scenario (SSP1). Countries in grey have insufficient historical data to be included in the forecasting model.

Figs. S12–S16 show end-of-century projected conflict risks for each country for each of the SSPs, based on Model 2. Table S9 reports the same information in tabular form.

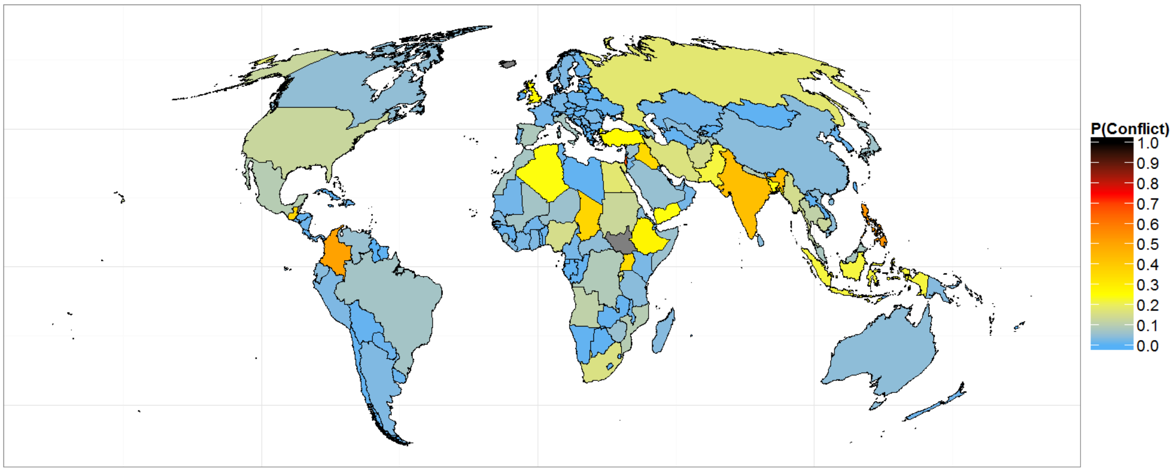

Figure S12. Projected probability of conflict in 2100, SSP1, Model 2.

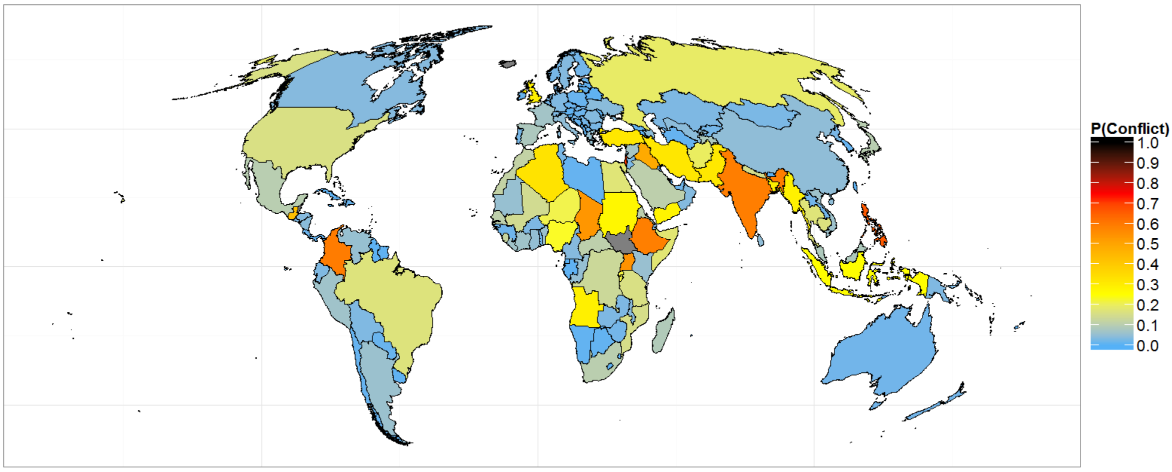

Figure S13. Projected probability of conflict in 2100, SSP2, Model 2.

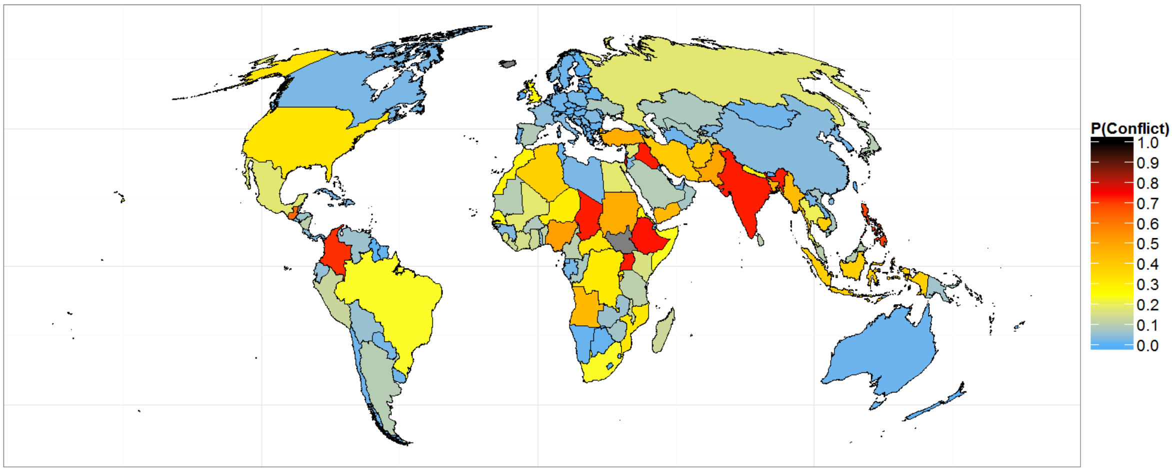

Figure S14. Projected probability of conflict in 2100, SSP3, Model 2.

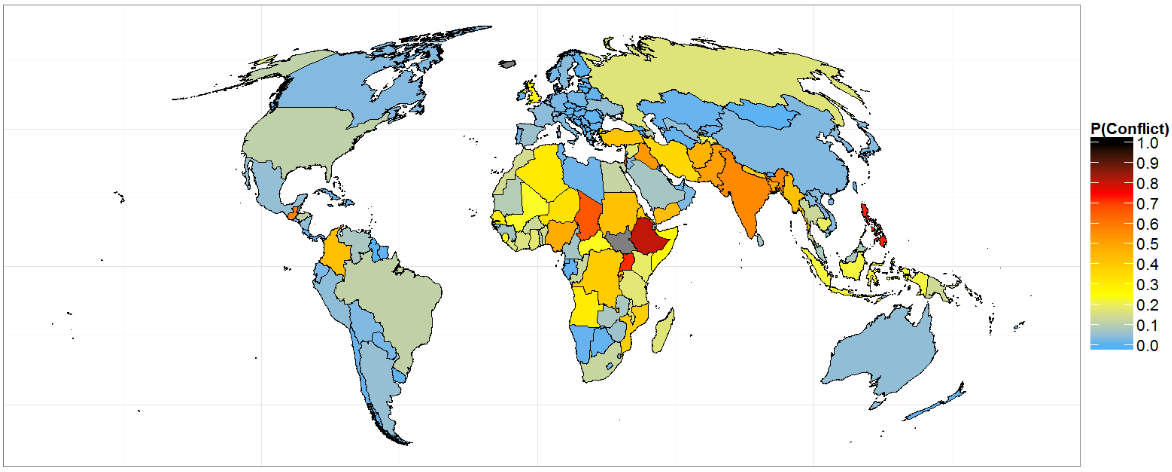

Figure S15. Projected probability of conflict in 2100, SSP4, Model 2.

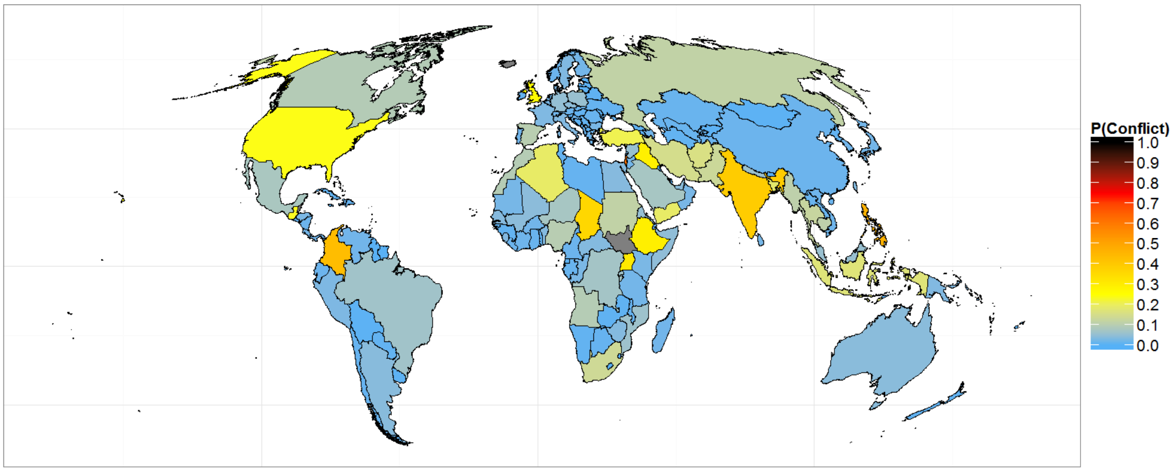

Figure S16. Projected probability of conflict in 2100, SSP5, Model 2.

Table S9. Projected probability of armed conflict in 2100 by country and SSP, Model 2.

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Afghanistan	14.3	19.9	40.0	46.1	15.8
Albania	0.9	0.6	0.7	2.6	0.9
Algeria	24.8	32.8	37.8	30.8	19.2
Angola	10.9	29.0	43.9	30.1	9.4
Argentina	3.0	5.8	9.5	5.1	3.7
Armenia	0.7	0.6	1.6	0.4	0.3
Australia	4.3	1.8	1.5	4.9	4.0
Austria	1.3	0.6	1.0	1.4	1.5
Azerbaijan	4.8	4.5	8.8	8.7	1.9
Bahrain	2.0	0.5	0.8	0.5	0.4
Bangladesh	24.7	29.7	45.9	49.1	18.6
Belarus	0.8	0.5	0.8	0.9	0.6
Belgium	3.7	1.8	1.2	4.5	2.5
Benin	1.5	5.7	11.3	13.8	3.3
Bhutan	0.6	0.4	0.6	0.4	0.3
Bolivia	1.0	3.1	5.4	3.0	0.5
Bosnia and Herz.	0.8	0.8	1.7	0.5	0.3
Botswana	0.5	0.7	1.0	0.8	1.0
Brazil	7.0	16.7	24.0	11.2	6.7
Bulgaria	1.4	2.5	1.1	1.2	2.3
Burkina Faso	1.7	2.8	8.5	12.9	1.8
Burundi	19.4	22.1	45.0	49.2	7.1
Cambodia	12.9	16.4	38.2	19.7	10.9
Cameroon	2.2	3.6	10.7	6.9	1.4
Canada	4.8	3.7	2.5	3.3	9.3
Cape Verde	0.4	0.5	0.5	0.3	0.2
Central Afr. Rep.	4.6	10.7	32.5	24.5	3.3
Chad	36.4	53.7	73.7	67.0	36.2
Chile	0.9	0.9	1.6	1.0	1.1
China	4.0	4.6	3.8	3.3	1.5
Colombia	50.5	59.6	72.2	42.7	43.4
Comoros	0.5	0.8	6.1	5.9	0.4
Congo	1.0	5.2	7.7	12.9	2.5
Congo, DRC	8.8	13.2	30.4	39.2	7.0
Costa Rica	0.5	1.3	4.4	1.0	2.0
Cote d'Ivoire	2.5	6.4	15.2	16.3	1.6
Croatia	4.0	1.8	4.9	1.7	1.5
Cuba	0.6	0.7	2.5	1.9	0.9
Cyprus	0.5	0.5	0.6	0.6	0.3
Czech Rep.	1.2	1.5	0.8	0.4	4.4
Denmark	1.2	1.9	1.2	1.2	2.9
Djibouti	2.1	3.6	3.4	4.7	1.4
Dominican Rep.	1.3	1.2	3.2	0.8	0.9
Ecuador	3.7	3.0	5.0	2.6	1.5
Egypt	18.0	17.5	18.5	12.0	3.7
El Salvador	1.6	2.9	4.0	3.6	0.6
Equatorial Guinea	0.5	0.3	0.9	0.4	0.3
Eritrea	4.2	10.5	27.1	39.5	5.1
Estonia	0.5	1.2	0.4	0.6	0.2
Ethiopia	27.6	58.8	74.5	80.6	29.4
Fiji	0.2	0.3	1.3	0.6	0.2
Finland	1.6	2.0	0.6	0.7	2.0
France	2.0	6.9	4.3	4.2	3.1
Gabon	0.8	0.7	2.4	0.9	1.3
Georgia	0.5	0.8	2.3	0.8	0.7
Germany	2.6	3.0	1.8	2.4	5.0
Ghana	2.9	5.1	13.4	18.4	1.2
Greece	0.8	5.3	1.8	2.8	1.6
Guatemala	36.6	42.6	63.3	58.3	24.1
Guinea	1.1	1.6	3.6	7.0	0.8
Guinea-Bissau	0.5	1.6	4.8	4.9	0.6
Guyana	0.2	0.4	0.5	0.3	0.1
Haiti	3.8	1.9	4.0	7.4	1.6
Honduras	1.1	3.6	6.1	11.3	2.5
Hungary	0.8	1.5	1.3	1.0	0.8
India	42.7	59.1	73.8	56.6	39.2
Indonesia	22.6	25.2	37.8	22.5	17.2
Iran	16.5	31.6	39.3	35.8	14.8
Iraq	35.2	48.6	73.8	53.4	29.0
Ireland	1.0	1.2	0.6	1.4	1.0
Israel	67.5	71.2	79.3	67.6	61.3
Italy	7.5	4.7	3.3	3.4	3.2
Jamaica	0.5	0.4	2.3	0.6	0.5
Japan	6.5	10.0	9.7	3.3	2.0
Jordan	2.1	2.6	2.8	3.2	1.9
Kazakhstan	1.9	2.9	8.3	1.2	1.3
Kenya	2.6	5.6	16.2	19.3	2.7
Kosovo	1.3	1.1	1.4	0.8	1.8
Kuwait	1.2	2.4	2.4	0.9	0.6
Kyrgyzstan	0.6	2.1	2.8	1.4	0.5
Laos	0.6	1.7	2.4	3.6	1.2
Latvia	0.4	0.6	0.5	0.6	0.4
Lebanon	2.2	4.7	3.8	4.8	1.6
Lesotho	0.8	0.3	0.9	2.3	0.3
Liberia	3.2	6.6	13.2	16.8	1.4
Libya	0.8	0.9	2.6	1.7	0.9
Lithuania	0.4	0.9	1.0	0.5	0.4
Luxembourg	0.7	0.3	0.6	0.4	0.3
Macedonia	0.5	1.5	1.9	0.8	0.5
Madagascar	3.6	8.8	13.1	17.0	1.8
Malawi	1.7	3.9	12.8	15.9	1.0
Malaysia	7.8	8.3	9.9	8.3	5.6
Mali	6.9	14.2	18.4	24.1	4.2
Mauritania	2.0	5.4	9.7	9.3	2.2
Mauritius	0.3	0.3	0.7	0.4	0.2
Mexico	9.7	10.0	17.9	5.0	7.8
Moldova	0.6	0.5	1.2	0.7	0.4
Mongolia	0.6	2.6	1.8	0.5	0.4
Montenegro	0.3	0.3	0.8	0.3	0.3
Morocco	7.4	11.7	28.1	14.5	9.4
Mozambique	9.6	15.2	31.4	38.4	6.2
Myanmar	14.6	28.8	43.7	42.5	10.8
Namibia	0.8	0.7	1.2	0.9	0.7
Nepal	9.1	14.8	29.0	39.0	5.7
Netherlands	3.7	2.5	2.0	2.2	1.8
New Zealand	1.7	1.9	0.5	0.7	0.7
Nicaragua	1.6	4.0	10.7	4.5	1.4
Niger	6.0	21.5	29.6	33.4	7.4
Nigeria	15.1	23.9	51.3	47.8	9.8
North Korea	1.1	2.4	2.9	4.7	0.8

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Norway	3.3	2.1	3.0	2.4	1.4
Oman	2.1	3.3	7.1	3.0	2.4
Pakistan	22.5	31.3	49.8	51.5	13.2
Panama	2.2	0.7	2.7	0.5	1.7
Papua New Guinea	3.7	3.1	6.5	13.6	3.1
Paraguay	1.3	1.2	2.4	2.2	0.7
Peru	2.8	6.4	12.6	4.4	2.7
Philippines	54.2	66.4	69.8	73.4	46.3
Poland	1.5	1.1	2.5	2.3	5.6
Portugal	2.0	2.2	1.1	1.3	1.7
Qatar	0.5	0.3	0.5	0.3	0.5
Romania	2.7	3.3	3.2	0.8	1.3
Russia	18.0	19.1	18.1	17.0	11.4
Rwanda	13.1	22.7	29.6	42.9	6.4
Saudi Arabia	5.3	10.7	9.3	7.4	7.4
Senegal	3.3	10.8	25.0	30.6	3.7
Serbia	2.1	2.1	2.1	1.3	0.7
Sierra Leone	6.3	12.5	16.8	24.6	3.3
Singapore	0.6	0.8	0.4	0.4	0.4
Slovakia	1.1	2.1	1.1	0.6	1.2
Slovenia	0.4	0.5	0.4	1.3	0.5
Solomon Is.	0.4	0.4	2.0	0.9	0.3
Somalia	5.9	17.8	24.4	26.5	4.5
South Africa	16.0	10.3	24.0	12.4	13.5
South Korea	1.5	0.9	1.5	2.8	1.8
Spain	8.5	8.1	9.0	6.1	9.9
Sri Lanka	4.1	4.7	10.1	7.0	2.3
Sudan	13.0	27.2	47.9	41.9	11.4
Suriname	0.6	0.6	1.0	0.6	0.3
Swaziland	0.7	0.4	5.0	1.3	0.2

Country	SSP1	SSP2	SSP3	SSP4	SSP5
Sweden	2.7	3.3	1.6	3.7	3.0
Switzerland	0.8	3.1	1.1	4.5	1.9
Syria	5.8	7.2	18.0	17.5	5.4
Taiwan	0.8	0.6	1.1	0.8	3.4
Tajikistan	7.8	8.5	11.6	20.8	1.5
Tanzania	4.0	15.8	10.7	17.7	2.1
Thailand	11.2	17.3	20.7	12.7	12.5
The Gambia	0.6	1.5	3.8	2.1	0.5
Timor Leste	0.5	0.7	5.5	1.9	0.2
Togo	0.8	1.7	4.9	9.6	0.6
Trinidad and Tobago	0.3	0.6	1.5	0.4	0.3
Tunisia	1.9	2.4	1.9	2.0	1.0
Turkey	26.1	31.5	47.8	40.8	21.2
Turkmenistan	1.0	1.0	1.6	0.9	0.9
Uganda	34.4	54.5	73.9	73.0	30.9
Ukraine	1.1	4.1	8.3	5.0	1.1
United Arab Emirates	3.6	1.7	2.8	1.6	4.0
United Kingdom	26.0	29.1	26.1	26.0	25.5
United States	12.7	15.8	32.6	11.1	24.5
Uruguay	1.2	0.5	1.8	0.6	0.5
Uzbekistan	3.8	4.2	7.8	4.5	1.2
Venezuela	5.7	5.4	6.2	7.6	1.7
Vietnam	4.5	6.1	7.5	3.7	1.7
Yemen	24.7	28.0	44.3	43.2	19.2
Zambia	0.9	2.8	6.0	7.8	0.6
Zimbabwe	5.6	2.0	6.7	6.2	3.5

S7.3 Some simulations with alternative scenarios

The operationalization of the five SSPs spans only a limited set of possible future scenarios. In Fig. S17, we show the projections for three variations of the SSPs where we have adjusted some underlying assumptions. The green and pink lines represent the original Sustainability (SSP1) and Fragmentation (SSP3) pathways. These projections are the same as in Fig. 3 in the main article and are included here for comparison.

The first additional scenario is labeled 'SSP3Nogrowth'. Here, we assume that no country has any growth in GDP per capita between 2013 and 2100, whereas population and education behaves similarly to the original. The forecasted incidence of armed conflict is somewhat higher than in SSP3, but not dramatically so – the strong population increase and weak economic growth already makes this is a high-conflict scenario. A scenario with systematic negative growth in GDP per capita (i.e., a scenario where economic growth is slower than population growth) would have yielded a higher proportion of countries in conflict.

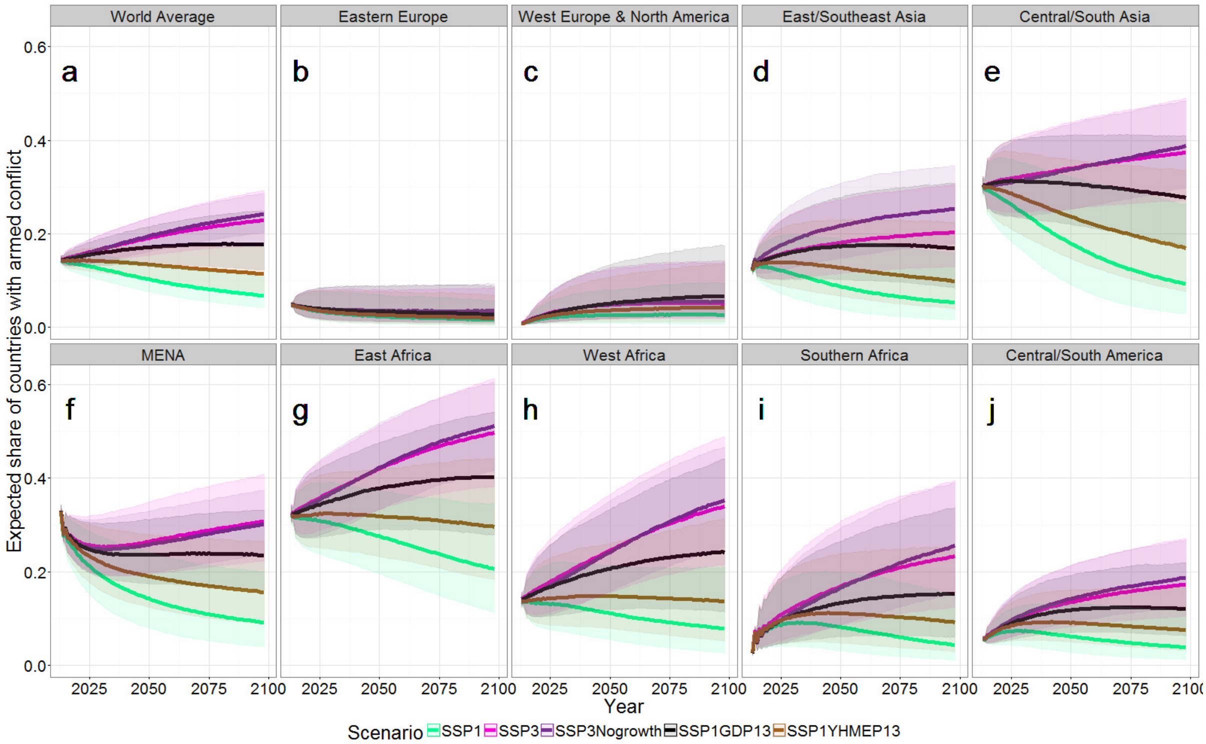

Figure S17. Projected proportion of countries in armed conflict by scenario and year, 2014–2100, Model 2, alternative scenarios. Panel **a** shows the world average results; panels **b–j** show regionally disaggregated estimates. Shaded areas represent the 50% prediction intervals.

The second additional scenario is labeled 'SSP1GDP13'. Here, GDP per capita is the average of GDP per capita in SSP1 and SSP3, but population and education/YMHEP are as in SSP1. This scenario yields a predicted proportion of countries in conflict somewhat higher than the midpoints between SSP1 and SSP3.

The third additional scenario is labeled 'SSP1YMHEP13'. Here, population and GDP per capita are as in SSP1, but YMHEP is the average of those projected in SSP1 and SSP3. The predicted incidence of armed conflict here is between those of SSP1 and SSP3. Comparing the two additional intermediate scenarios, they demonstrate that the variation in GDP per capita between scenarios covers a much wider range than the variation in education assumptions: Compared to the conflict predictions for SSP1, moving to the midpoint between SSP1 and SSP3 in terms of GDP per capita increases conflict incidence much more than moving to the midpoint in terms of education. This does not necessarily imply that GDP per capita is more important than education, however, only that there is more variation spanned in terms of the economic indicator.

S8 Adjustments to historical data and projections

S8.1 Conflict data

We made one slight modification to the conflict data. In the original UCDP/PRIO dataset, the attacks of 9/11 2001 are coded as a major civil armed conflict in the US, since the event satisfies the criteria for being classified as such: An organized non-state actor (Al-Qaeda) targeted the government of an independent state (the United States of America), and these strikes resulted in more than 1,000 casualties. In the UCDP/PRIO database, the subsequent US military operations in Afghanistan and elsewhere against Al-Qaeda troops are coded as a continuation of this conflict, meaning that the US is coded with a civil armed conflict in every year since 2001. We consider this a very special case (i.e., the fighting post-9/11 occurs exclusively outside the territory of the government involved in the conflict, unlike every other civil conflict in the database) and we thus decided to code the US as hosting a civil conflict in 2001 only.

S8.2 Education

The historical education data (1970–2010) are from the IIASA [22] whereas the projections (2010–2100) are obtained from Wittgenstein Centre for Demography and Global Human Capital [23]. We use version 1.1 of the projected education data. The earlier version (1.0) was used as input in the OECD ENV-Growth model. We would have preferred to use the same version to maximize consistency, but reconciling the historical data with version 1.1 projections was much less problematic since the end-point for historical data and start point for projections were the same (2010).

From these datasets, we used the measure 'number of males between 20–24 who have completed upper secondary school or higher'. We calculate the share of the relevant population with completed secondary by dividing by the number of educated males by the total size of the age cohort from the same source. Since the historical education data only cover years since 1970, we extrapolated country-specific values back to 1960 assuming similar country-level change rates as for 1970–2010.

These sources report data for current political entities also for periods before they were created. To make the data consistent with the Gleditsch and Ward historical list of independent states [6], used for this project, we reconstructed observations for states that do not longer exist. Hence, Montenegro, FYR Macedonia, Croatia, Bosnia and Herzegovina, Slovenia, and Serbia were merged into Yugoslavia for the period 1970–1990, using population-weighted averaging of the individual estimates. Similarly, we merged Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Azerbaijan, Georgia, Armenia, Belarus, Ukraine, Lithuania, Latvia, Estonia, Republic of Moldova, and Russia into the Soviet Union for the period 1970–1990; and the Czech Republic and Slovakia into Czechoslovakia 1970–1990. In addition, we merged Israel and the Occupied Palestinian Territories into a single entity for the entire period 1970–2100 (corresponding to how UCDP/PRIO Armed Conflict Dataset codes the Israel/Palestine conflict).

Kosovo, Taiwan, and South Sudan are missing from both the historical and the projected education datasets. For Kosovo, we assume the education levels to be similar to Bosnia-Herzegovina's. We assume the series for Taiwan are similar to those of Malaysia.

In addition, 19 countries that are included in the projected time-series are missing from the historical dataset. In order to estimate values for these cases, we consulted the Barro-Lee education dataset (version 1.3, 2013) [30] and UNESCO's December 2013 release of their Educational Attainment data [31]. Based on these sources, we filled in values by matching missing countries with countries with similar profiles that have education data. Table S10 lists the country matches chosen.

Table S10. Matching cases to replace missing information in the historical datasets

Country with missing observations in the IIASA or WDI datasets	Country selected as match for education data	Countries selected as match for conversion rates
Afghanistan	Pakistan	
Angola	Mozambique	
Barbados	Jamaica	
Botswana	Zimbabwe	
Brunei	Philippines	
Cuba		Dominican Republic
Czechoslovakia		Czech Republic
Djibouti	Ethiopia	
East Germany		West Germany
Eritrea	Ethiopia	
Fiji	Malaysia	
Kosovo	Bosnia-Herzegovina	
Libya	Egypt	
Mauritania	Morocco	
North Korea	Cambodia	Nepal (North Korea completely lacked data)
Oman	Bahrain	
Palestine		Jordan
Papua New Guinea	Laos	
Solomon Islands	Laos	
Somalia		Ethiopia
South Sudan	Sudan	Sudan (South Sudan completely lacked data)
Sri Lanka	Philippines	
Taiwan	Malaysia	South Korea
Taiwan/Malaysia	Malaysia	
Togo	Nigeria	
Uzbekistan	Tajikistan	
Yemen	Ethiopia	
Yugoslavia		FYR Macedonia
Zimbabwe		Zambia

S8.3 GDP per capita

To construct a complete historical dataset for GDP per capita, we combined data from World Development Indicators (WDI) [16], Maddison [18], and Penn World Tables v.8.0 [17]. The OECD ENV-Growth projections [21] we use for 2011 and beyond are in PPP-adjusted 2005 US Dollars (USD) based on WDI. Where WDI were missing data, we supplemented with data from the two other sources and rescaled values to have the same metric. We applied a simple conversion rate, calculated as the average of the ratio between the time series for overlapping years.

For eight countries, we lacked PPP data from WDI and could not calculate this ratio directly. Here, we used conversion rates from similar countries to translate these data to 2005 USD

PPP values, see Table S5. We interpolated values for years where needed and possible. GDP per capita values are usually generated by making a comprehensive survey for base years, while only deriving changes in sectors between base years [32]. Thus, for most years, even the main raw data are growth rates, making our procedure more suitable than if GDP per capita where derived each year from absolute numbers.

While GDP per capita observations for most countries are generally consistent across the three data sources, we observe large differences for Kuwait, Qatar, and the United Arab Emirates (UAE). For instance, in 1980, the UAE have USD 123,433 (2005 PPP) in WDI, while Maddison reports USD 27,709 (1990 PPP). Similar figures for 2010 are USD 37,688 (2005 PPP) and USD 13,746 (1990 PPP), respectively. This suggests that it would be inappropriate to apply a time-constant conversion rate. For these countries, we use our best judgment to develop reasonable compromises between the estimates in the different sources, but ultimately constraining the values to match the WDI.

For the UAE, we used WDI Constant USD before 1985 and PPP values after 1985. That way, GDP per capita does not reach extreme values, and we obtain a data series that goes back to independence. For Qatar, we use PWT 8.0 converted to USD 2005 PPP using the conversion rate method before 2003 and WDI PPP for more recent years. Maddison operates with very high estimates in the early years while PWT have high estimates for later years, compared to the other sources. Finally, for Kuwait, PWT converted to USD 2005 PPP is used for the period 1970–1979 and 1990–1994, Maddison without conversion is used before 1970, while WDI PPP is used after 1994.

For the GDP per capita projections, we use the information given in the OECD ENV-Growth source with the following modifications. The projections are calculated in 5-year intervals. We create yearly observations by applying log-linear interpolation for each country. For some countries, there is poor agreement between the historical record and the starting point of the SSP forecasts. This mismatch is particularly notable for the eight countries listed in Table S6. We attribute the inconsistencies partly to our approach to reconstruct observations in the PPP metric, partly to a recent revision in WDI (Barbados), and partly to what may be an error in the OECD ENV-Growth projections (Somalia). We opted to adjust the projections to match the historical dataset. We summarize these changes in Table S11. In most cases, GDP per capita values have been adjusted upwards relative to the original projections. This implies that the projections probably overestimate future GDP per capita in these countries, as the OECD ENV-Growth model would predict lower growth rates if GDP per capita had been higher at the outset.

Additionally, the OECD ENV-Growth forecasts exclude a small number of countries, namely Kosovo, South Sudan, and North Korea. To `impute' forecasts for North Korea, we identified a reasonably similar `model' country, Nepal, and rescaled the forecast trajectories to fit the observed 2010 levels for the imputation country. Further, we assume that Sudan and South Sudan will follow a similar trend. For Kosovo, we assume the same trajectory as Serbia, only starting at a lower level of GDP per capita. This procedure is likely to underestimate future GDP per capita in Kosovo relative to what the OECD-ENV model would have yielded.

Table S11. Modifications to projected GDP per capita estimates

Country	Problem	Change
Barbados	WDI use updated national accounts from November 2013. SSPs use old data. USD 17,576 in old data becomes USD 23,261 in new data for 2009.	Multiply SSP projection by 1.32.
Cuba	SSPs seem to be using current USD. PPP data are not available so we use Dominican Republic PPP conversion rates for historical data. Thus, a higher GDP per capita (USD 8,831 versus USD 5,747).	Multiply SSP projection by 1.54.
Cyprus	SSPs have USD 18,907 GDP per capita in 2010, WDI have USD 25,198 GDP per capita. Here, the WDI data appear to be incorrect (dimilar POP and GDP values, only it does not sum up in WDI).	None
Myanmar	We use Maddison without any conversion from 1990 to 2005 USD PPP, which is much higher than the number supplied by the SSPs (USD 3,709 versus 1,442). It is unclear which source the SSP data uses, however it is similar to the figure in CIA World Factbook. Maddison uses data from the Asian Development Bank. Maddison data looks reasonable, and is backed by more evidence than the value supplied by CIA. It is not entirely clear, however, and Myanmar's accounting is not very good, as can be seen from all the sources. Maddison suggests that Myanmar GDP per capita is 40% that of Thailand, 70% of that in Sri Lanka and triple that of Nepal. CIA data suggests that Myanmar is similar to Nepal. It might be that the CIA number is outdated some, as Myanmar have had high growth the last decade.	None
Nicaragua	SSPs have USD 2,499 GDP per capita in 2010, WDI have USD 3,256 GDP per capita. Population estimates are similar, GDP is much lower in SSPs (18.9 billion versus 14.467).	Multiplied SSP projection by 1.30
Sierra Leone	SSPs have USD 742 GDP per capita in 2010, WDI have USD 997 GDP per capita in the same year. Population is higher in SSPs, while GDP is lower.	Multiplied SSP projection by 1.34
Somalia	SSPs work with a very low GDP (USD 330 million). More accurate estimate is probably between 4 to 6 billion.	Use Ethiopia projection as template, adjust to Somalia at outset.
Zimbabwe	SSPs seem to use GDP per capita in constant 2005 USD instead of PPP data.	None

S8.4 Population

Empirical population data are based mainly on the 2012 revision of the United Nations World Population Prospects [15], which has data from 1950 to 2012 for most countries. For a few countries with missing values (Taiwan, Yemen, and East/West Germany), we use data from Maddison [33]. For the east/west share of the population in Germany, we used statistics from the German statistical office [34]. For Kosovo and Serbia after 2006, and South Sudan from 2011, we use WDI population figures [16].

As noted for the education data, the UN source reports population estimates for current political entities also for years before major secessions or state mergers. To reconstruct figures for the former USSR, Yugoslavia, or East and West Germany, we sum the values for the constituting territories to estimate total population for each of the historical countries. Hence, population numbers for Yugoslavia in 2005 are the sums of the populations reported for Serbia, Montenegro, and Kosovo, while the population figure for Serbia in 2006 are made up from Serbia and Kosovo estimates. Only in 2008, Kosovo is included as an independent state. For Israel, we use population figures that cover both Israel and the West Bank and Gaza.

The SSP population projections are from IIASA [22], and line up well with the empirical population data. The IIASA data lack information for Taiwan, Kosovo, and South Sudan. To generate projections for Taiwan, we identified South Korea as a reasonably similar model country, and assumed population growth rates, 2010–2100, to be similar in both. For Kosovo and South Sudan, we generated projections from disaggregated population growth estimates for Serbia and Kosovo, and Sudan and South Sudan, respectively.

S8.5 Regions

Each country in the sample is categorized into one of nine geographical regions in order to visualize and detect notable differences between regions in trends and projections (e.g., Figs. S2–S4 and S10 as well as Fig. 2 in the article). These regions are consistent with the regional projections climate change of the Global Change Assessment Model (GCAM) and other integrated assessment models. Table S12 provides a list of this categorization, including the three-letter country code from the Gleditsch and Ward system membership data [6] that are used to identify individual countries in Fig. 2 in the article.

Table S12. Region definitions

Region	Country	Code	Region	Country	Code
Southern Africa	Angola	ANG	East/Southeast Asia	Brunei Darussalam	BRU
	Botswana	BOT		Cambodia	CAM
	Lesotho	LES		China	CHN
	Malawi	MAW		Fiji	FJI
	Mozambique	MZM		Indonesia	INS
	Namibia	NAM		Japan	JPN
	South Africa	SAF		Korea, Democr. Peoples' Rep. of	PRK
	Swaziland	SWA		Korea, Rep. of	ROK
	Tanzania, United Rep. of	TAZ		Lao Peoples Democr. Rep.	LAO
	Zambia	ZAM		Malaysia	MAL
	Zimbabwe	ZIM		Myanmar	MYA
Central/South America	Argentina	ARG		Papua New Guinea	PNG
	Bahamas	BHM		Philippines	PHI
	Barbados	BAR		Singapore	SIN
	Belize	BLZ		Solomon Islands	SOL
	Bolivia	BOL		Taiwan	TAW
	Brazil	BRA		Thailand	THI
	Chile	CHL		Timor Leste	ETM
	Colombia	COL		Viet Nam	DRV
	Costa Rica	COS	West Africa	Benin	BEN
	Cuba	CUB		Burkina Faso	BFO
	Dominican Rep.	DOM		Cameroon	CAO
	Ecuador	ECU		Cape Verde	CAP
	El Salvador	SAL		Central African Rep.	CEN
	Guatemala	GUA		Chad	CHA
	Guyana	GUY		Congo	CON
	Haiti	HAI		Congo, the Democr. Rep. of the	DRC
	Honduras	HON		Cote dIvoire	CDI
	Jamaica	JAM		Equatorial Guinea	EQG
	Mexico	MEX		Gabon	GAB

Region	Country	Code	Region	Country	Code
	Nicaragua	NIC		Gambia	GAM
	Panama	PAN		Ghana	GHA
	Paraguay	PAR		Guinea	GUI
	Peru	PER		Guinea-Bissau	GNB
	Suriname	SUR		Liberia	LBR
	Trinidad and Tobago	TRI		Mali	MLI
	Uruguay	URU		Mauritania	MAA
	Venezuela	VEN		Niger	NIR
Eastern Europe	Albania	ALB		Nigeria	NIG
	Belarus	BLR		Senegal	SEN
	Bosnia and Herzegovina	BOS		Sierra Leone	SIE
	Bulgaria	BUL		Togo	TOG
	Croatia	CRO	East Africa	Burundi	BUI
	Cyprus	CYP		Comoros	COM
	Czech Rep.	CZR		Djibouti	DJI
	Estonia	EST		Eritrea	ERI
	Hungary	HUN		Ethiopia	ETH
	Latvia	LAT		Kenya	KEN
	Lithuania	LIT		Madagascar	MAG
	Macedonia	MAC		Mauritius	MAS
	Malta	MLT		Rwanda	RWA
	Moldova, Rep. of	MLD		Somalia	SOM
	Montenegro	MNG		Sudan	SUD
	Poland	POL		South Sudan	SSD
	Romania	RUM		Uganda	UGA
	Russian Federation	RUS	Western Europe and North America	Australia	AUL
	Serbia	SER		Austria	AUS
	Slovakia	SLO		Belgium	BEL
	Slovenia	SLV		Canada	CAN
	Turkey	TUR		Denmark	DEN
	Ukraine	UKR		Finland	FIN
	Yugoslavia, Fed. Rep. of	YUG		France	FRN
Middle East and North Africa (MENA)	Algeria	ALG		Germany	GFR
	Bahrain	BAH		Greece	GRC
	Egypt	EGY		Iceland	ICE
	Iran, Islamic Rep. of	IRN		Ireland	IRE
	Iraq	IRQ		Italy	ITA
	Israel	ISR		Luxembourg	LUX
	Jordan	JOR		Netherlands	NTH
	Kuwait	KUW		New Zealand	NEW
	Lebanon	LEB		Norway	NOR
	Libyan Arab Jamahiriya	LIB		Portugal	POR
	Morocco	MOR		Spain	SPN
	Oman	OMA		Sweden	SWD
	Qatar	QAT		Switzerland	SWZ
	Saudi Arabia	SAU		United Kingdom	UKG
	Syrian Arab Rep.	SYR		United States of America	USA
	Tunisia	TUN			
	United Arab Emirates	UAE			
	Yemen	YEM			
Central/South Asia	Afghanistan	AFG			
	Armenia	ARM			
	Azerbaijan	AZE			
	Bangladesh	BNG			

Region	Country	Code	Region	Country	Code
	Bhutan	BHU			
	Georgia	GRG			
	India	IND			
	Kazakhstan	KZK			
	Kyrgyzstan	KYR			
	Maldives	MAD			
	Mongolia	MON			
	Nepal	NEP			
	Pakistan	PAK			
	Sri Lanka	SRI			
	Tajikistan	TAJ			
	Turkmenistan	TKM			
	Uzbekistan	UZB			

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