World Inequality Lab – Working Paper N° 2022/20

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Août 2022

PNAS RESEARCH ARTICLE | SUSTAINABILITY SCIENCE

Climate change and the nonlinear impact of precipitation anomalies on income inequality

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Edited by Stephen Polasky, University of Minnesota, St. Paul, MN; received February 28, 2022; accepted August 16, 2022

Climate anomalies, such as floods and droughts, as well as gradual temperature changes have been shown to adversely affect economies and societies. Although studies find that climate change might increase global inequality by widening disparities across countries, its effects on within-country income distribution have been little investigated, as has the role of rainfall anomalies. Here, we show that extreme levels of precipitation exacerbate within-country income inequality. The strength and direction of the effect depends on the agricultural intensity of an economy. In high-agricultural-intensity countries, climate anomalies that negatively impact the agricultural sector lower incomes at the bottom end of the distribution and generate greater income inequality. Our results indicate that a 1.5-SD increase in precipitation from average values has a 35-times-stronger impact on the bottom income shares for countries with high employment in agriculture compared to countries with low employment in the agricultural sector. Projections with modeled future precipitation and temperature reveal highly heterogeneous patterns on a global scale, with income inequality worsening in high-agricultural-intensity economies, particularly in Africa. Our findings suggest that rainfall anomalies and the degree of dependence on agriculture are crucial factors in assessing the negative impacts of climate change on the bottom of the income distribution.

income inequality | climate change | precipitation

Significance

While evidence indicates that climate change is likely to increase income inequality between countries, its impacts across different income classes are less understood. Using global data on inequality indicators, we show that rainfall anomalies increase income inequality in economies that are heavily dependent on agriculture. Climate projections indicate that existing disparities are likely to worsen over time. Our findings underline the urgent need for inclusive and sustainable development policies, especially in highly exposed countries.

Robust evidence suggests that climate change will adversely affect economic and social conditions (1–3), impairing economic growth and hampering the development of disadvantaged economies (4–8). Several studies have indeed projected cross-country income inequality to increase in response to heterogeneous climate impacts, mitigation policies, and adaptation potentials (9–11). However, the effects of climate change on the distribution of income within national economies—i.e., within-country inequality—are poorly understood (12). On the one hand, relatively poorer people, especially those living in hotter climates, are among the most vulnerable to climate change (7, 13). On the other hand, the effect of weather shocks varies widely between economic sectors (14, 15), whose relative size starkly differs across countries and phases of development (16–18). As a consequence, the same weather event can have different impacts on the income distribution of countries with structurally different economies.

Agriculture is, by its very nature, one of the most exposed sectors to climate events and—notwithstanding adaptation—is already experiencing large productivity losses (19, 20), with potentially cascading effects on the macroeconomy (5, 14). Furthermore, agricultural prices and yields have been identified as key channels through which climate change will increase poverty (12). Nonetheless, the economic literature on the determinants of within-country income inequality (21, 22) typically overlooks climate anomalies as a potential source of increased disparities. More specifically, changing temperatures and extreme weather events have been convincingly shown to heterogeneously affect aggregate income, leading to divergent growth trajectories (1, 3, 23). The role of precipitation is still unclear and subject to debate (24, 25). Nonetheless, rainfall anomalies are often indicated as a major risk factor (26), especially for poor individuals in developing countries (27–29). Indeed, these households are not only often located in flood-prone areas and highly vulnerable to droughts (30), but are also remarkably dependent on income from rain-fed agriculture (31–33).

Our approach considers rainfall anomalies, along with temperature deviations, as a potential source of increased within-country income inequality. We use methods traditionally employed in econometric studies (5, 6) (*Materials and Methods*) to investigate the impact of local climate anomalies on the fraction of income earned by the population below the median percentile. Income-share quantiles are routinely employed to capture localized movements across the income distribution. They are usually utilized as alternatives to summary measures (e.g., the Gini index), given their higher sensitivity to changes in the tails, such as for the very poor (34). We hypothesize that the

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Author contributions: E.P., M.C., F.L., and A.R. designed research; E.P., M.C., F.L., and A.R. performed research; E.P. and M.C. analyzed data; and E.P., M.C., F.L., and A.R. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2203595119/-/DCSupplemental.

Published October 17, 2022.

Table 1. Estimated impacts of precipitation on the bottom-50%-income share, Models A0, A1, and A2

Model	No agricultural intensity A0	High vs. low agricultural intensity A1	Continuous agricultural intensity A2
Precipitation	0.002 (0.009)	0.032* (0.019)	−0.033** (0.016)
Precipitation^2	−0.002 (0.004)	−0.014** (0.005)	0.013** (0.007)
AI^L × Precipitation		−0.041** (0.020)	
AI^L × Precipitation^2		0.018*** (0.006).	
AI × Precipitation			0.001** (<0.001)
AI × Precipitation^2			−(<0.001)** (<0.001)
Temperature effects	✓	✓	✓
Sample size	2,363	2,363	1,984
Fit quality (within R^2)	0.4580	0.4767	0.2585

Clustered within-countries and heteroscedasticity robust SEs are in parentheses. *AI*, agricultural intensity. Polynomial of temperature and relative interaction terms are included (temperature effects) but not reported, as they are never significant. $^*P < 0.10$; $^{**}P < 0.05$; $^{***}P < 0.01$ (two-tailed). See *SI Appendix*, Table S5 for full results.

degree to which rainfall anomalies impact the distribution of income depends on the degree of agricultural intensity of a country, measured as the percentage of workers employed in agriculture out of total employment. Indeed, economies heavily dependent on the primary sector are inherently more exposed to weather fluctuations. To the extent that precipitation impacts agricultural income more than nonagricultural income, and with bottom earners being largely dependent on the former, climate anomalies can translate into a widening rich–poor gap in agriculturally intensive countries. By jointly modeling the response of both between- and within-country income distribution to climate change, our framework allows for a comprehensive accounting of the effects of climate anomalies on present and projected inequalities.

Precipitation Affects Income Distribution in Countries That Are Heavily Dependent on Agriculture

We start by modeling the response of the share of income earned by the poorest 50% of the population to climate anomalies. Given the highly right-skewed nature of income distribution, bottom-50%-income shares are customarily employed as robust indicators of movements in the poorest part of the population (35–37), without incurring methodological and measurement issues related to estimates for lower quantiles (38, 39) (*SI Appendix*, *Inequality Data and Measures*). In our most general setup, the inequality indicator depends on 1) a polynomial of climate variables (population-weighted yearly average temperature and total precipitation); 2) all time-invariant socioeconomic and geographic factors that influence countries' average values of the dependent variable (captured by country fixed effects); 3) region-specific macroeconomic shocks (captured by the interaction terms between year fixed effects y_t and regional dummies r_i); and 4) the degree of country agricultural intensity AI (*Materials and Methods*). We then employ econometric methods to estimate a set of models with different specifications and a battery of robustness checks (*SI Appendix*, *Robustness*). In particular, we identify climate-related effects through deviations from country-specific inequality levels shaped by institutional factors and from region-specific macro trends.

Our baseline strategy is to split countries into two distinct groups—high and low agricultural intensity (5, 6)—as captured by the dichotomous variable AI^L in Model A1. Grouping countries according to their relative position in the global distribution of agricultural employment shares has the main advantage of parsimoniously accounting for heterogeneous effects across a highly skewed distribution (*SI Appendix*, Fig. S1). Table 1 reports our estimates of Model A1 (see also Fig. 1*A*). We find evidence of an inverted-U-shaped relationship between precipitation and bottom income shares for high-agricultural-intensity countries; see also the solid line in Fig. 1*A*. In contrast, the coefficients for the low-agricultural-intensity group are of opposite signs and similar magnitude, indicating an almost absent effect of rainfall; see also the dashed line in Fig. 1*A*. Indeed, extreme levels of precipitation exacerbate income inequality only in countries whose employment is highly concentrated in agriculture. Notably, no statistically significant effect is detected for temperature (*SI Appendix*, Table S5), confirming rainfall as a key determinant of agricultural incomes (28, 40). The central role of agricultural intensity is evident from the estimates of Model A0 (Table 1). Precipitation does not exert any statistically significant effect when the grouping is removed. This highlights the nonlinear nature of the relationship between precipitation and income distribution: The estimated effect is stronger for extreme levels of rainfall, and it primarily emerges in the right tail of the agricultural intensity distribution.

Our findings are robust to a wide range of model specifications. The baseline definition of countries with high agricultural intensity—i.e., those above the 80th percentile of the global agricultural employment share distribution—is conservative. In fact, cutting the distribution at higher quantiles (e.g., countries above the 90th percentile) delivers markedly stronger estimated effects for the high-agricultural-intensity group. Conversely, cutoffs at lower percentiles (e.g., the 75th percentile) yield substantially unaltered estimations without reducing statistical uncertainty (*SI Appendix*, Fig. S5 and Table S1). Furthermore, the results are not exclusively driven by countries located at the very right end of the distribution (see estimates for Model A1 when excluding countries in the upper decile; *SI Appendix*, Fig. S5). Relevantly, grouping countries along alternative dimensions—e.g., income level or geographical region—delivers inconsistent and statistically weak estimates, suggesting that agricultural intensity truly drives our findings (*SI Appendix*, Table S10). Adopting alternative income-inequality indicators—top-10% and top-10% to bottom-50%-income-share ratios (36, 41)—grants qualitatively similar evidence (*SI Appendix*, Table S9). However, both measures entail greater statistical uncertainty, as they reflect movements in parts of the income distribution that are unlikely to be affected by precipitation anomalies (e.g., top earners). Finally, the results are robust to alternative formulations of region-specific fixed effects (*SI Appendix*, Table S7), as well as to different data sources (42) for the construction of our climate variables (*SI Appendix*, Table S8).

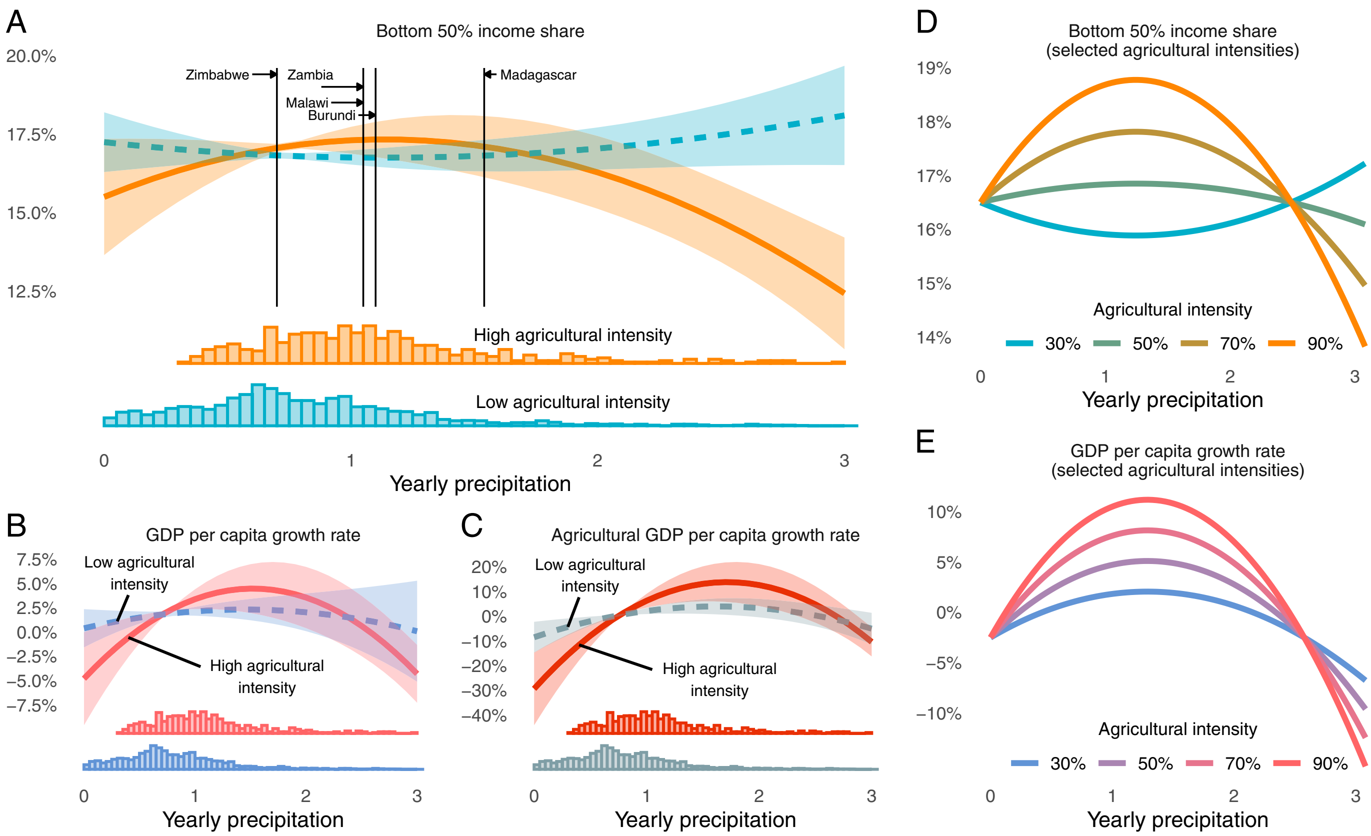

Fig. 1. Estimated impacts of precipitation on economic variables. (*A*) Estimated nonlinear impacts of population-weighted yearly total precipitation (in meters) on the bottom 50% shares in high-agricultural-intensity countries (solid line) and in low-agricultural-intensity ones (dashed line). Histograms show the pooled distribution of precipitation in the two groups. Vertical lines indicate precipitation for selected countries averaged over 1996 through 2010. Arrows represent movements in average precipitation between the period 1980 through 1995 and the period 1996 through 2010 (Table 1 and *SI Appendix*, Table S5). Shaded areas represent 90% confidence bands. SEs are clustered within countries and heteroscedasticity-robust. (*B*) As in *A*, but with per capita GDP growth as the dependent variable (*SI Appendix*, Table S3). (*C*) As in *A*, but with per capita agricultural GDP growth as the dependent variable (*SI Appendix*, Table S4). (*D*) Estimated impacts of precipitation on bottom 50% shares with continuous, time-varying agricultural intensity. Selected levels of agricultural intensity are shown (Table 1 and *SI Appendix*, Fig. S4). (*E*) As in *D*, but with per capita GDP growth as dependent variable (*SI Appendix*, Table S3 and Fig. S3). In *D* and *E*, the constant term is fixed to the average intercept in, respectively, *A* and *B*.

We conjecture that the nonlinear relationship between precipitation and income inequality arises from the interplay of asymmetric climate impacts on agricultural and nonagricultural incomes (5, 6) and the possible uneven distribution of bottom earners across sectors of economic activity. To investigate this hypothesis, we estimate two models analogous to Model A1 on two different dependent variables: per capita gross domestic product (GDP) growth rates (Model B1) and per capita agricultural GDP growth rates (Model C1). Our estimates indicate a nonlinear, inverted-U-shaped relationship between precipitation and agricultural GDP growth for countries with high agricultural intensity and a remarkably less pronounced, yet concave, relationship for countries with low agricultural intensity (Fig. 1*C* and *SI Appendix*, Table S4). Furthermore, extreme levels of precipitation correspond to negative growth rates of agricultural incomes, especially in agriculturally intensive countries (40), where rain-fed and small-farm agriculture vastly dominate farmland activities (43). When turning to aggregate GDP growth, the estimated effects of precipitation are qualitatively similar to those for agricultural income, albeit considerably lower in magnitude (Fig. 1*B* and *SI Appendix*, Table S3). More precisely, rainfall only moderately affects low-agricultural-intensity countries, and it is mostly associated with periods of positive GDP growth (25). Instead, the effects are particularly large in high-agricultural-intensity countries (4, 25). Since impacts on aggregate income are disproportionately smaller than those on agricultural income, and with bottom earners being largely dependent on the latter in high-agricultural-intensity countries, climate anomalies can translate into a widened rich–poor gap. Although disaggregated data are not systematically available, evidence shows that bottom earners in developing economies are indeed more frequently employed in the agricultural sector (31, 32, 43). In addition, the bottom-50%-income shares positively (negatively) correlate with agricultural (aggregate) income per capita in agriculturally intensive countries (*SI Appendix*, Table S2). Conversely, agricultural incomes in developed economies typically do not fall in the bottom half of the distribution (44). Finally, we tested whether our estimated effects could have been driven by the influence of climate change on agricultural and food prices (12, 13) beyond income growth rates. No robust or statistically significant impact was detected in our sample (*SI Appendix*, Table S13), suggesting that the mechanism hinges on altered productivity and output growth (19, 40).

We now relax the dichotomous grouping of countries to more flexibly inspect the interaction between precipitation and agricultural intensity. In our most general specification, we model the bottom-50%-income shares (Model A2 in *Materials and Methods*) and per capita GDP growth rates (model B2 in *Materials and Methods*) as functions of country-specific, time-varying agricultural intensity. Table 1 shows that the response of income inequality to precipitation in Model A2 is consistent with that in Model A1: Higher agricultural employment is associated with increasingly arched parabolas (Fig. 1*D* and *SI Appendix*, Table S5).

Similarly, a nonlinear response to rainfall is observed for GDP growth (Fig. 1*E* and *SI Appendix*, Table S3) and agricultural GDP growth (*SI Appendix*, Table S4). The results are robust to the removal of possible residual correlation among the error terms of the three dependent variables (*SI Appendix*, Table S6).

Moving to the analysis of temperature, our results (*SI Appendix*, Fig. S2 and Tables S3 and S4) confirm evidence of statistically significant and nonlinear impacts on GDP and, more markedly, on agricultural GDP growth (6, 8, 9). The absence of statistically significant differences between high- and low-agricultural-intensity countries suggests that the impact of temperature deviations from long-term trends on economic activities entails different mechanisms than rainfall anomalies do. At the same time, the sign and the magnitude of coefficients capturing such differential effects all point toward more pronounced impacts in high-agricultural-intensity economies. Thus, we cannot rule out the existence of such mechanisms for temperature anomalies as well, and more fine-grained data would be needed to investigate this issue with greater statistical power. Nonetheless, our results are broadly consistent with the lack of a significant effect of temperature changes on within-country income inequality (*SI Appendix*, Table S5).

It Never Rains But It Pours: Climate Change Might Reinforce Existing Disparities

We quantify the potential impacts of future precipitation and temperature changes by combining previously estimated nonlinear response functions (Models A2 and B2) with future economic and climatic trends. To this end, we merge a Representative Concentration Pathway (RCP) 8.5 future with historical long-run (1991 through 2010) trends in output growth and agricultural employment shares to obtain our baseline projection scenario. Hence, we project deterministic paths for the bottom-50%-income shares and GDP growth for our global sample of countries (Models $\tilde{A}2$ and $\tilde{B}2$ in *Materials and Methods*). The results are qualitatively consistent when considering a modified baseline scenario that accounts for long-run trends in income inequality (*SI Appendix*, Fig. S7) and five RCP–Shared Socioeconomic Pathway (SSP) combinations (*SI Appendix*, Figs. S9–S13 and Tables S18 and S19).

Given their relevance to income distribution, we start by analyzing the projected impacts of future precipitation only. Fig. 2*A* shows the projected values at the 2080 through 2099 period for both per capita GDP and the bottom-50%-income shares relative to a projection with constant climate for each country–climate model pair. Low-agricultural-intensity countries are projected to experience relatively mild consequences on both domestic income inequality and growth trajectories, with the bulk of country–model pairs being concentrated around the origin in Fig. 2*A*. This is due both to low vulnerability to precipitation changes (Table 1) and modest projected changes in total annual rainfall (*SI Appendix*, Table S17). However, for those cases where impacts are nonnegligible, we find evidence of a trade-off between reduced economic growth and increased income inequality. Countries with high agricultural intensity show a diverse pattern, captured by the bimodal distribution in the GDP-inequality space emerging from projections. For one cluster of countries, precipitation over the century will lower levels of economic activity and increase income inequality. A second cluster is projected to experience greater economic growth and a slightly more equal distribution of income, with the bottom 50% of earners increasing their income share by 1.08% on average. Remarkably, the first subgroup is primarily composed of relatively wet central African economies characterized by a disproportionate projected increase in precipitation (Figs. 2*B* and 3*B* and *SI Appendix*, Table S17).

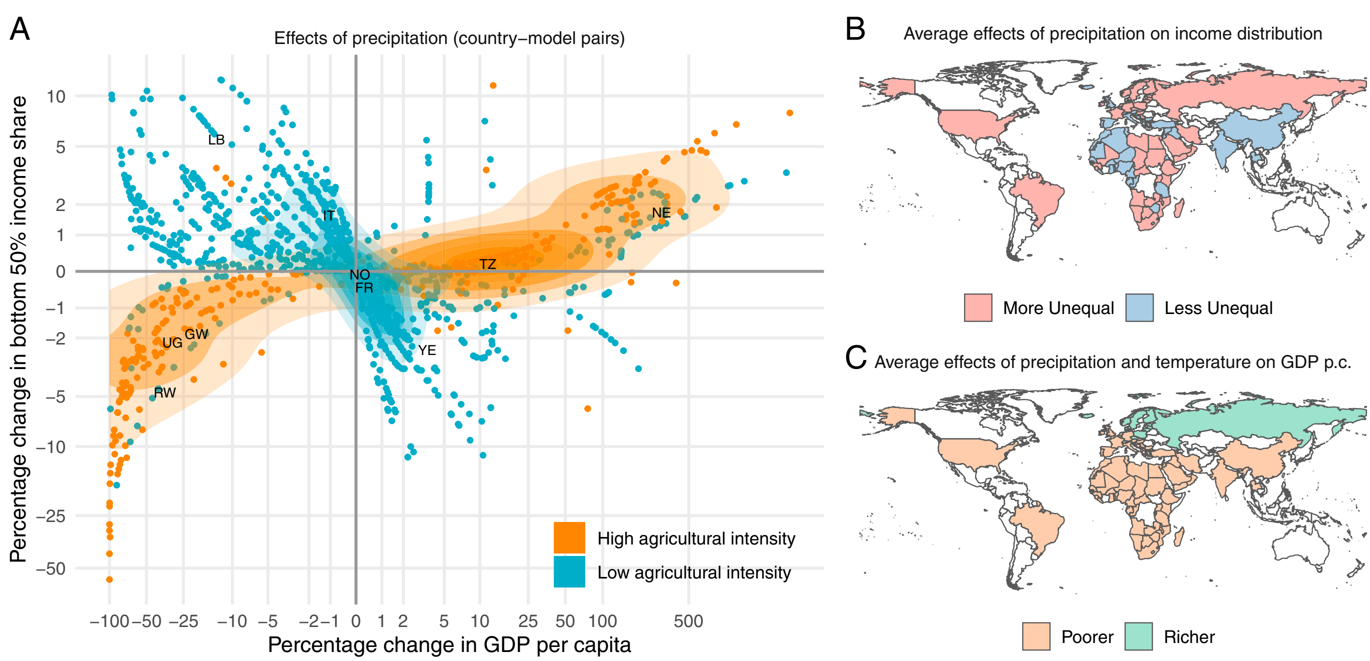

Fig. 2. Projected effects on the bottom-50%-income share and GDP per capita, evaluated at 2080 through 2099. (*A*) Projected percentage change in GDP per capita (*x* axis, no temperature impacts) and bottom 50% share (*y* axis) with respect to a projection with constant climate. RCP 8.5, historical trends (1991 through 2010) in per capita GDP growth, and agricultural employment share are shown. Each point represents a climate model–country pair. International Organization for Standardization (ISO) Alpha-2 codes are reported for selected country average effects. Shaded areas represent two-dimensional Gaussian kernel density estimations of climate model–country pairs for distinct agricultural intensity groups. An analogous chart including temperature effects is provided in *SI Appendix*, Fig. S8. (*B*) Average projected change (across climate models) in the bottom 50% share due to changes in precipitation, with respect to a projection with constant climate. Historical trends (1991 through 2010) in agricultural employment share are shown. (*C*) Average projected change (across climate models) in GDP per capita (p.c.) due to changes in precipitation and temperature, with respect to a projection with constant climate. Historical trends (1991 through 2010) in per capita GDP growth and agricultural employment share are shown.

In these areas, which are currently already very poor and unequal (*SI Appendix*, Fig. S1), climate change risks hampering the process of economic development and exacerbating existing imbalances. In turn, a delayed structural change of these economies would keep their vulnerability high due to reliance on the primary sector. The second subgroup is instead composed of dry countries (*SI Appendix*, Table S17), which are projected to benefit from future increases in rainfall. The estimated gains of bottom earners, however, are limited (Figs. 2*A* and 3). Overall, the majority of countries will experience worsened levels of income inequality (Fig. 2*B*). When including the impact of future temperature on economic growth, 86% of countries in our global sample are projected to become poorer with respect to a projection with constant climate (Fig. 2*C* and *SI Appendix*, Fig. S8). Some countries will become poorer in absolute terms (6) (*SI Appendix*, Table S20). Only Russian and Scandinavian economies are projected to improve GDP growth (6, 8, 45).

Uncertainty Analysis

Projected impacts may vary substantially across climate and socioeconomic futures and, within each of them, as a result of input variability. In our baseline scenario, uncertainty in projected income inequality mainly affects the most adversely impacted countries (Fig. 3). This is due to marked discordance about future precipitation patterns across different climate models. For example, in Sub-Saharan Africa, worst-case projections indicate that income shares of the poorest 50% will shrink by more than 10% as a result of rainfall changes, even though best-case projections indicate a tiny, yet positive, effect. In all other regions, and in developed economies in particular, the full range of impacts is smaller and considerably more centered around the median projections. Statistical uncertainty is generally low and affects only 6 (out of 101) countries. Comparing different projection scenarios (*SI Appendix*, Figs. S9–S13 and Tables S18 and S19), we find that the most negative impacts on both income inequality and per capita GDP are retrieved in the SSP3–RCP8.5 future and mainly affect the Middle East and Sub-Saharan Africa. In contrast, the largest positive effects are retrieved in SSP2–RCP6.0 for income inequality and SSP1–RCP2.6 for output per capita. This result points to different climatic and economic drivers behind income growth and income distribution. Finally, in the SSP5–RCP8.5 future, we find evidence of small effects of precipitation changes and sizable adverse impacts of temperature. Given the structure of our projections, economic growth is associated with lower agricultural intensity (*SI Appendix*, *Projections*). This clearly suggests that a sustainable (i.e., low carbon) industrialization path can be a promising strategy to jointly mitigate both the temperature- and precipitation-related impacts of climate change.

Overall Effects on Global Income Inequality

Leveraging our framework, which jointly accounts for the evolution of aggregate income and its domestic distribution, we are able to reconcile the impacts of projected climate change on both within- and between-country income inequality. Fig. 4 shows the global distribution of income, built by exploiting projected GDP levels and income shares. Projections point to a 24% [23%, 25%] increase in global inequality, measured through the Gini index, as a consequence of future climate change—i.e.,

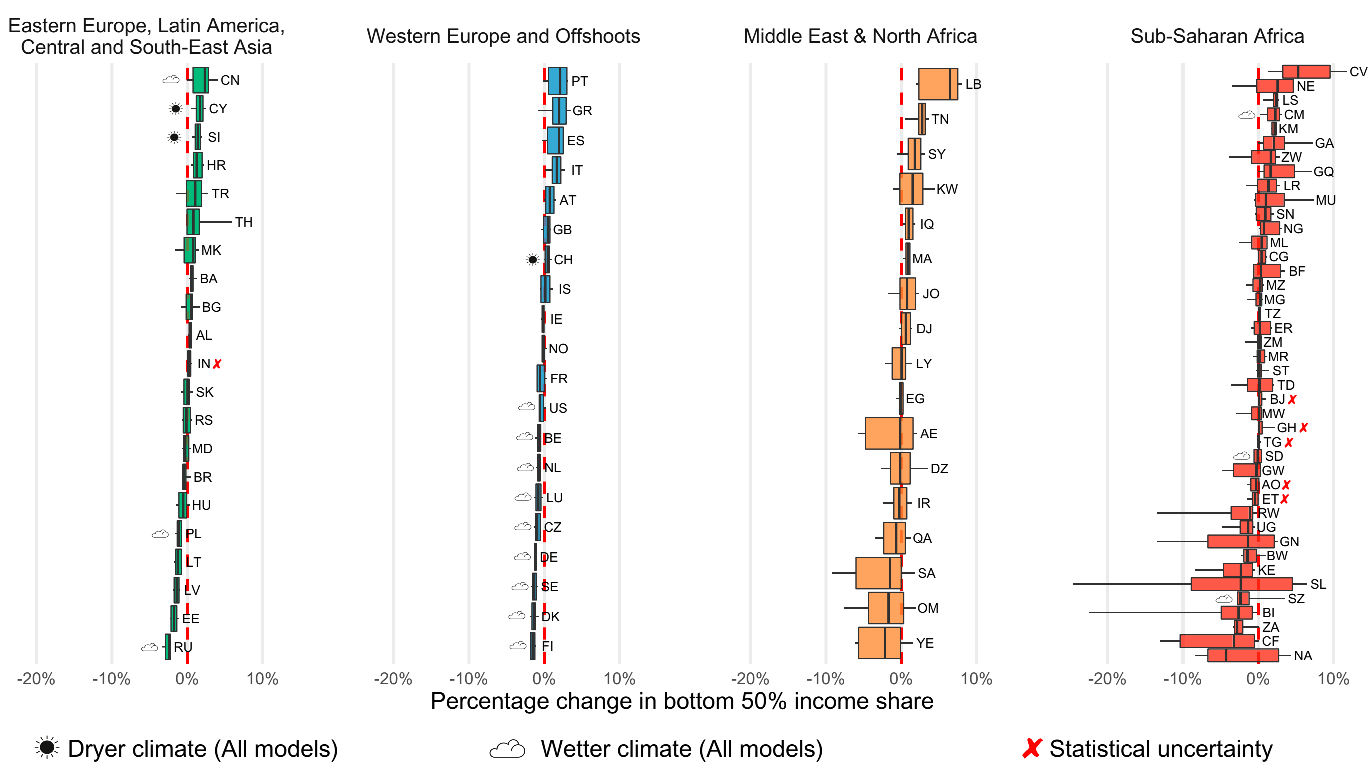

Fig. 3. Distributions of projected effects on the bottom-50%-income share (evaluated at 2080 through 2099) across climate models, by country. Projected percentage change with respect to a projection with constant climate is shown. RCP 8.5, historical trends (1991 through 2010) in agricultural employment share are shown. We show boxplots grouped by macroregion. Lower and upper hinges correspond to 25th and 75th percentiles, respectively; middle lines to medians; and lower and upper whiskers to 10th and 90th percentiles, respectively. ISO Alpha-2 codes are reported for each country. Dryer/wetter climate signs indicate whether all climate models agree on the direction of projected changes in yearly total precipitation with respect to 1991 through 2010 averages, for each country. The statistical uncertainty sign indicates countries whose effects are not statistically significant at the 5% level, when accounting for statistical uncertainty only (and not for climate uncertainty). See *SI Appendix*, *Simulated Effects on Poverty* for impacts on poverty implied by our estimates.

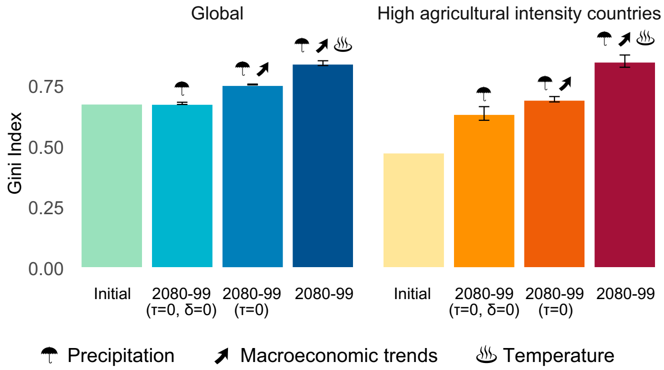

Fig. 4. Evolution of income inequality (Gini coefficients), globally and for high-agricultural-intensity countries, under different scenarios. The "2080-99 ($\tau = 0$, $\delta = 0$)" scenario accounts for precipitation changes alone. The "2080-99 ($\tau = 0$)" scenario accounts for precipitation changes along with trends in per capita GDP and agricultural employment shares. The "2080-99" scenario additionally accounts for temperature changes. Initial refers to historical averages (1991 through 2010). Multiplying projected bottom-50%-income shares by projected per capita GDP, we retrieve the per capita income for classes below and above the median (bottom 50% and top 50%), under the assumption of GDP being distributed as pretax national income. Gini coefficients are computed for each climate model and then averaged; they account for both within- and between-country income distribution. Error bars show 95% confidence bands. Two outlier countries (Bosnia and Herzegovina [BA] and Equatorial Guinea [EQ]) with highest average historical per capita GDP growth rates are excluded from the calculation.

precipitation and temperature—and trends in economic variables. The upsurge is remarkably higher for agriculturally intensive countries. Notably, precipitation anomalies alone explain 43% [41%, 45%] of the overall effect within this group of countries, with the Gini index surging from 0.48 to 0.64. Investigating global income inequality across SSP–RCP scenarios (*SI Appendix*, Fig. S14), it becomes apparent that achieving growth and industrialization in today's agriculturally intensive countries will substantially curb their vulnerability to future precipitation changes. Nonetheless, a fossil-fuel-based development pathway (SSP5–RCP8.5 future) will more than offset any gain obtained through structural change (as opposed to an SSP1–RCP2.6 scenario).

Conclusions

We provide an assessment of the relationship between climate anomalies, aggregate income, and its national distribution in a global sample of countries. Utilizing econometric techniques usually employed in the climate-economics literature, we uncover nonlinear impacts of precipitation on the bottom-50%-income shares, with extreme (low or high) levels of rainfall exacerbating within-country income inequality. Such impacts are particularly severe in countries that heavily rely on the primary sector, whereas they are modest in developed countries. Projected climate anomalies will further increase inequality in the global distribution of income, especially among the most agriculturally intensive countries. Crucially, in contrast to previous studies (6, 9), this result is found by jointly accounting for both within- and between-country income distribution. Further extensions of our analysis will require increased availability of inequality data disaggregated by sector of economic activity, regional information on precipitation spells and extreme rainfall events, and improved precipitation projections by climate models.

Our results support three conclusions. First, rainfall changes can considerably impair the distribution of income and hamper the process of economic growth. Such effects are much stronger in agriculturally intensive countries and may further increase their vulnerability to future precipitation patterns, possibly triggering a vicious cycle. Second, the materiality of climate risks calls for urgent action to support the processes of sustainable economic development and structural change of agriculturally intensive economies, which could alleviate the direct impacts of climate change beyond improving well-being (46). Third, fighting income inequality should gain additional momentum in countries that are most exposed to climate change.

Materials and Methods

Data and Code. We consider economic and climate variables observed at an annual frequency between 1980 and 2010 in 101 countries for which we have information on our main income-inequality indicator. Data on within-country income distribution are retrieved from the World Inequality Database (47). We employ measures based on market national income (pretax and transfers) to exclude any policy-related confounding factors–e.g., agricultural subsidies. Climate variables from ref. 6 comprehend population-weighted total precipitation and average temperature. Additional climate variables have been retrieved from ref. 42. Historical and projected unweighted climate variables are obtained from the 16 climate models selected by the Coupled Model Intercomparison Project 5–as provided by the World Bank Climate Change Knowledge Portal–to ensure comparability among model outcomes. See *SI Appendix*, Table S14 for the full list of models. Macroeconomic variables, such as agricultural and total per capita GDP and employment shares in agriculture, were retrieved from World Bank Open Data. Data on SSPs were retrieved from the SSP database (48). See *SI Appendix A* for a discussion on inequality-data quality. Data and code for our analyses are available at https://github.com/CoMoS-SA/climate inequality.

Econometric Models. All dependent variables $\mathbf{Y} \in \{bs, g, a\}$–bottom 50% share of national income, per capita GDP growth and per capita agricultural GDP growth, respectively–are modeled as functions of climate variables $\mathbf{C}$ and agricultural intensity $\mathbf{AI}$, a measure based on the share of workers employed in the agricultural sector:

$$\mathbf{Y} = f(\mathbf{C}, \mathbf{AI}). \qquad [1]$$

For each country i in year t, we consider both annual total precipitation (P_{it}) and yearly average temperature (T_{it}), each entering as a quadratic polynomial function (6). Thus, we use the compact notation C^{ω}_{jit} with $\omega \in \{1, 2\}$ and $j \in \{T, P\}$. $\mathbf{AI}$ represents either a dichotomous or a continuous variable, depending on the specification. We estimate a set of models investigating the impact of locally exogenous, short-term climate variations on all our variables of interest ($\mathbf{Y}$). In the first model, A0, the share of income received by the poorest bottom 50% of the population does not consider the impact of agricultural intensity ($\mathbf{AI} = 0$):

$$bs_{it} = \alpha + \sum_{j,\omega} \beta^{\omega}_{j} C^{\omega}_{jit} + \mu_i + y_t r_i + \epsilon_{it}, \qquad [\mathbf{A0}]$$

where μ_i are country fixed effects, accounting for all time-invariant socioeconomic and geographical factors, while region-specific macroeconomic shocks are captured by year fixed effects (y_t) multiplied by regional dummies (r_i). Regions are those used in ref. 5, with an additional subdivision of Sub-Saharan Africa, due to its high heterogeneity (*SI Appendix*, Table S7). In a second, more general specification (Model A1), we group countries according to their relative position in the global distribution of agricultural intensity. This is achieved by interacting all climate terms with the country-specific, time-invariant dummy variable AI^L_i:

$$bs_{it} = \alpha + \sum_{j,\omega} (\beta^{\omega}_{j} + \gamma^{\omega}_{j} AI^L_i) C^{\omega}_{jit} + \mu_i + y_t r_i + \epsilon_{it}, \qquad [\mathbf{A1}]$$

where AI^L_i identifies countries belonging to the low-agricultural-intensity group, defined as the set of countries characterized by an average share of workers employed in the agricultural sector below a given global quantile. Robustness checks with varying cutoffs are included in *SI Appendix*, Fig. S5. Our most general specification (Model A2) encompasses a continuous, time-varying term (AI_{it}) that identifies agricultural intensity for each country i in any year t:

$$bs_{it} = \alpha + \sum_{j,\omega} (\beta^{\omega}_{j} + \gamma^{\omega}_{j} AI_{it}) C^{\omega}_{jit} + \mu_i + y_t r_i + \epsilon_{it}. \qquad [\mathbf{A2}]$$

We estimate analogous models using per capita GDP growth rates (g) and per capita agricultural GDP growth rates (a) as dependent variables and include region-specific time trends ($tr_t r_i$) (6). The results are robust to the inclusion of country-specific flexible trends in the place of region-specific ones (*SI Appendix*, Tables S11 and S12). Thus, Model B1 for g with dichotomous specification for agricultural intensity is equal to:

$$g_{it} = \alpha + \sum_{j,\omega} (\beta_j^{\omega} + \gamma_j^{\omega} AI_i^L) C_{jit}^{\omega} + \mu_i + y_t + tr_t r_i + \epsilon_{it}. \qquad \textbf{[B1]}$$

Model C1 for a is:

$$a_{it} = \alpha + \sum_{j,\omega} (\beta_j^{\omega} + \gamma_j^{\omega} AI_i^L) C_{jit}^{\omega} + \mu_i + y_t + tr_t r_i + \epsilon_{it}. \qquad \textbf{[C1]}$$

Finally, Model B2, with a continuous specification for agricultural intensity, employed in projections (*SI Appendix*, *Projections*), is given by:

$$g_{it} = \alpha + \sum_{j,\omega} (\beta_j^{\omega} + \gamma_j^{\omega} AI_{it}) C_{jit}^{\omega} + \mu_i + y_t + tr_t r_i + \epsilon_{it}. \qquad \textbf{[B2]}$$

Projections. Population-weighted climate projections were obtained by first computing the compound growth rate of unweighted projected variables over unweighted historical averages and subsequently imposing them on weighted observed time series. For every model in our ensemble, we computed future trajectories of country-level bottom-50%-income shares and per capita GDP, exploiting estimates from our most general models, A2 and B2, respectively. The projected levels of the bottom-50%-income shares depend solely on future precipitation, since temperature does not have any statistically significant impact (*SI Appendix*, Table S5). Hence, the law of motion is given by:

$$bs_{it} = bs_{it-1} + \psi_{it}^{AI}(P_{pit} - P_{pit-1}), \qquad \textbf{[}\tilde{\textbf{A}}\textbf{2]}$$

where ψ_{it}^{AI} is the first derivative of Eq. **A2** with respect to precipitation (*SI Appendix*, *Projections*), and P_{pit} is projected precipitation. ψ_{it}^{AI} is a function of agricultural employment shares (AI_{it}), which are assumed to evolve according to the observed country-specific average yearly variation. Projected levels of per capita GDP are instead obtained following the methodology employed in ref. 6, but considering precipitation in addition to temperature:

$$GDPpc_{it}^{P} = GDPpc_{it-1}(1 + \delta_{it} + \eta_{it}^{AI} + \tau_{it}), \qquad \textbf{[}\tilde{\textbf{B}}\textbf{2]}$$

where δ_{it} is the country-specific average yearly growth rate (*SI Appendix*, *Projections* and Table S16 for scenarios with GDP trends using SSPs), η_{it}^{AI} is the difference between the fitted polynomial for growth rates informed with projected precipitation and the fitted polynomial for growth rates informed with average historical precipitation, while τ_{it} is given by the analogous difference in fitted polynomials informed with projected temperature. η_{it}^{AI} is also a function of agricultural employment shares (AI_{it}) (*SI Appendix*, *Projections*, Table S15, and Fig. S6). In Figs. 2 and 4, we consider different scenarios by selectively suppressing terms in Eq. $\tilde{\textbf{B}}$**2** (e.g., $\tau_{it} = 0$ for a scenario with no temperature impacts). We show future impacts relative to a projection with constant climate–i.e., only with trends in economic variables ($\psi_{it}^{AI} = 0$, $\eta_{it}^{AI} = 0$, and $\tau_{it} = 0$). Statistical uncertainty in Fig. 3 is assessed as follows: For each coefficient estimate ($\hat{\beta}$) in Model Ã2, we randomly draw 1,000 values (with replacement) from a truncated normal distribution $N(\hat{\beta}, \text{se}(\hat{\beta}))$, where $\text{se}(\hat{\beta})$ is $\hat{\beta}$'s SE. Truncation points are fixed at $\hat{\beta} \pm \text{se}(\hat{\beta})$. For each draw, we then construct projected values, keeping climate projections fixed at their country averages. Statistical significance is determined by constructing 95% CIs on all simulated paths.

Data, Materials, and Software Availability. Data and replication codes have been deposited in GitHub (https://github.com/CoMoS-SA/climate_inequality) (49). Previously published data were used for this work [Burke et al. (6) and Pretis et al. (42, 48)].

ACKNOWLEDGMENTS. This paper has received financial support from the European Union Horizon 2020 Research and Innovation programme under Grant Agreement No. 822781 (GROWINPRO). We thank Michele Andreottola, Marco Gaetani, Laura Magazzini, Maurizio Malpede, Martina Occelli, Marco Percoco, James Rising, Tommaso Rughi, and Salvatore Morelli, along with Editor Stephen Polasky, two anonymous reviewers, and participants in several conferences and workshops for useful comments.

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