

# Impacts of global warming on subnational poverty and inequality

Received: 21 November 2024

Accepted: 16 November 2025

Published online: 22 December 2025

 Check for updates

Hai-Anh H. Dang <sup>1,2,3,4</sup>✉, Stephane Hallegatte <sup>1</sup>, Minh Cong Nguyen <sup>1</sup> & Trong-Anh Trinh <sup>1,5</sup>

Higher temperatures are expected to impact globally on poverty and inequality, yet little cross-country analysis exists to quantify the effects. Here we analyse a panel dataset of subnational poverty in 130 countries covering the past decade and find that a 1 °C increase in temperature causes headcount poverty increases of 0.63–1.18 percentage points, using the daily poverty lines of US\$2.15 (corresponding to 8.3% and 15.6% increases), and increases in the Gini inequality index of 1.3–1.9%. These poverty estimates equal a projected increase of global poor by 62.3–98.7 million people by 2030 compared with a scenario without climate change. Poorer countries—particularly those in Sub-Saharan Africa—are more vulnerable, as are countries with higher agriculture shares in the economy. Estimates at the subnational level are larger than those using the country-level data, indicating that aggregated analysis may underestimate climate change risks.

The increasingly prominent threats of climate change have inspired a sizable body of economic research on a variety of outcomes, such as economic growth<sup>1,2</sup>, agriculture<sup>3–5</sup>, productivity<sup>6,7</sup>, human health and human capital<sup>8–14</sup> and crime and conflict<sup>15,16</sup>. Yet, although most country-specific studies observe negative impacts of higher temperature on poverty, scant empirical evidence exists on the global impacts of climate change on poverty and inequality. Furthermore, climate change's global impacts on inequality appears highly context specific<sup>17</sup>.

A possible explanation for the limited empirical evidence on global warming's impacts is the challenge of obtaining appropriate measures of poverty and inequality. Although household surveys—the main source of poverty and inequality statistics—are increasingly available, they remain unavailable or infrequent in many poor countries. In addition, poverty and inequality vary substantially within and across countries. Ignoring subnational variations could easily mask the dynamic relationship between these outcomes and climatic conditions, which are often location specific. Indeed, recent studies suggest that country-level data aggregation fails to capture the true effects of climate change on economic growth, which are better revealed through subnational analyses<sup>18,19</sup>.

To illustrate, in Fig. 1, we plot poverty and inequality against temperature at the subnational level for Indonesia, a populous country with a large share of the global poor. Large degrees of subnational

variation exist for both poverty and inequality. Poverty, as measured by the headcount poverty rate at US\$2.15 a day (in 2017 purchasing power parities (PPP)), is lowest in the Western regions (0.1%) but highest in the Eastern regions (42%). Inequality, as measured by the Gini index, ranges between 23% and 45%. Within the country, average temperature also widely varies between 20 °C and 32 °C. Such wide-ranging subnational variations are not revealed by simply looking at country-level averages of poverty, inequality and temperature (8%, 36% and 25 °C, respectively). With nonlinear relationships between climate and economic outcomes<sup>20</sup>, accurately assessing global warming effects on poverty and inequality cannot be done with an analysis at the national level. Using data at subnational level, we identify strong and statistically significant global effects of higher temperature on poverty and inequality and weaker effects on income growth. Our results show that a 1 °C annual increase in temperature causes headcount poverty increases of 0.63–1.18 percentage points (depending on the estimation models), using the daily poverty lines of US\$2.15 (which correspond to 8.3% and 15.6% increases). Depending on the selected scenario, these estimates correspond to an increase of the global headcount poverty by 62.3–98.7 million people by 2030. For inequality, a 1 °C rise in temperature causes 1.3–1.9% increases in the Gini index.

For both poverty and inequality, we find stronger climate change effects at the subnational level compared with country-level data,

<sup>1</sup>World Bank, Washington, DC, USA. <sup>2</sup>Indiana University, Bloomington, IN, USA. <sup>3</sup>IZA, Bonn, Germany. <sup>4</sup>University of Economics, Ho Chi Minh City, Vietnam.

<sup>5</sup>Monash University, Caulfield East, Victoria, Australia. ✉e-mail: [hdang@worldbank.org](mailto:hdang@worldbank.org)

indicating that the analysis of aggregated data may overlook critical impacts. The daily poverty lines of US\$2.15 and the Gini index are our default poverty line and inequality measure for analysis, unless noted otherwise. We offer robustness checks using other poverty lines and inequality measures in the 'Additional robustness checks' section of the Methods.

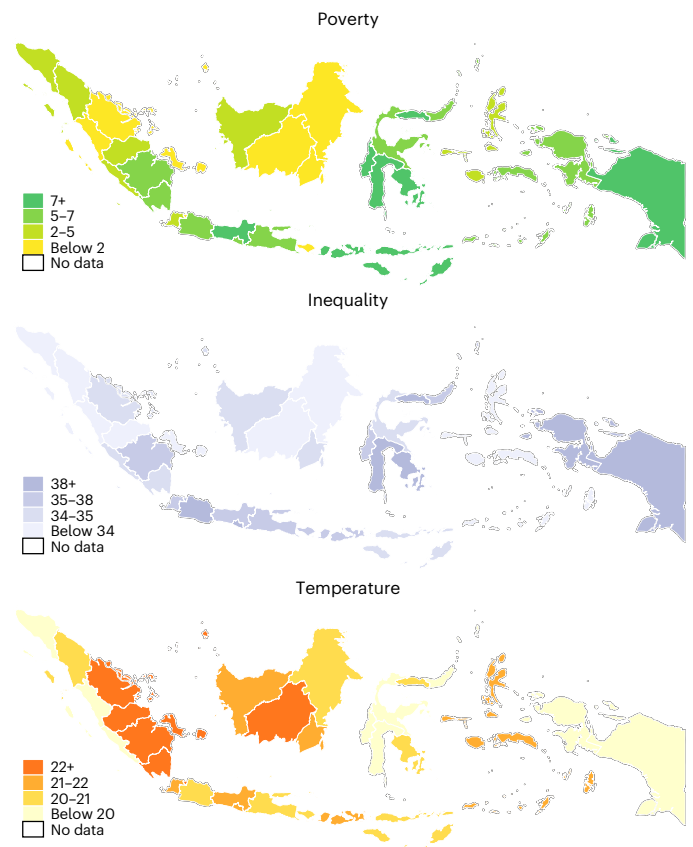
Further nonlinear analysis shows that these effects are largely driven by the highest temperatures, making hot countries more vulnerable, and are partly mediated by agricultural impacts. Country heterogeneity exists, where democratic regimes appear less vulnerable to climate impacts, whereas those with higher agricultural shares are more affected, and those with higher manufacturing shares are less affected. Heterogeneity analysis also reveals that poorer countries, particularly those in Sub-Saharan Africa and under hotter weather, are more vulnerable to warmer temperature. Some evidence also suggests that colder weather could result in less inequality for richer countries.

We make several contributions to the literature. First, we provide a global assessment of warmer temperature on both poverty and inequality, exploiting a novel global subnational panel database. Whereas our results for poverty are qualitatively consistent with earlier estimates based on simulation models<sup>21–23</sup> or empirical analysis<sup>24</sup>, recent studies typically focus on either poverty or inequality, but not both outcomes. Results based on the same data source offer more consistency.

There is inconclusive evidence on inequality in existing literature. For example, one study estimates that a 1% temperature increase is associated with a 0.5-percentage-point increase in the Gini index<sup>25</sup>. Another study finds that climate impacts increase the Gini index by up to six percentage points<sup>26</sup>. Some research suggests that climate change could reduce long-term inequality or increase inequality slightly in the short term<sup>27</sup>, although other work indicates that it affects inequality through precipitation only<sup>28</sup>. Indeed, one study observes that the linkages between short-term and longer-term responses to climate change are complicated and can theoretically reduce or increase inequality depending on policy responses (for example, if the government subsidizes housing protection with more resources going to more expensive houses, that is, richer households)<sup>17</sup>.

Notably, poverty and inequality are closely intertwined, but distinct, development outcomes. Poverty represents the lower part of the income (consumption) distribution that is below the specified poverty line, whereas inequality measures the spread of the whole income distribution. As such, poverty and inequality can theoretically move in the same direction or the opposite direction, which is supported by empirical evidence<sup>29,30</sup>. Furthermore, these two metrics are related with economic growth, under what has long been referred to as the 'triangle' relationship of growth, poverty and inequality<sup>31</sup>. Although growth is beneficial for poverty reduction, it can also come with higher poverty depending on inequality levels<sup>32,33</sup>. Consequently, examining both poverty and inequality together using cross-country survey data offers a more comprehensive picture of temperature changes' impacts. Our results, based on household surveys, appear stronger for poverty and inequality than for income growth, therefore complementing other studies based on income from national accounts.

Second, in contrast to the existing literature that largely relies on country-level analysis, we use disaggregated data on headcount poverty estimates and inequality indices for more than 1,600 subnational areas in 141 economies from 2004 to 2022, based on the Subnational Poverty and Inequality Database (SPID) database<sup>34</sup>. Derived from official household income and consumption surveys, the SPID distinguishes our study from prior country-level studies, which, although informative, were not able to capture the more nuanced, subnational dynamics of poverty, inequality and temperature change. Our example with Indonesia discussed above (Fig. 1) suggests that, similar to findings offered by previous studies on rainfall<sup>18,19</sup>, analysing country-level data probably underestimate the true impacts of temperature owing to measurement errors. Indeed, aggregate time series data are known



**Fig. 1 | Subnational poverty, inequality and temperature in Indonesia.**

**a.** Poverty. **b.** Inequality. **c.** Temperature. Poverty is measured by the Global Subnational Poverty Headcount Ratio using the daily threshold of US\$2.15. Inequality is measured by the Gini index. Temperature data are taken from the ERA-5. Poverty rate, inequality and temperature data are measured in the period 2004–2022 ( $n = 33$ ).

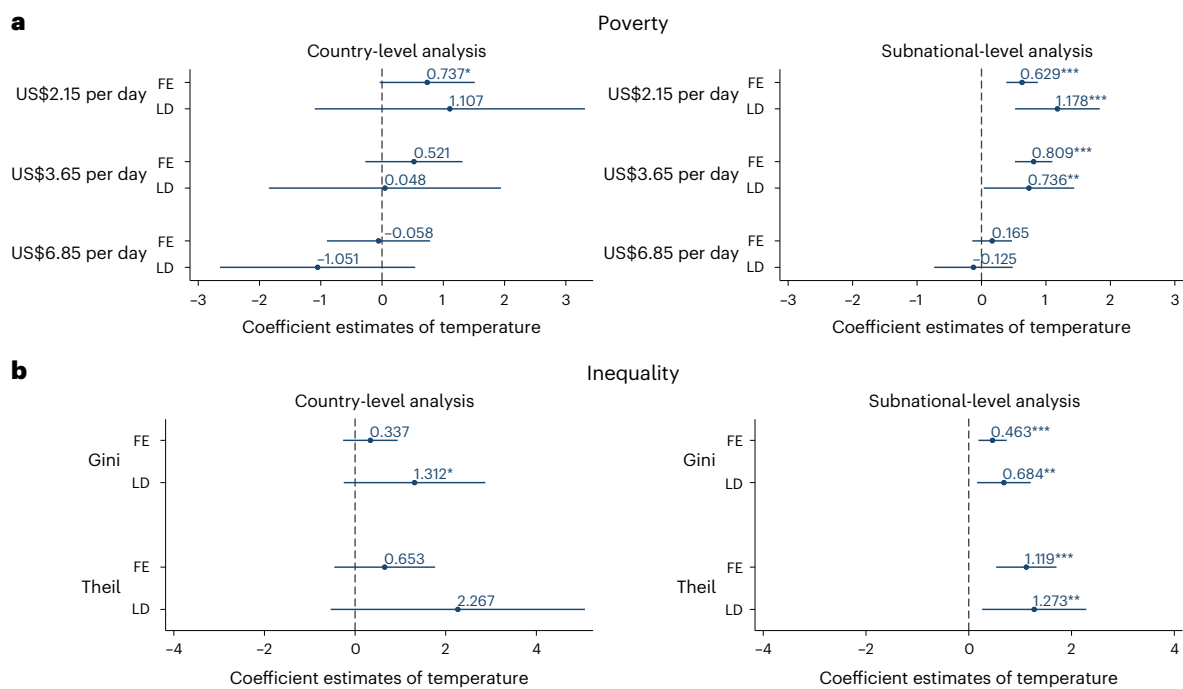
to cause various aggregation biases<sup>35,36</sup>. Our results show that analysis based on subnational data yields estimates that are stronger and more accurate than those based on country-level analysis.

Finally, few studies investigate the effects of colder temperature<sup>1,8,37,38</sup>. To our knowledge, none address the distributional effects of colder weather on poverty and inequality. As colder weather remains an important hazard in many regions of the world, understanding its effects is important.

## Effects on poverty

We start by examining the temperature effects on poverty and inequality at both country and subnational levels (Fig. 2). All the regressions control for key country characteristics such as gross domestic product (GDP) per capita, unemployment rates, the shares of added values for agricultural and manufacturing and population growth. For each outcome, we present the results of the panel fixed-effects (FE) model that captures the shorter-term effects, followed by the results of the long-differences (LD) model that captures the longer-term effects (see the Methods for discussion on the different models). Yet, the differences between the FE and the LD estimates are statistically insignificant (Supplementary Table 2).

Although the subnational-level estimates (Fig. 2b) have similar magnitudes to the country-level estimates (Fig. 2a), the subnational-level estimates are mostly statistically significant, whereas the country-level estimates are not (Supplementary Table 2). This suggests that studies relying on country-level analysis alone could mask the impacts of warmer temperature, aligning with previous research



**Fig. 2 | The effects of temperature on poverty and inequality.** **a**, Poverty. **b**, Inequality. Figures present point estimates (regression coefficients) as the measure of centre, with error bars indicating 95% confidence intervals from regressions of poverty in **a** and inequality in **b** on temperature, controlling for weather conditions (rainfall and humidity), GDP per capita, unemployment rates, the shares of added values for agricultural and manufacturing, population

growth (and fixed effects for FE models). Poverty is measured using the US\$2.15 per day, US\$3.65 per day and US\$6.85 per day poverty lines in 2017 PPP. Inequality is measured by Gini and Theil indices. The temperature data are taken from the ERA-5. Left: a country-level analysis using two models: an FE model ( $n = 504$ ) and an LD model ( $n = 104$ ). Right: a subnational-level analysis using two models: an FE model ( $n = 6,052$ ) and an LD model ( $n = 1,292$ ).

on economic growth using subnational data<sup>18,19</sup>. One implication is that the assessment of poverty impacts of climate change and natural disaster cannot be done sequentially by first assessing the macroeconomic impact on national GDP (or national economic growth) and subsequently assessing its subsequent poverty and distributional implications. Even a more direct assessment of subnational GDP and growth would probably provide inaccurate estimates for the impacts of temperature change on poverty.

Focusing on the subnational analysis, we find that a 1 °C temperature increase raises poverty by 0.629 percentage points (Supplementary Table 2, column 1, FE model) to 1.178 percentage points (Supplementary Table 2, column 2, LD model), equivalent to 8.3% and 15.6% rises given the mean poverty rate of 7.5%. For higher poverty lines, the impacts are smaller and have weaker statistical significance. The corresponding figures are between 0.809 and 0.736 percentage point increases for the US\$3.65 line, translating to relative increases of 4.3–4.7%. The estimates using the US\$6.85 per day are, however, statistically insignificant. These results could reflect the greater vulnerability of poorer households, who have fewer resources to cope with climate change.

### Effects on inequality

Similar to the results for poverty, we obtain statistically significant estimates of warmer temperature effects on income inequality at the subnational level but not the country level (Fig. 2b). But the results appear to have stronger statistical significance than those for poverty. A 1 °C temperature increase raises the Gini index by 0.463–0.684 percentage points and the Theil index by 1.119–1.273 percentage points. Compared with the sample means (Supplementary Table 3), these correspond to increases of 1.3–1.9% for the Gini index and 4.5–5.1% for the Theil index. Our results range from being similar to slightly higher than those found in a previous study for the Gini index<sup>25</sup>.

To contextualize our findings, Italy is among the more equal countries with a Gini index of 34.6, whereas Namibia is among the more

unequal with a Gini index of 53.8. Fig. 3b shows that temperature change has little or no effect on inequality in Italy but significantly increases inequality in Namibia. Our estimated Gini index increase of 0.463 percentage points (using the FE model) therefore implies that a 1 °C rise in temperature would widen the inequality gap between these two countries by about 2.4% ( $= 100 \times 0.463 / (53.8 - 34.6)$ ). This shift is substantial, considering the cumulative impacts over time and across different countries.

### Heterogeneity analysis

We expect warmer temperature's effects to be heterogeneous across income levels and countries. Poorer countries, particularly in low-income regions, can be less prepared for climate change and face more challenges in recovery and reconstruction. To explore this, we split our sample into lower-income and higher-income areas (with lower-income countries defined as low- and lower-middle-income and higher-income countries defined as upper-middle and high income, on the basis of the World Bank income classification) for separate estimation. Several results stand out (Table 1).

First, the temperature effects on poverty are more statistically significant and have stronger magnitudes in poorer areas, as shown consistently across both FE and LD models (Table 1, columns 1 and 2). However, there is also some evidence of statistically significant and opposite effects, albeit weaker, in richer areas (Table 1, column 4). Second, the effects of warmer temperatures on inequality hold more for poorer areas than richer areas, with both the FE and LD estimates having strong statistical significance for poorer areas (Table 1, columns 1 and 2). Only the FE estimate is statistically significant for richer areas, and it has weaker magnitude (Table 1, column 3). Finally, there are strong statistical significances for the differences between the FE and LD estimates for poverty between lower-income areas and higher-income areas, as shown by the equality tests for higher income versus lower income areas. Similar to poverty, these results further highlight that

**Table 1 | The effects of temperature on poverty and inequality by income group**

	Lower income		Higher income	
	FE	LD	FE	LD
	(1)	(2)	(3)	(4)
Panel a: Poverty rate at US\$2.15				
Temperature	1.945*** (0.503)	5.001*** (1.062)	0.005 (0.040)	-0.554*** (0.174)
Subnational/year FE	Yes	Yes	Yes	Yes
Observations	2,363	603	3,689	689
Equality test (FE versus LD)	P=0.001		P=0.001	
Equality test (lower income versus higher income)	P=0.000			
Panel b: Gini index				
Temperature	1.140*** (0.310)	1.550** (0.603)	0.244* (0.133)	0.004 (0.223)
Subnational/year FE	Yes	Yes	Yes	Yes
Observations	2,363	603	2,780	591
Equality test (FE versus LD)	P=0.425		P=0.221	
Equality test (higher income versus lower income)	P=0.001			

In panel a, poverty rate is measured by the Subnational Poverty Headcount Ratio at US\$2.15 a day. In panel b, inequality is measured by the Gini index. The poverty and inequality data are taken from SPID (version 2). The LD estimation is based on cross-sectional data with a smaller sample size compared with panel data. The equality test *P* values show the *t*-test between the FE results and LD results and the differences between the FE and LD estimates for the lower-income areas versus those for the higher-income areas. Lower-income countries include both low- and lower-middle-income countries, whereas higher-income countries include upper-middle- and high-income countries, on the basis of the World Bank income classification, available at ref. 45. Lower- and higher-income groups are defined according to the income level of each subnational unit at its first observed data point. Control variables include rainfall and humidity, GDP per capita, unemployment rates, the shares of added values for agricultural and manufacturing, population growth and FE. All statistical tests are two-sided, and no adjustments were made for multiple comparisons. \*\*\**P*<0.01, \*\**P*<0.05, \**P*<0.1.

higher-income regions have greater capacity to mitigate the adverse effects of temperature change, probably through better infrastructure, economic diversification and policy responses.

To further delve into differences by country incomes, we categorize daily temperature into 3 °C bins, where the estimated coefficients can be interpreted as the effects of experiencing 1 day with temperatures falling in a given bin relative to the reference 'comfortable' bin (that is, 18–21 °C). We plot the estimates for poverty and inequality separately for poorer versus richer countries (Fig. 4). This figure indicates that hotter temperatures, especially for poorer countries with daily temperatures in the range of 30 °C or higher, increase both poverty and inequality (Fig. 4a). These results suggest that the effects detected on poverty and inequality are largely driven by changes in the frequency and intensity of high-temperature episode, underscoring the nonlinearity of the climate–economic relationship. By contrast, although warmer daily temperatures compared with the reference bin do not produce the same result for richer countries, colder temperatures could result in less inequality for richer countries (Fig. 4b).

Further plotting the temperature effects by country, with each country's marker proportional to its real GDP per capita, shows that countries bearing the largest effect of global warming on poverty tend to be poorer and hotter countries. These include African countries such as Madagascar, Malawi, Zambia, Congo DRC, Burundi, Lesotho, Mozambique and Rwanda (Fig. 3a). Global warming, however, also increases inequality for a number of low-income to

upper-middle-income countries, including South Africa, Chile, Honduras, Colombia, Brazil, Namibia, Mexico, Bolivia, Zambia, Botswana and Mozambique (Fig. 3b).

We further assess the heterogeneity of temperature effects across different country characteristics. First, we examine whether a country's institutions may affect the impacts of temperature. This is motivated by the fact that institutions may influence adaptation to climate change through which incentives for individuals and collective action are structured. We use the democracy index from the 2020 report of the Economist Intelligence Unit and categorize countries into different types of regime: (1) democracy, (2) authoritarian and (3) hybrid. The results presented in Supplementary Table 4 show evidence that countries with a democratic regime appear to be less vulnerable to temperature change (Supplementary Table 4a). We also examine the heterogeneous impacts of temperature by other country characteristics. For example, countries near the equator have more inequality due to temperature increases and consequence of their current climate (Supplementary Table 4b). In addition, temperature effects on both poverty and inequality are more pronounced in countries with a higher share of agriculture or a lower share of manufacturing in the economy, suggesting that structural change reduces the vulnerability to climate change (Supplementary Table 4c,d). Finally, we find negligible and statistically insignificant effects among countries with a lower share of trade (Supplementary Table 4e). We return to discussion with more country characteristics in the 'Additional robustness checks' section in the Methods (Supplementary Table 16).

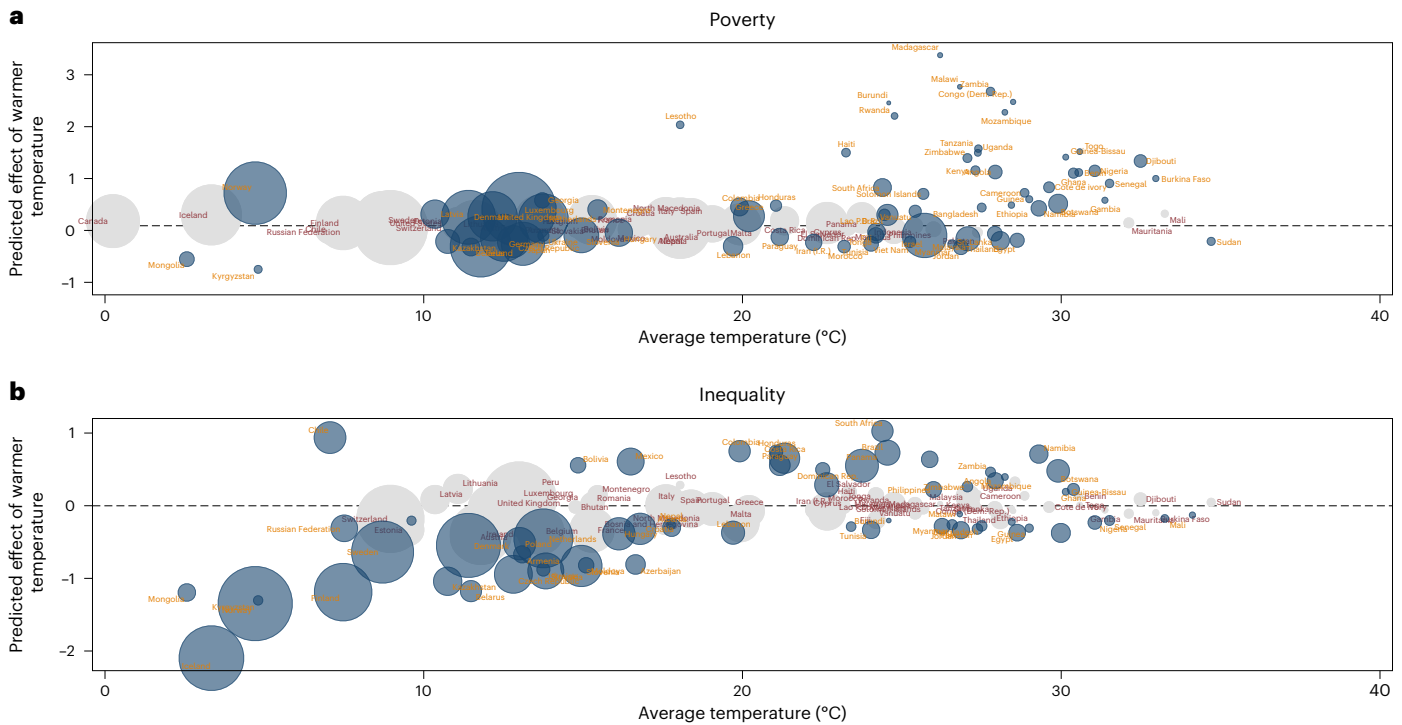
## Potential mechanisms

Poor countries, often located in tropical areas with higher temperatures, rely heavily on climate-sensitive agriculture and bear extreme temperature's negative effects on crop yields<sup>39–41</sup>. To investigate agriculture's mediating role between temperature and socio-economic outcomes, we use causal mediation analysis. We use the normalized difference vegetation index (NDVI) and soil moistures as proxies for vegetation health and crop yields, which are available across large spatial and temporal scales. The results (Supplementary Table 5) indicate that agricultural factors partially, but not fully, explain the observed relationships between temperature, poverty and inequality. The mediation through NDVI is statistically significant for inequality, accounting for roughly one quarter of the total effect (28%), whereas the mediation through soil moisture is significant for poverty, explaining about 7% of the overall impact. These findings highlight that agriculture constitutes an important transmission channel linking higher temperatures to worsening distributional outcomes, although other mechanisms, such as labour-productivity losses, migration responses or conflict, are also likely to contribute<sup>17,42</sup>.

## Projected impacts under future climate change

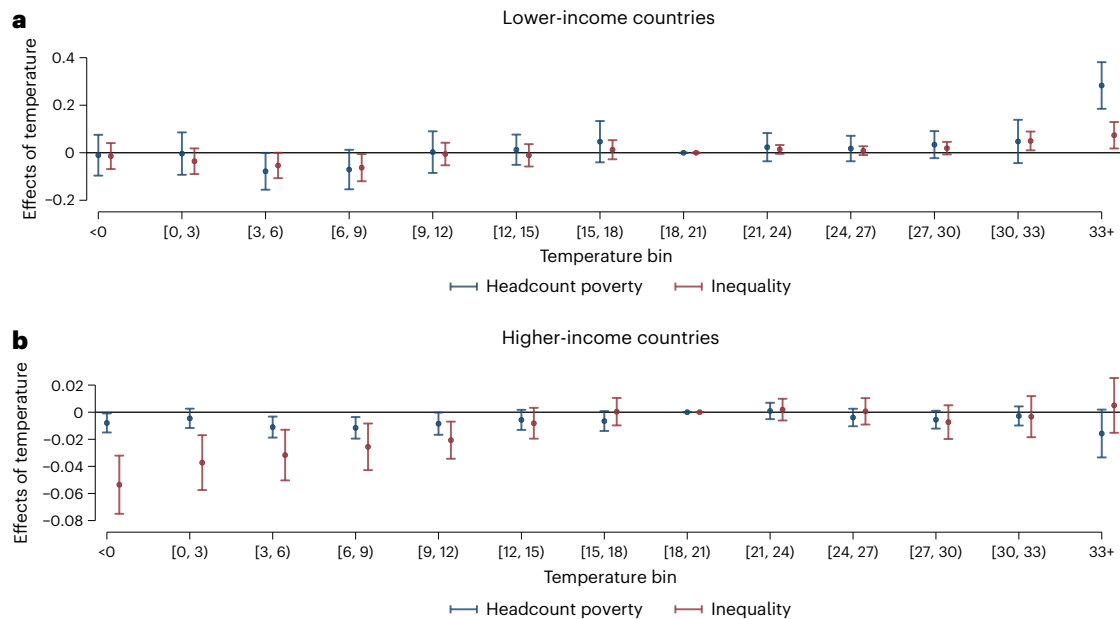
Following established methods<sup>19,43</sup> and combining model estimates from Fig. 2 and simulated weather data (from the Coupled Model Inter-comparison Project Phase 6, CMIP6), we project future temperature effects on poverty under different scenarios. We use annual temperature data from European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5) to construct historical averages and probability distributions for 1979–2022. Projected temperature changes are calculated as the difference between CMIP6 projections and these historical averages. Finally, we calculate poverty (inequality) changes by multiplying the temperature changes with the baseline estimates in Supplementary Table 2, columns 1, 3 and 5 and Supplementary Table 3, columns 1 and 3.

We summarize projected temperature and poverty changes under different emission pathways (Supplementary Table 6). By 2030, average temperatures across the countries in our sample are expected to rise by 1.2–1.9 °C compared with the baseline using the historical averages for 1979–2022, leading to a 0.75–1.2 percentage points (10–15.9%)



**Fig. 3 | The effects of temperature on poverty and inequality across countries adjusted by real GDP. a, Poverty. b, Inequality.** The graphs shows the point estimates of temperature and the country dummies using regression with weather conditions (rainfall and humidity), GDP per capita, unemployment rates, the shares of added values for agricultural and manufacturing, population growth and FE. In **a**, the headcount poverty rate is measured by the Subnational Poverty Headcount Ratio at US\$2.15 a day ( $n = 116$ ). In **b**, inequality is measured by the Gini index ( $n = 122$ ). Each country's marker is proportional to its real GDP

per capita using the World Development Indicators database (that is, a larger size indicates a higher GDP per capita level). We select Indonesia as the reference for the poverty figure and Madagascar for the inequality figure. The dashed line represents the temperature effect for the reference country (0.092 for Indonesia in **a** and 0.024 for Madagascar in **b**). The coloured countries indicate significant effects, whereas grey countries are those where the estimated temperature effect on poverty is not statistically significant. The coefficient estimates are shown in Supplementary Table 17(appendix).



**Fig. 4 | Heterogeneity analysis by income. a, Lower-income countries. b, Higher-income countries.** Graphs present point estimates (regression coefficients) as the measure of centre, with error bars indicating 95% confidence intervals from regressions controlling for weather conditions (rainfall and humidity), GDP per capita, unemployment rates, the shares of added values for agricultural and manufacturing, population growth and FE. Robust standard errors are clustered at the subnational level. The headcount poverty is measured using the US\$2.15 per day poverty line in 2017 PPP. Inequality is measured using the Gini coefficient.

In **a**, lower-income countries ( $n = 2,220$ ) include both low- and lower-middle-income countries, whereas higher-income countries in **b** ( $n = 3,834$ ) include upper-middle- and high-income countries, on the basis of the World Bank income classification over time, available in ref. 45. The reference temperature bin is [18, 21) °C. Unlike the main analysis, which uses region year average temperatures, the temperature-bin approach relies on daily temperature data aggregated into annual counts of days in each temperature range.

poverty increase, using the US\$2.15 daily poverty line (Supplementary Table 6a). Using the World Bank's current projection of 622 million people living in extreme poverty (under the US\$2.15 daily poverty threshold) by the year 2030<sup>44</sup>, the increase in the number of global poor due to global warming would be in the range of 62.3–98.7 million people. Put differently, if temperatures had remained at their 1979–2022 level, the number of people living in poverty would have been lower by 62.3–98.7 million people by the year 2030. These numbers fall between the simulation-based optimistic scenario of 32.2–67.7 million people falling into poverty and pessimistic scenario of 42.0–131.5 million people falling into poverty provided in a previous study<sup>22</sup>.

Similarly, the Gini index is projected to increase by 0.56–0.88 percentage points, which translate into 1.6% to 2.5% increases respectively (Supplementary Table 6b). The largest increases in poverty and inequality are predicted under scenarios with higher greenhouse gas emissions.

## Discussion

Although the evidence of climate change's macroeconomic impacts is growing, its global effects on poverty and inequality remain underexplored. A major limitation has been the lack of disaggregated data for accurate analysis across and within countries. Analysing a new global panel dataset covering subnational areas in around 130 countries, we find that hotter temperature increases poverty and inequality. Interestingly, although these estimates are generally not statistically significant at the country level, they are strongly statistically significant at the subnational level. Although poorer countries appear to suffer more from warmer temperature regarding both poverty and inequality, some evidence suggests richer countries can have less inequality under colder temperature. This suggests that country-level analyses underestimate the consequences of global warming and are unable to uncover the nuanced dynamics at the subnational level.

Our findings contribute to policy discussions on reducing future losses from global warming. Specifically, certain countries (for example, those with democratic regimes or richer countries) appear less vulnerable to climate impacts, whereas poorer countries, especially in Sub-Saharan Africa, or those with higher agricultural shares are more affected.

Subnational poverty and inequality data also open new research opportunities. Although our study highlights agriculture's role in climate-induced poverty and inequality, alternative factors such as civil conflicts and labour productivity merit further exploration. Research on these areas can provide valuable policy insights for addressing global warming.

## Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41558-025-02516-6>.

## References

- Dell, M., Jones, B. F. & Olken, B. A. Temperature shocks and economic growth: evidence from the last half century. *Am. Econ. J. Macroecon.* **4**, 66–95 (2012).
- Callahan, C. W. & Mankin, J. S. Globally unequal effect of extreme heat on economic growth. *Sci. Adv.* **8**, eadd3726 (2022).
- Deschênes, O. & Greenstone, M. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *Am. Econ. Rev.* **97**, 354–385 (2007).
- Schlenker, W. & Roberts, M. J. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proc. Natl Acad. Sci. USA* **106**, 15594–15598 (2009).
- Cinner, J. E. et al. Potential impacts of climate change on agriculture and fisheries production in 72 tropical coastal communities. *Nat. Commun.* **13**, 3530 (2022).
- Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G. & Lobell, D. B. Anthropogenic climate change has slowed global agricultural productivity growth. *Nat. Clim. Change* **11**, 306–312 (2021).
- Somanathan, E., Somanathan, R., Sudarshan, A. & Tewari, M. The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *J. Polit. Econ.* **129**, 1797–1827 (2021).
- Deschênes, O. & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *Am. Econ. J. Appl. Econ.* **3**, 152–185 (2011).
- Barreca, A. I. Climate change, humidity, and mortality in the United States. *J. Environ. Econ. Manag.* **63**, 19–34 (2012).
- Graff Zivin, J., Hsiang, S. M. & Neidell, M. Temperature and human capital in the short and long run. *J. Assoc. Environ. Resour. Econ.* **5**, 77–105 (2018).
- Graff Zivin, J., Song, Y., Tang, Q. & Zhang, P. Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China. *J. Environ. Econ. Manag.* **104**, 102365 (2020).
- Kephart, J. L. et al. City-level impact of extreme temperatures and mortality in Latin America. *Nat. Med.* **28**, 1700–1705 (2022).
- Salas, R. N. et al. Impact of extreme weather events on healthcare utilization and mortality in the United States. *Nat. Med.* **30**, 1118–1126 (2024).
- Zhang, Y. et al. The burden of heatwave-related preterm births and associated human capital losses in China. *Nat. Commun.* **13**, 7565 (2022).
- Burke, M., Hsiang, S. M. & Miguel, E. Climate and conflict. *Annu. Rev. Econ.* **7**, 577–617 (2015).
- Heilmann, K., Kahn, M. E. & Tang, C. K. The urban crime and heat gradient in high and low poverty areas. *J. Public Econ.* **197**, 104408 (2021).
- Dang, H. A. H., Hallegatte, S. & Trinh, T. A. Does global warming worsen poverty and inequality? An updated review. *J. Econ. Surv.* **38**, 1873–1905 (2024).
- Damania, R., Desbureaux, S. & Zaveri, E. Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *J. Environ. Econ. Manag.* **102**, 102335 (2020).
- Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production: evidence from a global panel of regions. *J. Environ. Econ. Manag.* **103**, 102360 (2020).
- Burke, M. & Hsiang, S. M. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527**, 235–239 (2015).
- Diffenbaugh, N. S. & Burke, M. Global warming has increased global economic inequality. *Proc. Natl Acad. Sci. USA* **116**, 9808–9813 (2019).
- Jafino, B. A., Hallegatte, S., Rozenberg, J. & Walsh, B. *Revised Estimates of the Impact of Climate Change on Extreme Poverty by 2030* (World Bank Group, 2020); <http://documents.worldbank.org/curated/en/706751601388457990>
- Budolfson, M. et al. Climate action with revenue recycling has benefits for poverty, inequality and well-being. *Nat. Clim. Change* **11**, 1111–1116 (2021).
- Azzarri, C. & Signorelli, S. Climate and poverty in Africa South of the Sahara. *World Dev.* **125**, 104691 (2020).
- Paglalunga, E., Coveri, A. & Zanfei, A. Climate change and within-country inequality: new evidence from a global perspective. *World Dev.* **159**, 106030 (2022).
- Gilli, M., Calcaterra, M., Emmerling, J. & Granella, F. Climate change impacts on the within-country income distributions. *J. Environ. Econ. Manag.* **127**, 103012 (2024).

27. Emmerling, J. et al. A multi-model assessment of inequality and climate change. *Nat. Clim. Change* **14**, 1254–1260 (2024).
28. Palagi, E., Coronese, M., Lamperti, F. & Roventini, A. Climate change and the nonlinear impact of precipitation anomalies on income inequality. *Proc. Natl Acad. Sci. USA* **119**, e2203595119 (2022).
29. Ferreira, F. H. G. Distributions in motion: economic growth, inequality, and poverty dynamics. In *Oxford Handbook of the Economics of Poverty* (ed. Jefferson, P. N.) 427–462 (Oxford Univ. Press, 2012).
30. Dang, H. A. & Serajuddin, U. Tracking the sustainable development goals: emerging measurement challenges and further reflections. *World Dev.* **127**, 104570 (2020).
31. Bourguignon, F. *The Poverty–Growth–Inequality Triangle* (SSRN, 2004).
32. Cerra, M. V., Lama, M. R. & Loayza, N. Links between growth, inequality, and poverty: a survey. In *How to Achieve Inclusive Growth* (eds Cerra, V. et al.) 32–73 (Oxford University Press, 2022).
33. Ferreira, I. A., Salvucci, V. & Tarp, F. in *Handbook of Labor, Human Resources and Population Economics* (ed. Zimmermann, K. F.) 1–45 (Springer, 2023).
34. Nguyen, M. C., Yang, J., Dang, H. A. & Sabatino, C. *On the Construction of the World Bank’s Subnational Poverty and Inequality Databases: Documentation* (World Bank, 2023).
35. Angrist, J. D. & Krueger, A. B. Empirical strategies in labor economics. In *Handbook of Labor Economics* (eds Ashenfelter, O. C. & Card, D.) 1277–1366 (North-Holland, 1999).
36. Gardes, F., Duncan, G. J., Gaubert, P., Gurgand, M. & Starzec, C. Panel and pseudo-panel estimation of cross-sectional and time series elasticities of food consumption: the case of US and Polish data. *J. Bus. Econ. Stat.* **23**, 242–253 (2005).
37. Oudin Åström, D., Forsberg, B., Ebi, K. L. & Rocklöv, J. Attributing mortality from extreme temperatures to climate change in Stockholm, Sweden. *Nat. Clim. Change* **3**, 1050–1054 (2013).
38. Cook, N. & Heyes, A. Brain freeze: outdoor cold and indoor cognitive performance. *J. Environ. Econ. Manag.* **101**, 102318 (2020).
39. Deschênes, O. & Moretti, E. Extreme weather events, mortality, and migration. *Rev. Econ. Stat.* **91**, 659–681 (2009).
40. Schlenker, W. & Lobell, D. B. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* **5**, 014010 (2010).
41. Jacoby, H. G., Rabassa, M. & Skoufias, E. Distributional implications of climate change in rural India: a general equilibrium approach. *Am. J. Agric. Econ.* **97**, 1135–1156 (2015).
42. World Bank Group. *People in a Changing Climate: From Vulnerability to Action—Insights from World Bank Group Country Climate and Development Reports Covering 72 Economies* (World Bank, 2024); <http://hdl.handle.net/10986/42395>
43. Burke, M. & Emerick, K. Adaptation to climate change: evidence from US agriculture. *Am. Econ. J. Econ. Policy* **8**, 106–140 (2016).
44. World Bank. *Poverty, Prosperity, and Planet Report 2024: Pathways out of the Polycrisis* (World Bank, 2024).
45. World Bank. *The World by Income* (World Bank, 2025); <https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html>

**Publisher’s note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2025

## Methods

This study relies on an extensive and diverse range of data sources to investigate poverty, inequality and their interactions with climate variables. The core of our analysis is grounded in a novel dataset that offers a detailed view of poverty and inequality at the subnational level.

### Poverty data

We employ a novel dataset that provides a granular perspective on poverty and inequality at the subnational level. In particular, we draw on the SPID, a collaborative effort among different teams at the World Bank over a period of time<sup>34</sup>. The SPID is built on countries' official household income (consumption) surveys, covering more than 1,600 subnational areas in 141 economies from 2004 to 2022, with more than 90% of the data ranging from 2010 to 2022. In most cases, a subnational unit refers to a province or state (that is, first-level administrative boundaries) but can also be a group of regions determined by the specific sampling strategy of household surveys.

Poverty rates at the subnational level are derived from official household or income surveys for global poverty tracking. These rates correspond to the specific household or income survey they originate from. Creating a consistent panel data for poverty at an area level is challenging owing to potential changes in country borders and survey representation over time. To maintain a consistent and comparable dataset across different regions and periods, the World Bank team has used different measures including redefining areas to align with previous definitions or increasing the granularity of geographical breakdown over time. In the current panel data version, a typical country has information for 14 regions over the period of 3 years.

For the main outcomes, we utilize the (headcount) poverty rate at US\$2.15 a day, as estimated by the percentage of the population living on less than US\$2.15 a day at the 2017 purchasing power parities (PPP) prices. For robustness checks, we also use other poverty lines of US\$3.65 and US\$6.85 a day. Note all numbers expressed in US dollars in the paper are at 2017 PPP prices. Supplementary Fig. 1 shows that Sub-Saharan Africa currently has the highest poverty rates, with the poorest countries including Tanzania (51.3%), Mozambique (54.7%) and the Democratic Republic of Congo (72.9%).

### Inequality data

We use the Gini index and Theil index, which are the most commonly used measures of income inequality. These indices are computed on the income available to households after government taxes and transfers. All income measures are converted to real terms using 2017 PPP dollars. Supplementary Fig. 1 provides a global map of income inequality at the subnational level, which shows the substantial variation of inequality across regions within a country. The Gini index is our preferred measure of inequality.

### Weather and other data

We match our poverty and inequality data with the ERA-5 satellite reanalysis data from the European Centre for Medium-Range Weather Forecasts Reanalysis 5. The ERA-5 provides hourly estimates of several climate-related variables at a grid of approximately 0.25 longitude by 0.25 latitude degree resolution with data available since 1979. An advantage of the ERA-5 data is that they combine information from ground stations, satellites, weather balloons and other inputs with a climate model. Our measures of weather variables include air temperature, precipitation and humidity. We then aggregate the gridded data to the region level by computing area-weighted averages (that is, averaging all grid cells that fall into a region). The distribution of temperature is presented in Supplementary Fig. 2.

To understand the potential effects of climate change on poverty and inequality, we utilize weather data from the CMIP6. This project provides various scenarios including SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5. Each scenario shows a different path for global

growth, energy use, policy actions and climate responses and thus enables a detailed study of the possible impacts of climate change in different situations.

For a more comprehensive analysis, our Analysis utilizes data from different sources. To examine the role of agriculture as a mechanism, we rely on the gridded daily NDVI derived from the Surface Reflectance Climate Data Record provided by the National Oceanic and Atmospheric Administration. This dataset presents global, grid-based vegetation index, with a 0.05° resolution, spanning from 1981 to present. We provide description and summary statistics of the main variables in Supplementary Table 1.

### Empirical specifications

Our first empirical approach identifies the effects of hotter temperature on poverty and inequality by estimating the following panel data model with FE:

$$Y_{i,t} = \beta_{FE} T_{i,t} + \gamma_{FE} W_{i,t} + \delta_{FE} X_{i,t} + \alpha_i + \pi_t + \varepsilon_{i,t}, \quad (1)$$

where  $Y_{i,t}$  represents the poverty rate and inequality in location  $i$  in year  $t$ . Depending on the specific specification, location  $i$  is either country in the country-level analysis or the subnational unit in the subnational analysis.  $T_{i,t}$  is the temperature variable, and the coefficient of interest  $\beta_{FE}$  is expected to be positive (that is, global warming probably increases poverty and inequality).

Following previous studies' suggestion that precipitation and temperature are historically correlated and should be included in the same regression to obtain unbiased coefficients<sup>1</sup>, we control for other weather conditions ( $W_{i,t}$ ) including precipitation and humidity in all the regressions. We also control for time-varying country characteristics ( $X_{i,t}$ ) to capture macroeconomic and demographic factors that may influence poverty and inequality independent of climate<sup>46–49</sup>. These include GDP per capita, unemployment rates, the shares of value added from agriculture and manufacturing and population growth.  $\alpha_i$  is the location (country or subnational) FE that controls for unobserved time-invariant factors that may be correlated with location-specific climate or economic patterns;  $\pi_t$  is the year FE that controls for unobserved temporal changes affecting poverty and inequality each year. We cluster the errors  $\varepsilon_{i,t}$  at the specified location level to facilitate potential serial correlation over time within a region (or a country).

Although we can causally interpret  $\beta_{FE}$  in equation (1), it is probably derived from short-run responses to temperature change, given the nature of the annual panel data analysed in this equation. Consequently,  $\beta_{FE}$  is not necessarily representative of households' responses to temperature change in the longer term. In other words, long-term responses to temperature change may fundamentally differ from short-term responses to weather fluctuations because the former type of responses better accounts for potential household adaptation over time. Therefore, we address the shortcoming of equation (1) by utilizing the LD approach to estimate the accumulated effects of temperature change over longer periods of time (that is, adaptation strategies)<sup>43</sup>:

$$\Delta Y_i = \beta_{LD} \Delta T_i + \gamma_{LD} \Delta W_i + \delta_{LD} \Delta X_i + \omega_i. \quad (2)$$

In equation (2),  $\Delta Y_i$  represents changes in poverty (or inequality) in the same location between two periods, and  $\Delta T_i$ ,  $\Delta W_i$  and  $\Delta X_i$  are the corresponding changes in temperature, other weather conditions and country characteristics. Specifically, we calculate differences between the first and last years of observation for each subnational unit, for both the outcomes and all control variables. Under the LD approach, any time-invariant location-specific factors are differenced out. As with equation (1), the coefficient of interest,  $\beta_{LD}$ , is expected to be positive. Comparing the differences between the FE and LD estimates provides insights on the extent of adaptation.

In both the panel FE and LD models, we assume the effects of temperature change to be in linear form. To enable a more flexible functional form of temperature, we also use a temperature bin approach that offers estimates of nonlinear effects

$$Y_{i,t} = \sum_{j=1}^{12} \beta_{TB,j} T_{i,j,t} + \gamma_{TB} W_{i,t} + \delta_{TB} X_{i,t} + \alpha_i + \pi_t + \vartheta_{i,t}. \quad (3)$$

Specifically, we categorize daily temperature into 13 temperature bins, where each bin (indexed by  $j$ ) captures temperature change in increments of 3 °C (for example, the first bin is [0 °C, less than 3 °C), the second bin is [3 °C, less than 6 °C) and so on). The two extremes of low and high temperature are respectively defined as less than 0 °C and greater than 33 °C. The temperature shock variable,  $T_{i,j,t}$ , reflects the number of days when the daily average temperature in a region is within a specific bin in a particular year. We use the most thermally comfortable temperature bin, which is [18 °C, less than 21 °C), as the reference group. The coefficients of interest  $\beta_{TB,j}$  are thus interpreted as the effects of exchanging a day in the 18–21 °C reference bin with a day in the other bins.

Several remarks are in order. First, the maximum temperatures differs between the estimation samples for temperature-bin approach with equation (3) and that for equations (1) and (2). The bin-based variable captures the full daily distribution, which includes days above 33 °C, whereas the hottest annual mean temperature across all regions and years is observed to be lower at slightly more than 31 °C (Supplementary Table 1). Second, whereas the bin approach is more flexible than the linear regression approach, the trade-off is that the bin approach may not be able to capture the strong effects of temperature change as the linear regressions.

To generate Fig. 3, we revise equation (1) and add the interaction terms between temperature and country dummy variables  $\delta_{FE} T_{i,t} \times C_k$ , where  $C_k$  denotes country dummy variables. We also drop the subnational FE  $\alpha_i$  (because on average, we have slightly more than 12 regions for each country only). Specifically, we estimate a set of interaction terms between temperature and country dummy variables, controlling for rainfall, humidity and other country characteristics.

The estimation equation is as follows:

$$Y_{i,t} = \beta_{FE} T_{i,t} + \sum_{k=1}^K \delta_{k,FE} T_{i,t} \times C_k + \gamma_{FE} W_{i,t} + \delta_{FE} X_{i,t} + \pi_t + \tau_{i,t}, \quad (4)$$

where subnational unit  $i$  is within country  $k$ .

For each of the poverty and inequality outcomes, we select a country with the average value that is as close to the sample average as the reference country. That is, we select Indonesia for poverty (7.9%) and Madagascar for inequality (35.4%). The estimates on the interaction terms are thus interpreted as increases in the poverty rate (or Gini index) per 1 °C increase in temperature compared with the reference country. We plot the results for each country the estimated coefficient  $\delta_{k,FE}$  from equation (4) against its average temperature (Fig. 3). We further highlight countries' income levels by making each country's marker proportional to its real GDP per capita.

**Causal mediation analysis.** In addition to our main analysis, we are also interested in the mechanisms linking temperature to poverty and inequality. In particular, we formally assess whether agricultural production mediates the association between temperature and these outcomes, using causal mediation analysis<sup>50,51</sup>. This approach requires estimating two models: one for the mediator  $M_{i,t}$  (NDVI or soil moisture) conditional on the treatment  $T_{i,t}$  (that is, temperature) and covariates  $W_{i,t}$  (weather conditions such as precipitation and humidity) and another for the outcome (poverty or inequality) conditional on the treatment and covariates. We do not control for other country characteristics in the following regressions to focus on agriculture as the main channel of impacts.

The estimation equations are specified as follows:

$$M_{i,t} = \beta_M T_{i,t} + \gamma_M W_{i,t} + \alpha_i + \pi_t + \zeta_{i,t}, \quad (5)$$

$$Y_{i,t} = \beta_Y T_{i,t} + \lambda_Y M_{i,t} + \gamma_Y W_{i,t} + \alpha_i + \pi_t + \psi_{i,t}. \quad (6)$$

The mediation analyses determine the proportion of the total effect of temperature on the outcomes that is mediated by agriculture, that is  $(\beta_M \times \lambda_Y) \times 100\% / \beta_{FE}$ .  $\beta_{FE}$  is the coefficient on temperature in equation (1).

**Further heterogeneity analysis.** Although economic growth is not a focus of our Analysis, we plot in Supplementary Fig. 3 the estimated effects of temperature on household income (or consumption) per capita per day using the FE model with temperature bins specified in equation (3). Overall, there is evidence that hotter temperatures negatively affect household income, with one additional hotter day reducing daily household income per capita by about US\$0.02 (in 2017 PPP). This translates to a 0.14% decrease, based on the mean income of US\$14.662 (Supplementary Table 1). These findings are qualitatively consistent with the studies discussed earlier (Main). However, these estimated effects appear to have weaker statistical significance than those for poverty and inequality (Fig. 2).

**Additional robustness checks.** Our results suggest that when accounting for nonlinearity of temperature effects, we find strong evidence of the adverse impacts of hotter temperature on poverty and inequality, especially for lower-income countries (Fig. 4). We also note that the distribution of temperature in our sample predominantly aligns with the hotter ranges, as shown in Supplementary Fig. 2. Therefore, we focus on the linear models (FE and LD) as the primary models for analysis in our study, but we provide supplementary analysis using the nonlinear model where relevant.

We provide a number of robustness checks in the Supplementary Information (appendix B), including using different thresholds (temperature bins) to define hot and cold days and dividing each country's temperature distribution into deciles to better account for temperature variation across countries (Supplementary Fig. 4), different measures of poverty (including poverty gap measures that focus on the poorer groups) (Supplementary Tables 7 and 8), varying choices of temperature measures (Supplementary Table 9), different data subsamples and time periods, including clustering the standard errors at the country level (Supplementary Tables 10 and 11), analysing poverty and inequality data from other source (Supplementary Tables 12 and 13), using alternative time-varying classification of country's income (Supplementary Table 14), as well as conducting a placebo test that randomizes the temperature of a region and shows no evidence of temperature effects on poverty (Supplementary Fig. 6). For Fig. 3, estimates using median temperature instead of average temperature (Supplementary Fig. 7) offer qualitatively similar findings.

Finally, as an additional robustness check, we estimate the FE model and control for a wider range of country-level characteristics from the World Development Indicators database. These include variables on education, macroeconomic indicators, life expectancy and institutional quality. The results, shown in Supplementary Table 16, are consistent with our main findings. These regression analysis results also confirm the negative impacts of global warming shown in Fig. 3, where GDP per capita has negative effects on these impacts both for the subnational unit level and country-level analysis.

We provide more detailed discussion regarding robustness checks in supplementary appendix B.

## Data availability

The data are fully described in the Methods. The links to the data sources are provided in Supplementary Table 1. Source data are provided with this paper.

## Code availability

Weather data were collected using QGIS. The data analysis was performed in STATA. All the codes are available in the Harvard Dataverse: <https://doi.org/10.7910/DVN/HCF147>.

## References

46. Kraay, A. When is growth pro-poor? Evidence from a panel of countries. *J. Dev. Econ.* **80**, 198–227 (2006).
47. Ravallion, M. Why don't we see poverty convergence?. *Am. Econ. Rev.* **102**, 504–523 (2012).
48. Santos, M. E., Dabus, C. & Delbianco, F. Growth and poverty revisited from a multidimensional perspective. *J. Dev. Stud.* **55**, 260–277 (2019).
49. Erumban, A. A. & de Vries, G. J. Structural change and poverty reduction in developing economies. *World Dev.* **181**, 106674 (2024).
50. Imai, K., Keele, L. & Tingley, D. A general approach to causal mediation analysis. *Psychol. Methods* **15**, 309–334 (2010).
51. VanderWeele, T. J. & Tchetgen Tchetgen, E. J. Mediation analysis with time varying exposures and mediators. *J. R. Stat. Soc. Ser. B* **79**, 917–938 (2017).

## Acknowledgements

We thank C. Azzarri, E. Barbier, R. Catavassi, A. Dabalén, B. Davis, D. Johnston, W. Kopczuk, A. Leroux, H. Nguyen, P. Oliva, P. Raschky, R. Smyth, J. Steinbuks and participants at the Frontiers in Development Policy Conference (KDI), the 'Revisiting Climate Damages' conference (IMF) and seminars at Food and Agriculture Organization and Monash University for useful comments on earlier versions. We would like to thank Matthias Kalkuhl for helpful advice on data and Brenan Andre

for assistance with the global maps. We are grateful for funding support from the UK Foreign Commonwealth and Development Office (FCDO)'s Knowledge for Change (KCP) grant for the World Development Report 2021 'Data for Better Lives' (grant no. P175301 to H.A.D. and T.A.T.) and the Data and Evidence for Tackling Extreme Poverty (DEEP) Research Programme (grant no. P175686 to H.A.D.) and University of Economics Ho Chi Minh City, Vietnam (UEH) (grant no. P1510/QyĐ-ĐHKT-QLKHHTQT to H.A.D.).

## Author contributions

H.A.D.: methodology, writing, final editing and supervision. S.H.: feedback, final editing and supervision. T.A.T.: data analysis, methodology and writing. M.N.: data curation.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary information** The online version contains supplementary material available at <https://doi.org/10.1038/s41558-025-02516-6>.

**Correspondence and requests for materials** should be addressed to Hai-Anh H. Dang.

**Peer review information** *Nature Climate Change* thanks François Bareille, Chengzheng Li and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

**Reprints and permissions information** is available at [www.nature.com/reprints](http://www.nature.com/reprints).