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Global economic impact of weather variability on the rich and the poor

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Temperature and precipitation variability and extremes impact production globally. These production disruptions will change with future warming, impacting consumers locally as well as remotely through supply chains. Due to a potentially nonlinear economic response, trade impacts are difficult to quantify; empirical assessments rather focus on the direct inequality impacts of weather extremes. Here, simulating global economic interactions of profit-maximizing firms and utility-optimizing consumers, we assess risks to consumption resulting from weather-induced production disruptions along supply chains. Across countries, risks are highest for middle-income countries due to unfavourable trade dependence and seasonal climate exposure. We also find that risks increase in most countries under future climate change. Global warming increases consumer risks locally and through supply chains. However, high-income consumers face the greatest risk increase. Overall, risks are heterogeneous regarding income within and between countries, such that targeted local and global resilience building may reduce them.

Climate change already causes considerable economic impacts[1,2]. In addition, increasing extreme events[3,4] and changing variability[5,6] will continue to disrupt economic activity and growth[7–10]. Overall, the impacts of climate change are unevenly distributed across the globe[11]. Econometric studies on the impacts of temperature variability and extremes[8] as well as rainfall on economic activity[9] find large regional heterogeneity in macroeconomic impacts.

With regard to the socioeconomic dimension of impacts, low-income populations suffer more under climate change[12,13], which may become a roadblock to poverty eradication without appropriate adaptation[14]. Showing the bidirectional interconnection of climate change and inequality, it may also hinder mitigation efforts[15]. One driver of inequality of weather extremes is exposure, as exemplified by landslides mainly affecting mainly informal settlements[16], larger flood exposure for countries with lower incomes[17] as well as for lower incomes within the United States[18], and exposure to storms and resulting floods affecting disenfranchised populations more strongly[19]. Empirical studies on the relationship between inequality and climate change have identified a regressive impact of heat extremes[20] and increased macroeconomic inequality between countries[21]. Further studies on weather extremes find that, within countries, low-income groups are impacted more severely than their high-income counterparts[22]. For example, rainfall extremes have been shown to enhance inequality[23].

Here we focus on consumption risks along two dimensions of inequality by income: (1) within countries and (2) between countries. Production disruptions are driven by temperature and rainfall variability and extremes. These disruptions propagate through supply chains up to the final consumer. While we compare the risks associated with changing climate conditions over a three-decade period, our simulations do not project overall economic development and resulting risks. Instead, this study can be interpreted as a stress test under changing climate conditions to identify risk factors, which contribute to higher vulnerability of specific consumer groups or 'hotspot' regions. In this assessment, socioeconomic conditions (trade relations, economic capacity and incomes) are kept fixed, such that we do not model long-term impacts or adaptation. We use an updated version of the Acclimate model[24], which simulates trade relations between firms up to utility-maximizing consumers, disaggregated to five income

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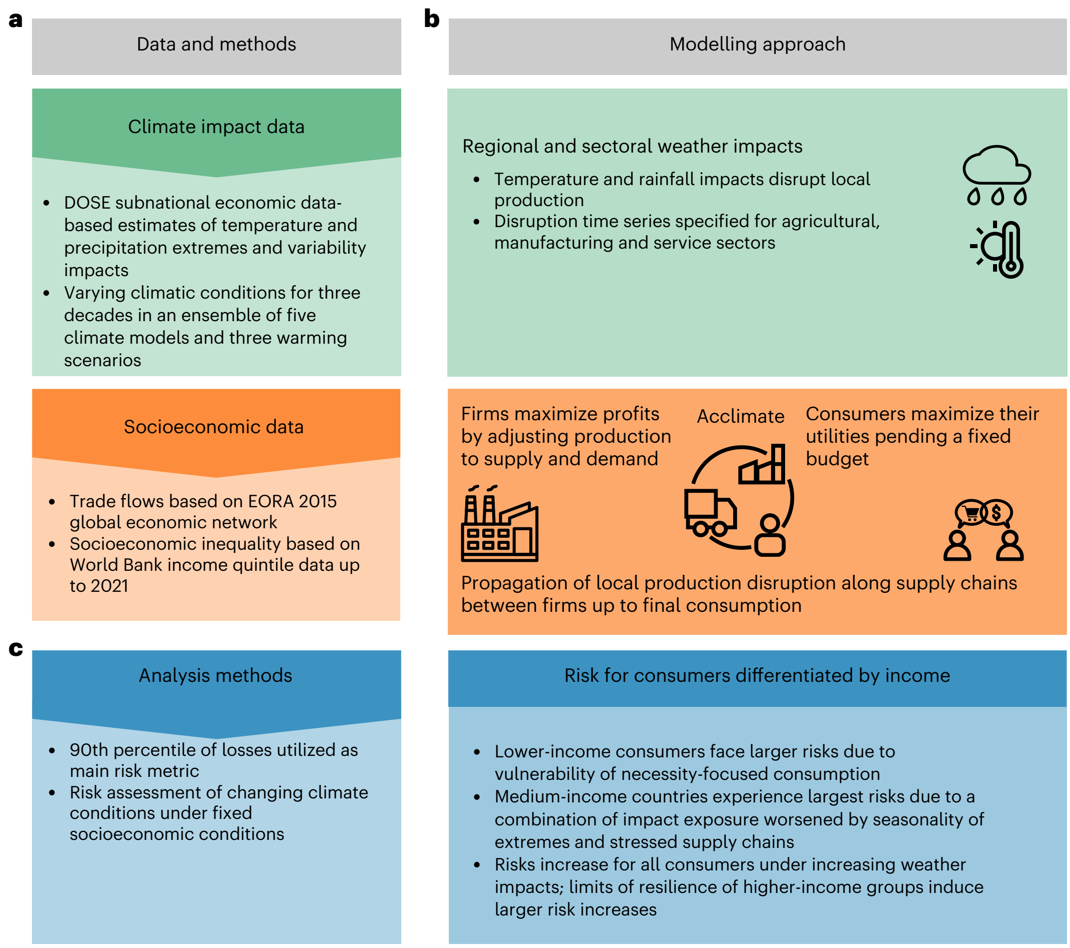

Fig. 1 | Schematic overview of data, methods, modelling and main results. a, Details on data inputs. **b**, The flow from weather impact ensemble through the Acclimate economy to impacts on consumers. **c**, Analysis methods and a summary of main results. More details are provided in Extended Data Fig. 1. Credit: icons in **b**, www.pixaby.com (clouds) or canva.com (all other).

quintiles by country. The dynamics result from propagation of economic disruptions, for example, due to weather extremes, along supply chains. Previously, Acclimate has been used to, for example, assess the global economic response to river floods[25] or the amplification of extreme weather-induced consumption losses through repercussions in the global supply network[26].

An overview of the data and metrics used is shown in Fig. 1a. We use econometric estimates[8,9] to approximate the impacts of temperature and precipitation variability and extremes on daily production for three economic sectors—agriculture, manufacturing and services. From these estimates, we generate an impact ensemble based on three emissions pathways (representative concentration pathways[27] 2.6, 7.0 and 8.5) for five climate models of the sixth round of the Climate Model Intercomparison Project (CMIP6)[28], which are bias corrected towards observational data[29] and provided by the Inter-Sectoral Model Intercomparison Project[30]. Aggregating these grid-level impact estimates, we generate production disruption time series for the regions considered in the Acclimate model. On the basis of these production disruption time series, we estimate the climate-driven changes in production levels for three decades (recent past (2011–2020), present (2021–2030) and near future (2031–2040)). Since most of the future warming is already committed to by past emissions due to the inertia of the climate system and since differences between emissions pathways are within natural variability for this time frame[31,32], we do not distinguish between the emissions pathways.

We then use Acclimate[24] to simulate the short-term indirect repercussions of these direct production disturbances along global supply chains between regions with profit-maximizing firms in 26 sectors up to the final consumption (Fig. 1b). Final consumption is disaggregated to five income quintiles within countries, which optimize consumption utility under a constrained budget. On the basis of empirical studies on the income dependence of consumption[33,34], we assume low-income quintiles to spend larger shares of their budget on hard-to-substitute necessities such as food, while this spending share declines with increasing income. Between countries, we distinguish four income groups, according to the World Bank's income level classification[35] (Supplementary Fig. 1c): low-income countries (LICs), lower medium-income countries (LMICs), upper middle-income countries (UMICs) and high-income countries (HICs). To assess short-term impacts in Acclimate, we compare consumption quantities with the undisturbed state of the economic network ('baseline'). We quantify consumption risks via the consumption loss expected on one in ten days, that is, the 90th percentile of baseline relative consumption reductions (refer to Methods for further details).

Results

Inequality of risks by income quintile

We find that lower-income quintiles face higher loss risks for all country income levels and across changing climate conditions (Fig. 2). Heterogeneity within countries is larger in UMICs and HICs, where the risks of the lowest-income quintile are about twice as large as for the highest-income quintile (Fig. 2b,d). By contrast, in LICs, low-income groups face a smaller additional loss risk of about 30%

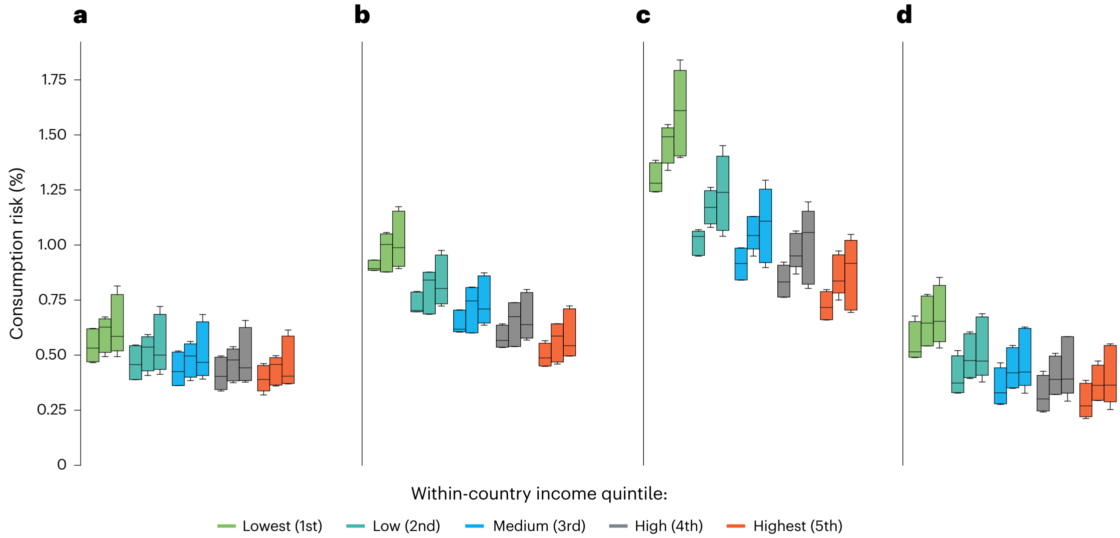

Fig. 2 | Heterogeneous risks by country income level and between income quintiles. a–**d**, Consumption risks (90th percentile of consumption losses) by income quintile (colour code) for LICs (**a**), LMICs (**b**), UMICs (**c**) and HICs (**d**) for the past decade (2011–2020; leftmost bars), the present decade (2021–2030; middle bar) and the near-future decade (2031–2040; rightmost bars). Income quintiles are numbered from lowest income (first) to highest income (fifth). Middle lines, boxes and whiskers denote median values, 25th–75th percentile ranges and 17th–83rd percentile ranges with respect to climate model ensemble ($n = 15$; 5 climate models × 3 shared socioeconomic pathway (SSP) emission scenarios), respectively.

(Fig. 2a and Supplementary Tables 3–5 provide the corresponding data). This within-country inequality is grounded in the differences in the substitutability among the different goods, resulting from unequal baseline shares of consumption (Extended Data Fig. 2). Since low-income consumers spend a larger share of their budget on hard-to-substitute necessary goods, they are more vulnerable to supply shocks. By contrast, high-income consumers spent larger shares of their budget on easier-to-substitute goods, such that they suffer smaller reductions of consumption. The risk factor of higher consumption of necessities by lower-income groups is supported by empirical evidence[33,34,36]. In addition, inequality in consumption patterns might induce market mechanisms, where higher-income consumers can afford higher prices for necessities, thereby inflating prices and pressuring lower-income groups, either locally or along supply chains. Importantly, relative risks to consumption are more concerning for low-income consumers living close to the subsistence line compared with consumers with higher incomes. These inequalities in risks are robust to variations in risk percentile levels (Supplementary Figs. 1–5).

We complement our analysis of consumption risk changes by analysing changes in the full distribution of consumption losses (Extended Data Fig. 3). Under the climate conditions of 2011–2020, median consumption quantities are just slightly below baseline levels (and even very slightly above for the wealthiest quintile in HICs and UMICs) (Supplementary Table 6). They further decline with global warming in the present-day and near-future periods (Supplementary Tables 7 and 8), which suggests an amplification of consumption risks under global warming as detailed in the following. The lowest-income quintiles perceive the largest risks across all three study periods. The high baseline levels of inequality with more than 40% of consumption concentrated on the highest incomes (Extended Data Fig. 2) imply a weighting by baseline consumption shares, showing that the aggregated risk to the macro-economy is dominated by high-income quintiles (Extended Data Fig. 4).

Heterogeneous risks between countries

UMICs and LMICs (Fig. 2b,c) face about double the risks of LICs or HICs (Fig. 2a,d). While these differences emerge from the interaction of a multitude of factors, we focus on three risk factors that differentiate countries grouped by income level.

First, local climate impacts are highly heterogeneous, especially with respect to seasonal weather patterns. Since overall economic impact is dominated by heat extremes in Northern Hemisphere summer (Supplementary Figs. 6 and 7), summer heat extremes (Supplementary Figs. 8 and 9) and their repercussions coincide with seasonal rainfall extremes driven, for example, by monsoon systems in subtropical countries (Supplementary Figs. 10 and 11). This coincidence probably leads to a compounding effect in LICs, LMICs and UMICs, which are located mostly in the subtropics, as opposed to HICs, which are located mostly in the mid-latitudes of the Northern Hemisphere.

Second, assessing the origins of baseline consumption for each income level up to the second-order trade flows (Extended Data Fig. 5), we find that consumption is sourced mostly from countries of the same income level, except for LICs importing most consumption goods from higher-income countries. This dependency on countries of the same income level increases with income, from ~75% for LMICs and ~80% for UMICs to ~95% for HICs. By contrast, the self-dependency of LICs is much lower (~12.5%) since they import most of their consumption from HICs (~65%). Thus, despite similar climatic conditions, LICs' diversified sourcing of consumption—especially the large share of imports from resilient HICs—may reduce risk by reduced exposure to local impacts in comparison with LMICs and UMICs.

Third, comparing characteristics of economic production by income level, HICs have the largest baseline production (Fig. 3a), UMICs (including China) fall in a similar range, while LMICs and LICs have orders of magnitude smaller production capacity. Impacts on production are distributed heterogeneously; here the 90th percentile production disruption in UMICs is about twice as large as in other countries (Fig. 3b). This production disruption translates into an actual production reduction (Fig. 3c), with some dampening due to increased production through activation of idle capacities and replacement of regional supplies by remote supplies. Notably, HICs show the largest dampening, hinting at a more efficient compensation of production disruptions, enabled by large production capacities and their central position in the supply network. Finally, these production losses translate into reductions in final consumption, where HICs again show a comparably stronger dampening from production to consumption risk (Fig. 3d).

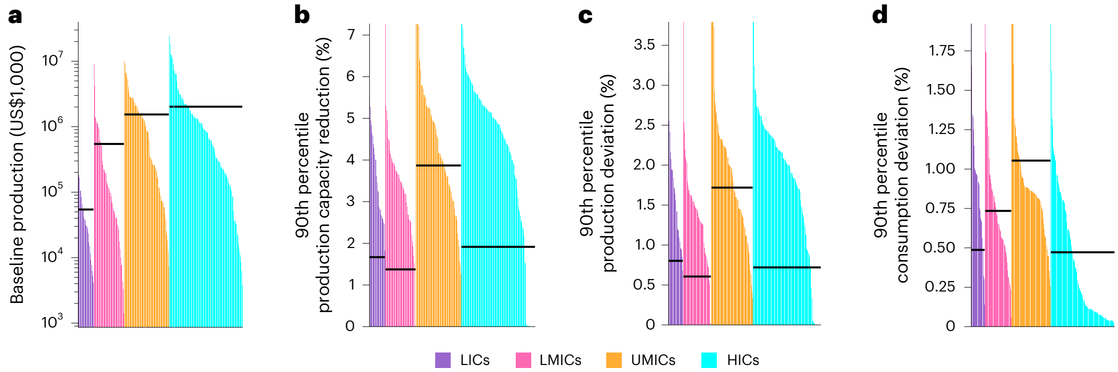

Fig. 3 | Direct and indirect effects on production and resulting consumption risks by country income levels. Consumption risks arising for direct exposure to temperature and precipitation variability and extremes due to direct exposure, resulting indirect trade effects and resulting price effects for consumers by countries and subnational regions for the United States and China. **a**, Regional baseline production aggregated for all sectors (log scale). **b**–**d**, 90th percentile of reduction in production capacity (direct effect) (**b**), actual production deviation (direct + indirect effects) (**c**) and consumption averaged across all income quintiles (**d**). In each panel, regions are sorted by *y* values. Thick horizontal lines mark the overall average across the respective income level (**a**) and the respective resulting aggregate risks by income level (**b**–**d**). The *y* axes are limited to values <97.5th percentile for visualization.

To explain this stronger dampening of direct impacts in HICs, we compute the correlation of production and consumption as a proxy for the resilience of consumption to domestic production disruptions (Fig. 4). This correlation is considerably lower for HICs, revealing a comparably weaker spillover from impacts on domestic production to consumption risk.

In conclusion, consumers in LMICs and UMICs face the largest risks due to a combination of three risk factors: (1) the seasonality of production disruptions and resulting deviations, which are probably aggravated by concurrence of global heat stress with seasonal regional impacts driven (Supplementary Figs. 6 and 7), (2) strong trade dependencies between LMICs and UMICs, respectively (Extended Data Fig. 5) and (3) a comparably strong transmission of risk from production to consumption (Fig. 3).

We next illustrate some risk factors by comparing exemplary countries within each country income level (see Supplementary Table 2 for a risk summary for all countries). Among LICs (Supplementary Fig. 13), North Korea shows the highest consumption risk (~2.1%), driven by its very limited supply-chain integration and the resulting strong self-dependencies, as indicated by the high correlation between domestic production and consumption (~0.82). For comparison, the consumption risk of Syria is roughly one-third lower (~1.31), probably due to Syria's lower self-dependency (~0.51).

For LMICs, we contrast Ukraine and Uzbekistan with the Philippines (Supplementary Fig. 14) and observe a risk-enhancing effect of within-country inequality. Within-country inequality is higher in the Philippines than in Ukraine and Uzbekistan. It seems plausible that inequality contributes to the Philippines' consumption risk being twice as high as production risk, whereas, in Ukraine and Uzbekistan, consumption risk is about 25% lower than production risk.

Similarly, regarding UMICs (Supplementary Fig. 15), in strongly directly impacted and comparably equal Iraq and Kazakhstan, risk is dampened from production to consumption (by ~−20% and ~−50%, respectively), whereas it increases slightly from production to consumption in Colombia and Thailand, which are also strongly directly impacted but more unequal. This risk-enhancing effect of inequality may result from domestic competition for necessary consumption goods in times of crisis, where high-income consumers can afford higher prices and thus low-income consumers face additional price increases.

In HICs (Supplementary Fig. 16), supply chains seem more important than local disruptions. Consumption risks for Spain and Germany are similar, but Germany faces larger direct impacts and production risks. This suggests that Germany's larger economy and central position in supply chains enables effective consumption risk mitigation. This is also illustrated by the relatively weaker risk dampening from production to consumption in New Zealand and Japan, which have less-central positions in the supply-chain network. For the case of New Zealand, the low correlation between domestic production and consumption risk but a small dampening between production and consumption risk probably indicates a higher sensitivity to imported risks. Notably, the highly interconnected states of the United States are able to almost completely avoid risk transmission from production to consumption.

Overall, this illustrative comparison of countries reveals that dependence on domestic production, within-country inequality and competition for goods may increase risks for consumers, whereas an advantageous position along supply chains can moderate these risks.

Global risk amplification in a warming climate

Under recent climate conditions (2011–2020), consumption risks are distributed heterogeneously across the globe, with Mongolia facing the highest consumption risk. By contrast, the United States is facing comparably low consumption risks. To show the regional heterogeneity of within-country risk inequality, we map the risk difference between the lowest- and highest-income quintiles averaged across climate conditions of all three decades (Extended Data Fig. 6). We find that the lowest-income quintile faces larger risks than the highest-income group in almost all countries. Regarding regional heterogeneity, the large inequalities of risk in Latin America, South Africa and the Philippines are probably driven by high economic inequality.

Comparing consumption risk levels under recent (2011–2020), present (2021–2030) and near-future (2031–2040) climate conditions, we find an increase in risk for all country income levels and income quintiles with global warming. While the lowest-income quintiles continue to face the highest risks, the consumption risks from weather extremes and variability disrupting production increase for all income levels and income quintiles (Fig. 5). On the level of individual countries (Fig. 6), we find increasing risks for most countries with changing climate, but these risk increases are heterogeneous (Fig. 6b,c). The United States is subject to the strongest relative increases in consumption risks, which can be attributed to their low risk levels under recent climate conditions (2011–2020).

In LICs, median consumption risks increase by 15% (17th to 83rd percentile: 6–26%) for all income quintiles (Fig. 5a) from recent (2011–2020) to present (2021–2030) climate conditions. In HICs over the same period, the median risk increases more strongly for the highest-income quintile (27% (14–35%)) than for the lowest-income quintile (17% (8–24%)) (Fig. 5b). LMICs show the smallest median risk

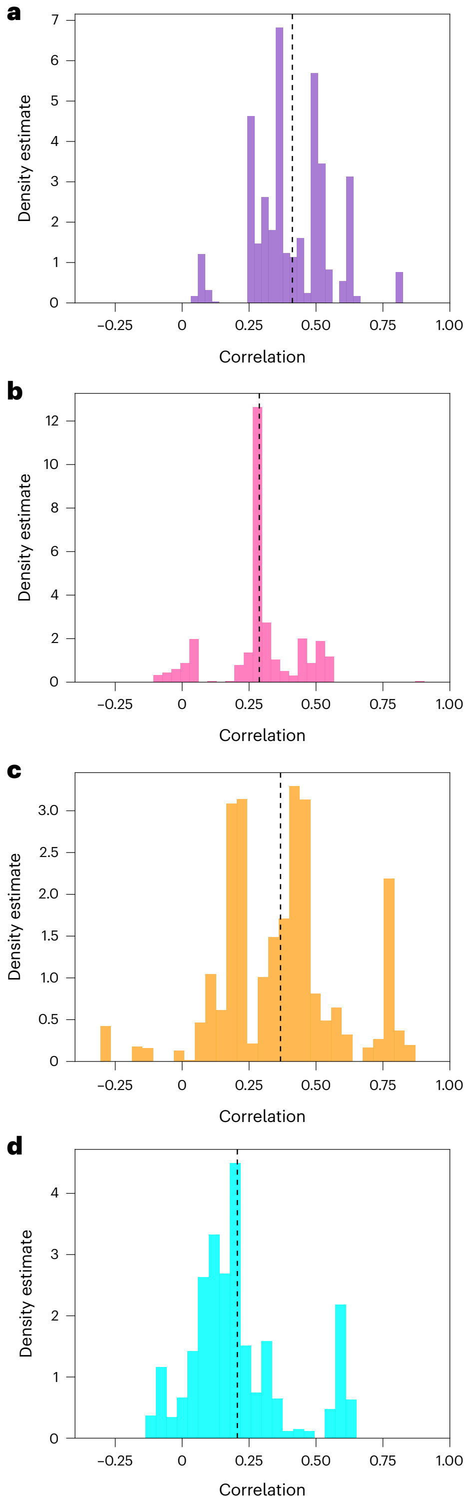

Fig. 4 | Distributions of correlation between production and consumption by country income indicate differences in resilience of consumption to production disruption. a–d, Distribution of Pearson correlation between production and consumption across all simulation years 2011–2040 computed on the basis of individual income quintiles and weighted by the quintiles' baseline consumption for LICs (**a**), LMICs (**b**), UMICs (**c**) and HICs (**d**). Black dashed lines indicate average correlations.

amplification, ranging from 11% (6–15%) for the lowest-income quintile to 15% (10–17%) for the highest-income quintile (Fig. 5c). The already highly exposed UMICs show a heterogeneous increase in median risks between 14% (6–19%) for the lowest-income quintile and 20% (12–25%) for the highest-income quintile. For the near-term future climate, these trends continue for all country income levels and income quintiles, while uncertainty increases due to larger variation between ensemble members. LICs face a comparably small median risk amplification with large uncertainty (28–36% (−2 to 52%)). Here the 16.6th percentile of the highest-income quintile shows even a slight decrease of median risk of 2.4%. All other country income levels face heterogeneous risk increases between income quintiles—most pronounced in HICs, where the highest-income consumers face a median risk increase of 51% (28–80%) compared with 28% (12–41%) for the lowest-income quintile (Supplementary Tables 9 and 10). This heterogeneously increasing risk across income quintiles within countries—in contrast to the higher baseline exposure of low-income quintiles—does not mitigate the high risk exposure of low-income consumers, but shows that the higher resilience of higher incomes might be offset by increasingly adverse climate conditions, leading to macroeconomic risks due to the large share of total consumption by high-income consumers. Again, this finding remains robust under variations of the considered loss percentiles (Supplementary Figs. 17–21).

Discussion

We have performed a global analysis on the distributional impacts of temperature and precipitation variability and extremes through direct production disruptions, trade-induced supply failures and associated price effects across (1) different income groups of countries and (2) income quintiles of consumers within each country.

Our finding that lower-income populations within countries face larger climate-related risks is in line with econometric studies on regressive impacts of weather extremes[22,23]. Using a dynamic supply-chain model, we can extend these previous studies by capturing the remote trade-related consequences of climate impacts. This allows us to study the complex differences in risk factors across the different income groups of countries as well as between individual countries, which result from the interaction of impact distributions, capacity to compensate for lost production, and market and supply-chain effects. An important consequence of the large inequality between low- and high-income consumers is that the same relative losses are likely to be more harmful to low-income consumers. Despite considering deviations in consumed quantity rather than dollars spent, this aggravates the higher risks for low-income groups. The importance of accounting for trade-related risks has also been highlighted recently during the COVID-19 pandemic[37,38]. Accounting for indirect effects complements recent work on long-term impacts of weather variability and extremes on economic growth[39]. While this assessment is based on the same underlying econometric damage estimates[8,9], the different mechanisms and timescales of impacts considered lead to complementary results. Most important, ref. 39 studies the long-term impacts of climate on output growth throughout the twenty-first century as described by the shared socioeconomic pathways[32,40], which—by design—do not account for the impacts of climate change on development. We complement this long-term perspective focused on output growth by a risk assessment of short-term consumption losses resulting from the spreading of production deviations through the global trade networks. To isolate the impact of changing climatic conditions from the impact of economic development, we keep the baseline economic conditions, that is, the undisturbed production and consumption levels and the trade network, fixed.

With regard to limitations, our consumer model is simplistic, assuming myopic utility-optimizing behaviour without savings. Assuming savings are distributed at least as unequally as consumption, this limitation would imply a potential underestimation of inequality effects between income quintiles since higher income might enable large savings, increasing resilience to short-term shocks. This buffering effect of savings is counterbalanced by the assumption of a static consumption budget, implying no impacts on income from short-term economic disruptions. Further, when examining inequality, social

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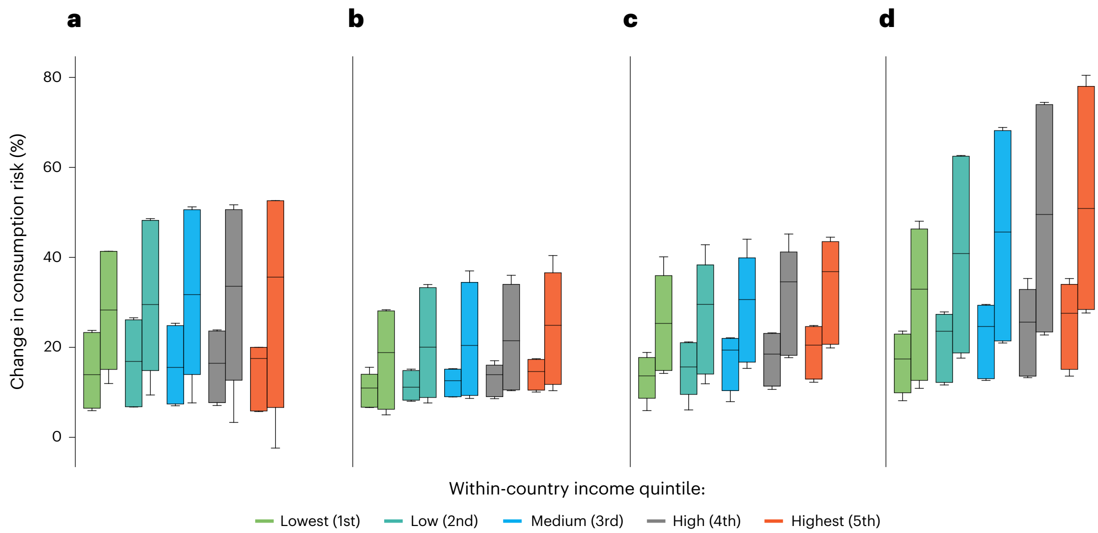

Fig. 5 | Heterogeneous risk increase by country income level and between income quintiles. **a**–**d**, Changes in consumption risk (90th percentile of consumption losses) by income quintile (colour code) for LICs (**a**), LMICs (**b**), UMICs (**c**) and HICs (**d**). Bars show amplification for the present decade (2021–2030, left bars), for the near-future decade (2031–2040, right bars) compared with the past decade (2011–2020). Income quintiles are numbered from lowest income (first) to highest income (fifth). Middle lines, boxes and whiskers denote median values, 25th–75th percentile ranges and 17th–83rd percentile ranges with respect to climate model ensemble (n = 15; 5 climate models × 3 SSP emission scenarios), respectively.

relations play an important role[41]. In particular, high-income countries and high-income populations within countries have more means to cope with impacts than their respective low-income counterparts, be it through adaptation to local climate change impacts or possibly adaption of trade relations[42]. In addition, regarding adaptation to future risks, higher incomes are likely to enhance adaptive capacity[43]. As it is based on global trade relations, our study cannot include those that are not part of such relations. In particular, our results do not allow drawing direct conclusions about livelihoods based on subsistence (for example, smallholder farmers). Still, for these groups, direct impact due to climate change is the crucial factor[44] and more local studies[45] focusing on local conditions complement global risk assessments. Should these groups join global trade networks, they are likely to also face trade-related risks such as those discussed in this study. Hence, our results have to be interpreted within this economic scope, such that the risks we identify are only a part of the overall climate-related risks to consumers.

Our comparison of consumption risks under changing climatic conditions reveals a broad range of factors contributing to risks for consumers, either locally or along supply chains. Most important, we observe the following risk factors, going from more local to more global factors:

- Higher vulnerability of low-income consumers due to focus on consumption of necessary goods.
- Higher vulnerability of countries that depend strongly on domestic production.
- Risk-enhancing effects of within-country inequality may be driven by market effects, where high-income parts of the population crowd out low-income groups. This effect could also occur between countries at different income levels.
- The interaction of local seasonality of extremes and global seasonal patterns may increase risks in regions where seasonal weather extremes coincide with global repercussions of Northern Hemisphere heat stress.
- Trade dependencies can reduce risks, when consumption is sourced mainly from less-affected regions (for example, for LICs from HICs), but also enhance risks, when consumption is sourced mainly from strongly impacted regions as is the case for LMICs and UMICs.
- While current risk levels are lowest for high-income consumers, climate-driven risk increases may be largest. This may reduce adaptation advantages of higher-income consumers and thus result in substantial macroeconomic risks.

Typically, the risk profile of a country or an income group of consumers within a country is determined by a combination of several of these and other risk factors. Our analysis may therefore help to identify tailored adaptation priorities for local measures and multi-lateral cooperation on risk reduction through trade.

In summary, our study offers the following policy-relevant insights. First, climate-related risks for consumers are widespread and affect most countries, already in the present climate (Figs. 2 and 6a) and maybe more in the near future under ongoing anthropogenic warming (Figs. 5 and 6c). This underscores the importance for countries to develop and implement national adaptation plans[46]. Second, our study reveals how important it is that these efforts go beyond the local measures that are typically employed to cope with, and build resilience to, disasters[12,47,48] and include effective measures to build resilience against weather-induced supply-chain disruptions. While potential supply-chain disruptions should be considered, diversified trade relations lead to reduced dependencies on locally produced goods and thus can be an effective means to mitigate local climate risks to consumers. Third, while impacts intensify heterogeneously, poverty alleviation to reduce vulnerability of lower-income quintiles should remain a priority since risk levels remain by far the highest for lower-income quintiles, stressing the importance of reaching the Sustainable Development Goal on poverty eradication[49]. Further, our country-by-country comparison reveals that increased resilience to climate-related consumption risks could be an important co-benefit of policies reducing within-country inequalities.

While increasing risks for lower-income groups hinder poverty eradication and the reduction of inequalities, risks for higher-income groups may result in substantial macroeconomic losses. Thus, adaptation to the increasing volatility in local production and resulting trade shocks due to weather variability and extremes should be strengthened. Reducing risk factors may serve to mitigate the risks to consumers and the wider economy.

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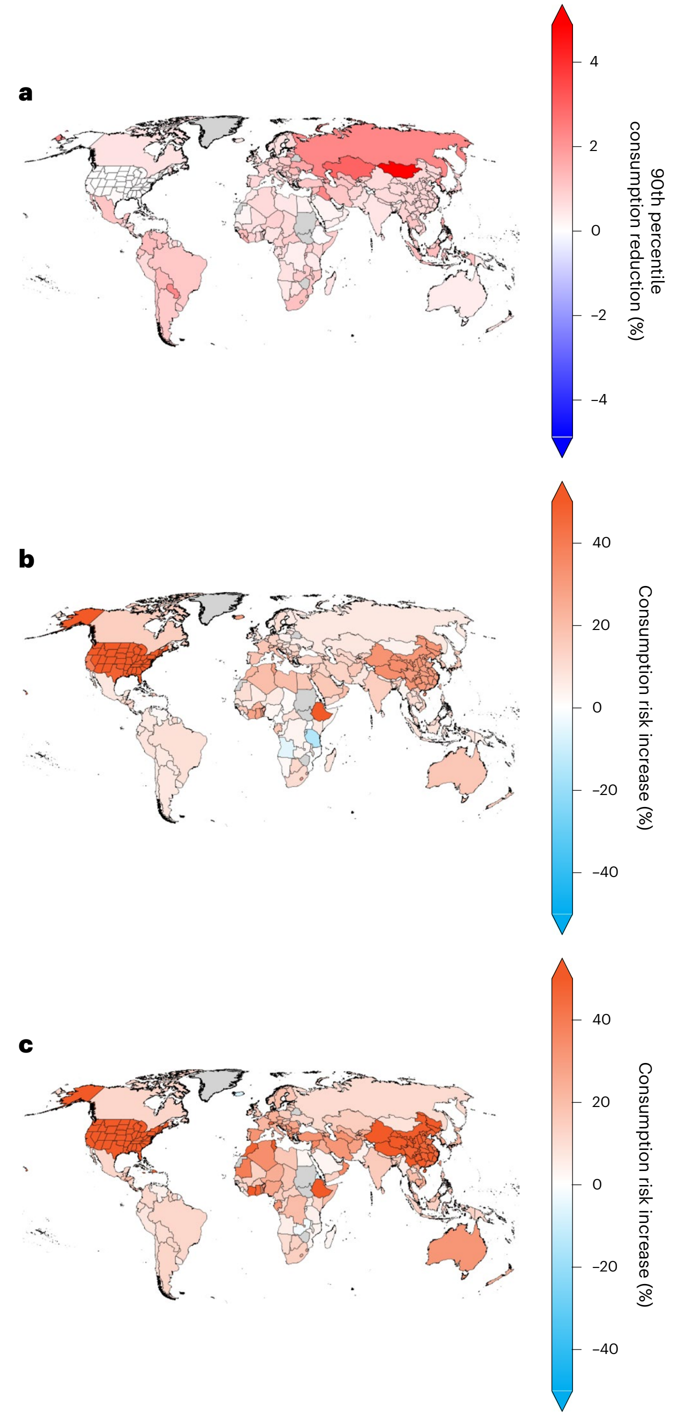

Fig. 6 | Regional consumption risk changes and inequality. **a**, Regional consumption risk, defined as 90th percentile of consumption losses, over the past decade, 2011–2020. **b**,**c**, Relative risk amplification for the present decade (2021–2030) (**b**) and the near-future decade (2031–2040) (**c**). Grey shading indicates countries with low data quality or without data. Maps based on GADM (v.4.1)[56] boundaries.

Methods

Acclimate

To model the spreading of indirect losses in the global supply network, resulting price effects and consumption responses, we use the agent-based global supply-chain model Acclimate[24] (Fig. 1), which is designed to simulate short-term economic shocks and resulting deviations from a baseline undisturbed economy. As baseline data for the model, we use global national multi-regional input–output tables of the EORA project[50]. In addition, disaggregating China to province and the United States to state-level resolution[51], we obtain a network with 264 regions (excluding regions with poor data quality). We consider 26 regional sectors and final consumption, which we disaggregate into five income groups (income quintiles) of consumers per region. Each of the quintiles is modelled as a representative utility-optimizing agent and has three consumption baskets of 'necessary', 'relevant' and 'other' goods, which are imperfect substitutes (see Supplementary Table 1 for a classification of the 26 EORA sectors into the three baskets). Substitutability between goods is described by constant elasticity of substitution (CES) utility functions, as detailed in the following section or in ref. 52. To disaggregate by income quintiles, the final consumption from the EORA tables is distributed by income share[35], assuming the shares of basic food items consumed from the EORA sectors agriculture, food production and fisheries are equal per capita and re-balancing remaining sectors. While this is a simplified representation of consumption inequality within countries, its main feature of a more variable consumption for higher-income groups while lower-income groups depend mainly on few necessary goods is grounded in the established theory of Engel's law[33,34,36].

Utility function for Acclimate consumers. We use a two-level CES utility function for each income quintile of consumers to describe imperfect substitutability between the different categories of goods (consumption baskets). The CES function for the representative consumer for income quintile q in country r reads

$$U_{rq} = \left(\sum_{i=1}^{B}\left(b_i^{\frac{1}{\theta}}\left[\sum_{k=1}^{M_i}\left(a_k^{\frac{1}{\sigma_i}} x_{k\to rq}^{\frac{\sigma_i-1}{\sigma_i}}\right)\right]^{\frac{\sigma_i}{\sigma_i-1}}\right)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}, \quad (1)$$

where $x_{k\to rq}$ denotes consumption of good k for the considered representative consumer, maximizing its utility across its B consumption baskets. Further, σ_i for $i \in \{1, ..., B\}$ denotes the substitution elasticities of consumption in basket i, and θ denotes the elasticity of inter-basket substitution. Further, the share of good k in basket i for $k = 1, ..., M_i$ reads

$$a_k = \frac{x^{\star}_{k\to rq}}{\sum_{i=1}^{M_i} x^{\star}{}_{i\to rq}}, \quad (2)$$

where M_i denotes the number of goods in basket i, and the basket share factor b_i reads

$$b_i = \frac{\sum_{i=1}^{M_i} x^{\star}{}_{i\to rq}}{\sum_{i=1}^{M} x^{\star}{}_{i\to rq}}, \quad (3)$$

where M denotes the overall number of sectors and $(\cdot)^{\star}$ denotes the baseline state.

In our simulations, we consider $M = 26$ EORA sectors grouped into $B = 3$ consumption baskets for necessary, relevant and other goods (Supplementary Table 1). We choose the corresponding consumption substitution elasticities $\sigma_{\text{necessary}} = 0.25$, $\sigma_{\text{relevant}} = 2$, $\sigma_{\text{other}} = 8$, and $\theta = 0.5$ for the elasticity of inter-basket substitution.

Estimation of direct production losses

We generate impact time series on the basis of recent subregional and sectoral econometric analysis with respect to temperature[8] and precipitation[9]. These works provide yearly marginal effects for the period 1979–2018 (ref. 8) respectively up to 2019 (ref. 9) on the basis of the subnational economic data of the DOSE dataset covering three economic sectors (agriculture, manufacturing and services)[53].

To this end, we combine bias-adjusted[29] CMIP6 climate data from five climate models—GFDL-ESM4, IPSL-CM6A-LR, UKESM1-0-LL, MPI-ESM1-2-HR and MRI-ESM2-0—using model data from the historical scenario (1979–2014) to match the DOSE estimation period with the sectoral subnational marginal effects based on the DOSE data to estimate daily impact functions. Since the econometric estimates used to calibrate the damage functions are based on historic observational reanalysis data, the use of bias-corrected data, which is corrected to match observational data better, ensures consistency between the training data and the data used to project impacts.

Using least-squares minimization, we estimate free parameters of generic daily damage functions such that the aggregated daily damages are fitted to the yearly damages for the calibration time of the yearly functions (1979–2014). Since the yearly estimates necessarily include some indirect effects, we make the rather conservative assumption that half of the observed damages are caused by indirect effects. Since these are simulated within Acclimate, we reduce the estimated daily forcing by 50% to avoid double counting. Using these subnational parameter estimates, we generate future impacts for each impact channel based on climate model data by applying the damage functions with their regionalized parameters on a grid-cell level, aggregating to the reduction in daily production capacity (forcing) for country r and sector s, $f_{r,s}(x)$, using population as a proxy weight for economic activity. The resulting impact time series are independent by design, such that we can combine the damage time series $d_i(x)$ by multiplication to get the total forcing $f_{r,s}(\text{tas}, \text{pr})$. To reduce daily fluctuations due to the approximate nature of our daily damage functions, we use a 7 day rolling mean of the forcing time series as input shock time series for our loss propagation model. This approximates the non-resolved short-term lag between regional climate impact and economic production reduction.

This approach necessarily is not precise on a daily estimate, but in the aggregate it reproduces the core features such as seasonality and fluctuations of impacts. We provide detailed equations with regard to the estimation procedure in the following section.

In summary, while our impact estimation introduces multiple uncertainties, the resulting impact estimate benefits from the subnational resolution of econometric estimates as well as the sectoral specification distinguishing agriculture, manufacturing and services as mapped to EORA sectors in Supplementary Table 1. These two key features of sectoral and regional specification are fitting for the qualitative assessment of consumption impacts we conduct here. Especially to assess changing risks in a changing climate, we consider only deviations from recent climate conditions with the same damage parameterization; thus, the detected differences are not dependent on the exact specification of impact parameters.

Description of impact channels

We estimate five independent impact channels on the basis of econometric estimates of the impacts of temperature variability and extreme temperatures[8] as well as precipitation and its extremes[9].

We estimate the impacts of extreme temperatures using a quadratic threshold function,

$$\begin{aligned} d(T_{\text{daily}_r}) = \alpha_{r,s} \max\left(0, \left(T_{\text{daily}_r} - T_{\text{heat}_{r,s}}\right)\right)^2 \\ +\beta_{r,s} \max\left(0, \left(T_{\text{cold}_{r,s}} - T_{\text{daily}_r}\right)\right)^2 + \gamma_{r,s}. \end{aligned} \tag{4}$$

This damage function corresponds to the damages for changes in daily mean temperature. Since there is econometric evidence for threshold behaviour, we choose to estimate a baseline effect $\gamma_{r,s}$, critical temperature $T_{\text{heat}_{r,s}}$ for heat-related damages with coefficient $\alpha_{r,s}$, as well as a critical temperature $T_{\text{cold}_{r,s}}$ for cold-related damages with coefficient $\beta_{r,s}$. To show the resulting spatial heterogeneity of the parameters, Supplementary Fig. 24 depicts the critical heat temperature deviation from the regional historical mean temperature, and Supplementary Fig. 25 shows the respective $\alpha_{r,s}$ coefficient. While thresholds for heat stress are higher in more tropical regions, indicating regional adaptation to higher temperatures, the impact coefficients are larger for these regions as well, indicating the more severe impact of heat stress at higher baseline temperatures. For cold stress, in most regions the effects are negligible, with exceptions of very small impacts in high-latitude or more continental regions (Supplementary Figs. 26 and 27).

For daily temperature variability, we estimate the deviation from the monthly mean[9] and use a simple linear functional form with slope $\alpha_{r,s}$,

$$d(T_{\text{daily}_r}) = \alpha_{r,s}(|T_{\text{daily}_r} - T_{\text{mean}_{\text{month}}}|) + \beta_{r,s}. \tag{5}$$

We use a similar damage function for damages caused by daily rainfall exceeding the 99.9th percentile of precipitation, that is,

$$d(\text{pr}_{\text{daily}_r}) = \alpha_{r,s} \max\left(0, \text{pr}_{\text{daily}_r} - P_{99.9}\left(\text{pr}_{r,s}\right)\right) + \beta_{r,s}, \tag{6}$$

and for wet day (rainfall > 1 mm) precipitation,

$$d(\text{pr}_{\text{daily}_r}) = \alpha_{r,s} \max(0, \text{pr}_{\text{daily}_r} - 1\,\text{mm}) + \beta_{r,s}. \tag{7}$$

For the effect of mean annual total rainfall, we calculate the deviation of the rolling annual total starting at day i from the long-run mean of annual total rainfall from 1979 to 2014 $m_{1979-2014}(\text{pr}_{\text{annual}})$ (the estimation period for the marginal effects) and again estimate a linear relationship,

$$d(\text{pr}_{\text{daily}_r})(i) = \alpha_{r,s}\left(\sum_{t=i}^{i+364} (\text{pr}_{\text{daily}_r}(t)) - m_{1979-2014}(\text{pr}_{\text{annual}})\right) + \beta_{r,s}. \tag{8}$$

Specifying these functional forms, we use climate model data from the calibration period of the marginal effects parameters (1979–2014) to estimate the parameters for each subnational region and sector. First, we calculate the annual time series for Y years of the respective yearly marginal effect i as $\text{ME}_i(r, s)(\text{year})$. Now we estimate the parameters of the specified function $d_i(r, s)$ minimizing the mean squared error,

$$\text{MSE} = \frac{\left(\text{ME}_i(r, s)(y) - \sum_{t\in y} d_{i,r,s}(x_r(t))\right)^2}{Y}, \tag{9}$$

where $x_r(t)$ is the subnational aggregate of the daily climate variable for the impact function. To proxy the distribution of economic activity, we weight all grid-level-based data by a fixed population grid[54].

These subnational parameter estimates are then used to generate impact time series on the basis of bias-corrected CMIP6 climate model simulation data[28,29] for all regions of Acclimate. Here the impact in each grid cell is weighted again by population[54] as a proxy for spatial distribution of production.

Since our downscaling of yearly damage estimates to daily data includes interannual indirect effects along supply chains that amplify the yearly impact, we reduce the magnitude of the resulting production disruption by a rather conservative estimate of 50% due to indirect effects to avoid double counting of indirect damages from the estimation procedure. Since the marginal effects are independent by definition, we combine them by multiplication into an overall impact. For the main simulations, we use a rolling average of 7 days to account for potential short-term lags in the impacts. For an alternative window size of 14 days, we find qualitatively similar, but due to the very strong smoothing of extremes and especially variability, considerably smaller risks in Supplementary Figs. 28–30—due to very small initial risk levels, relative amplification is large, especially for low- and high-income regions. While this forcing specification neglects high-frequency impacts, the qualitative patterns between country income levels remain in Supplementary Fig. 29, thus strengthening the robustness of the trade-network-related heterogeneities between regions.

Considering potentially consecutive impacts, while our estimates of direct impact are agnostic to the temporal evolution of forcing, the supply-chain propagation model we employ would result in a stronger impact of consecutive impacts compared with disjoint same-level single-day impacts. While this neglects potential threshold processes caused by, for example, floods occurring only after a certain amount of total rainfall, supply-chain effects are likely to be one of the main drivers of consecutive impacts being larger than individual events.

Seasonal characteristics of the resulting production disruptions are shown in Supplementary Fig. 6—Northern Hemisphere summer dominates the forcing, which is strongest for UMICs. In summary, while the estimation methodology can be improved in future work, we are confident that the seasonal and sectoral differentiation is a possible realistic simulation of current and future impacts of extreme temperatures and temperature variability, as well as rainfall and its extremes.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The data that support the findings of this study are available in the public repository for this publication (https://doi.org/10.5281/zenodo.8250110) (ref. 55). The EORA multi-region input–output data are available from worldmrio.com. Region shapefiles used for plotting are openly available from the GADM (v.4.1) project[56] at gadm.org.

Code availability

Analysis code is available in the public repository for this publication (https://doi.org/10.5281/zenodo.8250110) (ref. 55). The utility-maximizing consumer module v.3.4.0 of the Acclimate model is available as open source via Github (https://doi.org/10.5281/zenodo.12751087) (ref. 57).

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Author contributions

All authors designed the study. S.N.W., C.O. and A.L. developed the original Acclimate model. L.Q. developed the consumer extension with S.N.W. L.Q. conducted the forcing downscaling, Acclimate simulations and analysis. All authors discussed the results. L.Q. wrote the paper with inputs from all authors. All authors approved the final paper.

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Competing interests

The authors declare no competing interests.

Additional information

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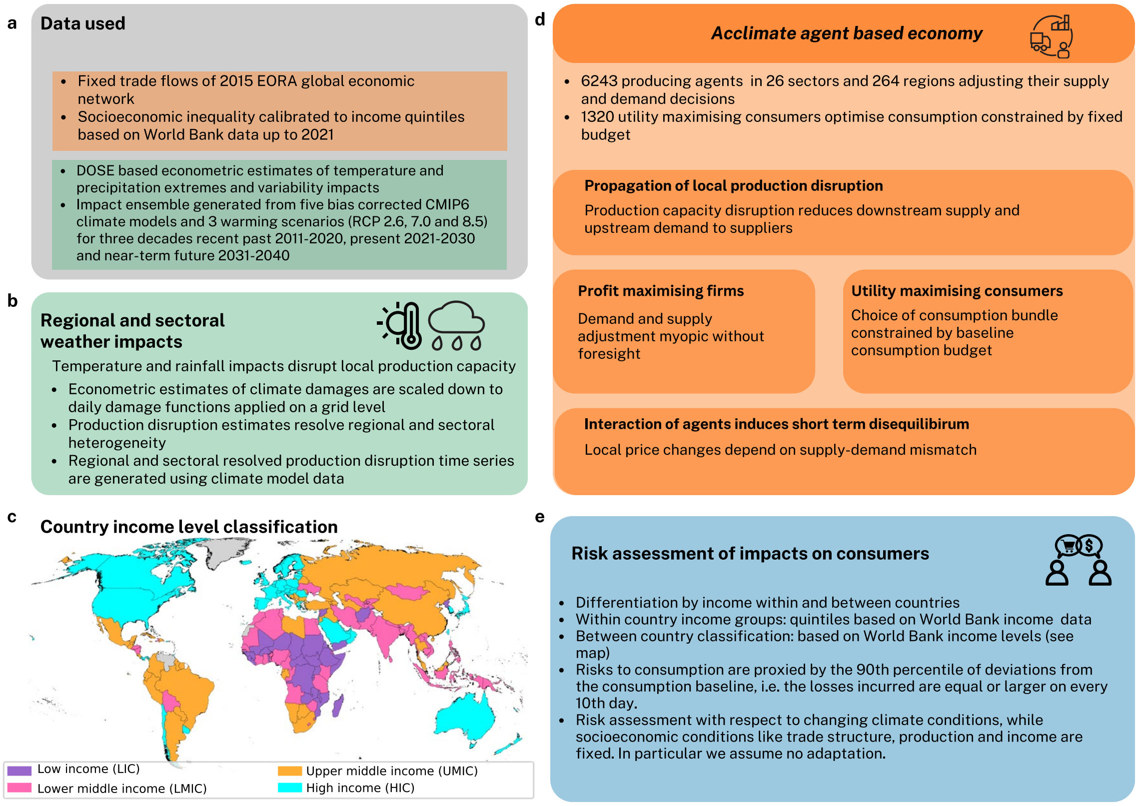

Extended Data Fig. 1 | Detailed schematic of used data, simulation approach, and main results. **a** used data, **b** summary of production disruption impact generation, **c** map of World Bank income level classification, **d** sketch of *Acclimate* modelling structure, and **e** summary of main results. Illustrations under the free license of www.pixaby.com(clouds) or canva.com (all other). Maps use GADM (v4.1) boundaries.

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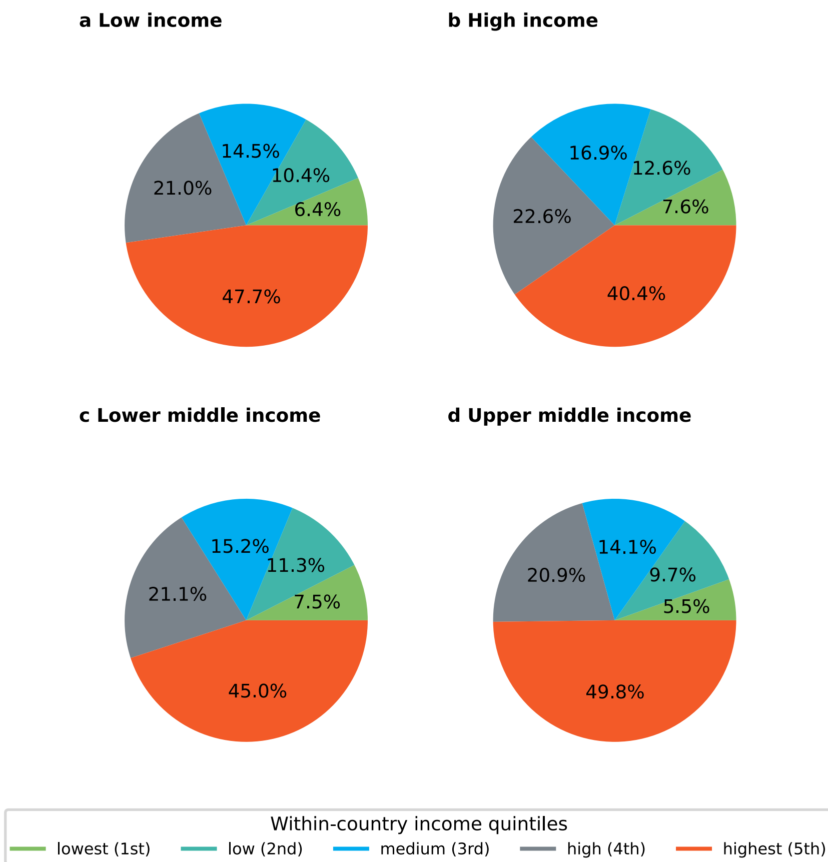

Extended Data Fig. 2 | Varying inequality between country income levels. Baseline shares of consumption by income quintile. **a** Low income countries, **b** high income countries, **c** lower middle income countries, and **d** upper middle income countries.

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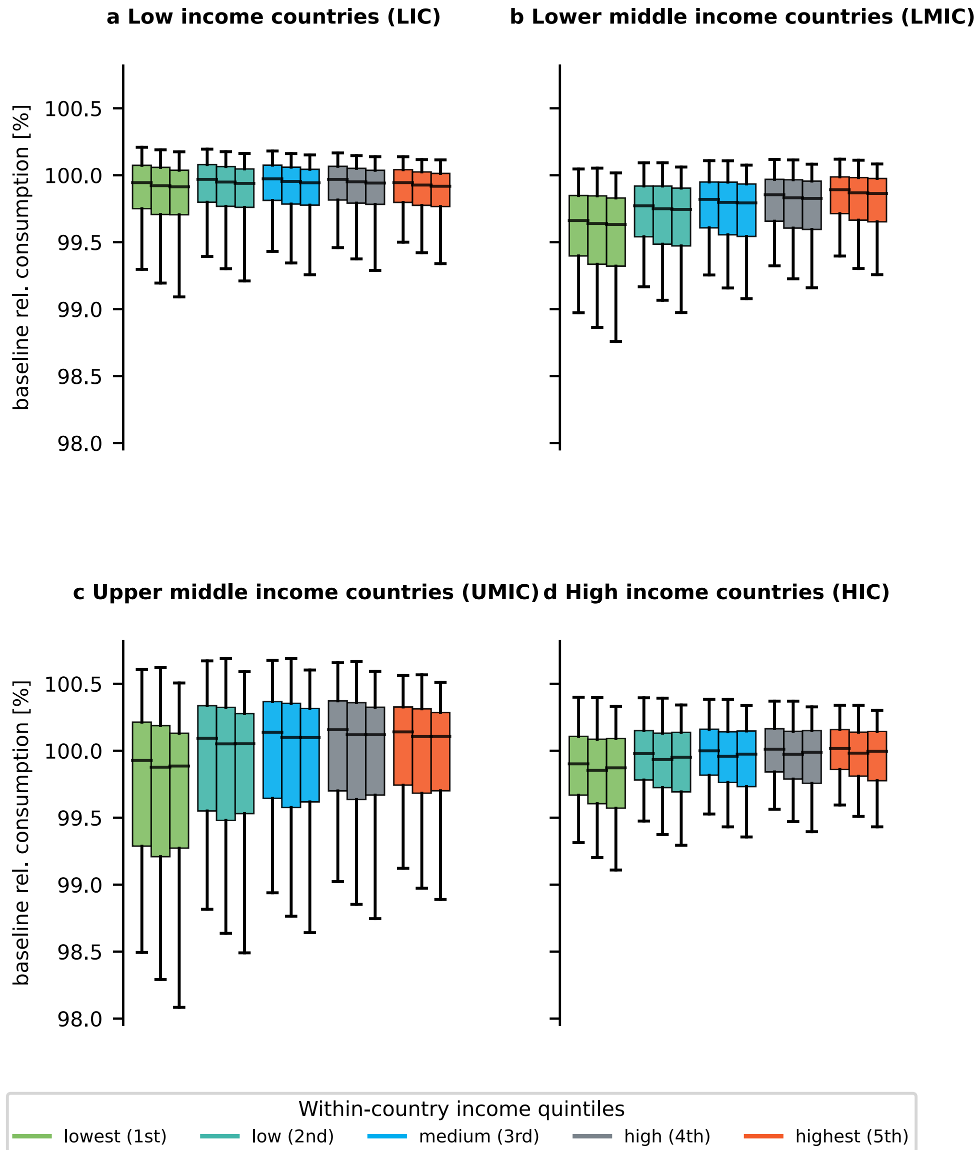

Extended Data Fig. 3 | Heterogeneous consumption distribution by country income level and between income quintiles. Baseline relative consumption by income quintile. Left 2011–2020, middle 2021–2030, and right 2031–2040 climate. Middle line shows median, box (25th, 75th) percentile, whiskers (5th, 95th) percentiles w.r.t. climate model ensemble (n = 15; 5 models x 3 SSPs). Subfigures show results by country income level: **a** Low-income countries (LIC), **b** lower middle-income countries (LMIC), **c** upper middle-income countries (UMIC), and **d** high-income countries (HIC).

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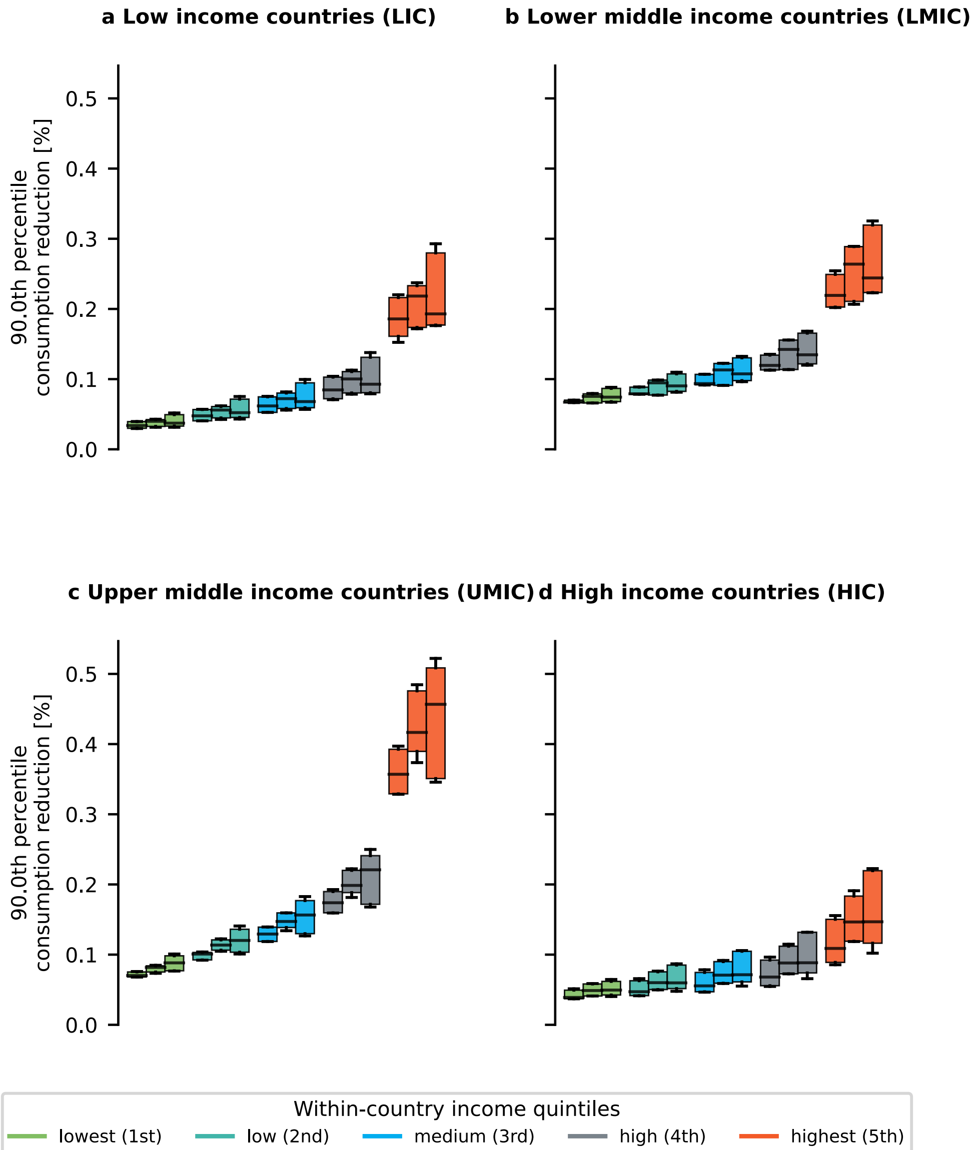

Extended Data Fig. 4 | High income risks dominate under weighting by share of total consumption. Percentile by income quintile. Left 2011–2020, middle 2021–2030, and right 2031–2040 climate. Middle line shows median, box (25th, 75th) percentile, whiskers (17th, 83rd) percentiles w.r.t. climate model ensemble (n = 15; 5 models x 3 SSPs). Subfigures show results by country income level: **a** Low-income countries (LIC), **b** lower middle-income countries (LMIC), **c** upper middle-income countries (UMIC), and **d** high-income countries (HIC).

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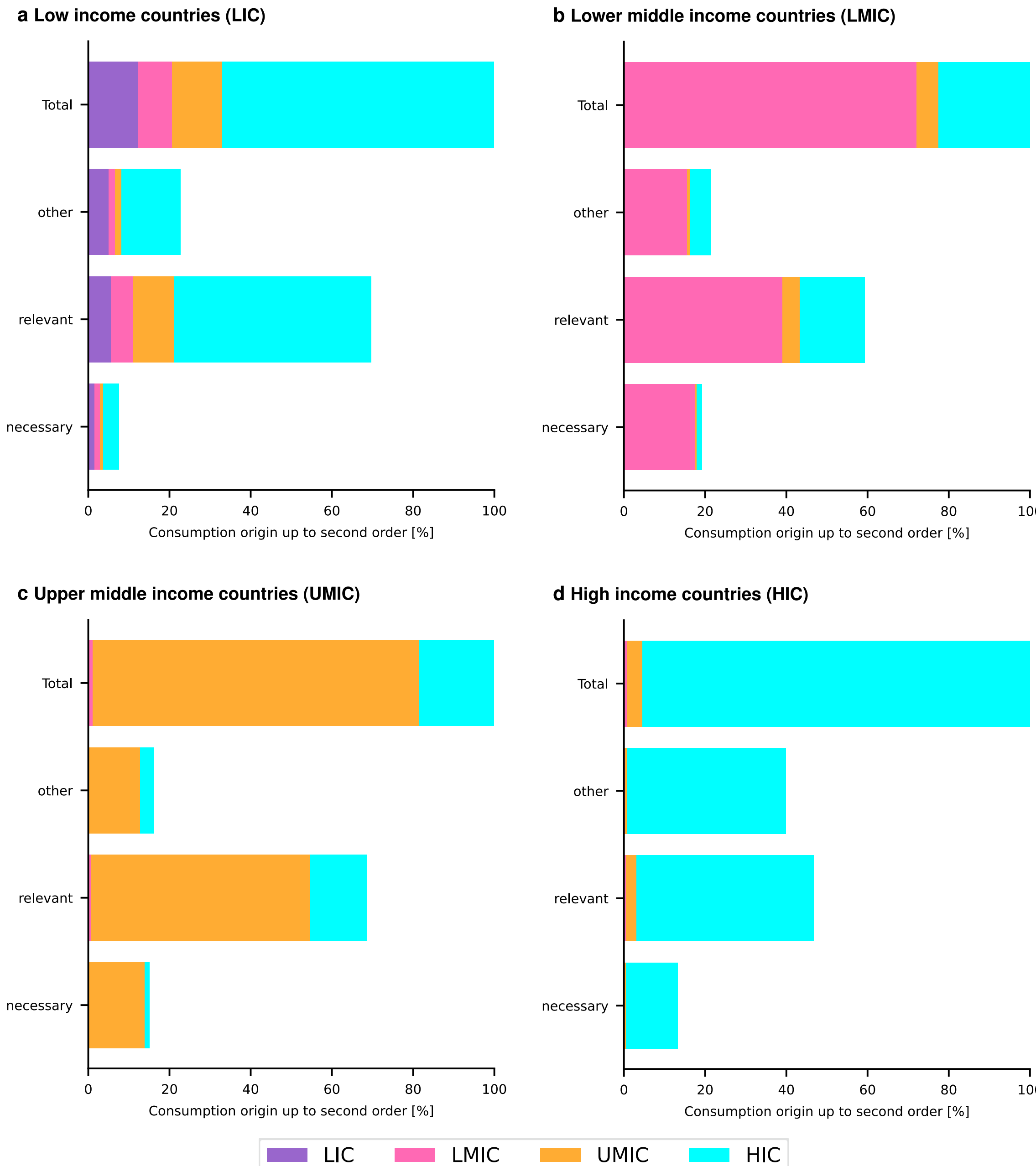

Extended Data Fig. 5 | Heterogeneous imports of consumption goods by baskets and country income level. Panels show percentage of value originating from the different country income levels (color code) including second order suppliers for **a** low-income countries (LIC), **b** lower middle-income countries (LMIC), **c** upper middle-income countries (UMIC), and **d** high-income countries (HIC). Bars show total consumption and the individual categories of consumption goods.

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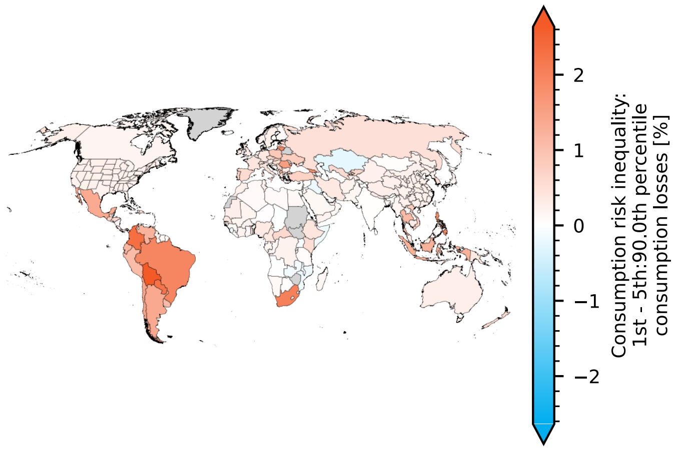

Extended Data Fig. 6 | Risk inequality between 1st and 5th quintile. Difference between the 90th percentile of consumption losses of lowest minus highest income in baseline relative consumption (%). Combined data for all decades of the ensemble median difference between lowest and highest income quintile. Grey shading indicates countries with low data quality or without data. Maps use GADM (v4.1) boundaries.

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☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

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Life sciences study design

All studies must disclose on these points even when the disclosure is negative.

Sample size	*Describe how sample size was determined, detailing any statistical methods used to predetermine sample size OR if no sample-size calculation was performed, describe how sample sizes were chosen and provide a rationale for why these sample sizes are sufficient.*
Data exclusions	*Describe any data exclusions. If no data were excluded from the analyses, state so OR if data were excluded, describe the exclusions and the rationale behind them, indicating whether exclusion criteria were pre-established.*
Replication	*Describe the measures taken to verify the reproducibility of the experimental findings. If all attempts at replication were successful, confirm this OR if there are any findings that were not replicated or cannot be reproduced, note this and describe why.*
Randomization	*Describe how samples/organisms/participants were allocated into experimental groups. If allocation was not random, describe how covariates were controlled OR if this is not relevant to your study, explain why.*
Blinding	*Describe whether the investigators were blinded to group allocation during data collection and/or analysis. If blinding was not possible, describe why OR explain why blinding was not relevant to your study.*

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	*Briefly describe the study type including whether data are quantitative, qualitative, or mixed-methods (e.g. qualitative cross-sectional, quantitative experimental, mixed-methods case study).*
Research sample	*State the research sample (e.g. Harvard university undergraduates, villagers in rural India) and provide relevant demographic information (e.g. age, sex) and indicate whether the sample is representative. Provide a rationale for the study sample chosen. For studies involving existing datasets, please describe the dataset and source.*
Sampling strategy	*Describe the sampling procedure (e.g. random, snowball, stratified, convenience). Describe the statistical methods that were used to predetermine sample size OR if no sample-size calculation was performed, describe how sample sizes were chosen and provide a rationale for why these sample sizes are sufficient. For qualitative data, please indicate whether data saturation was considered, and what criteria were used to decide that no further sampling was needed.*
Data collection	*Provide details about the data collection procedure, including the instruments or devices used to record the data (e.g. pen and paper, computer, eye tracker, video or audio equipment) whether anyone was present besides the participant(s) and the researcher, and whether the researcher was blind to experimental condition and/or the study hypothesis during data collection.*
Timing	*Indicate the start and stop dates of data collection. If there is a gap between collection periods, state the dates for each sample cohort.*

Data exclusions	*If no data were excluded from the analyses, state so OR if data were excluded, provide the exact number of exclusions and the rationale behind them, indicating whether exclusion criteria were pre-established.*
Non-participation	*State how many participants dropped out/declined participation and the reason(s) given OR provide response rate OR state that no participants dropped out/declined participation.*
Randomization	*If participants were not allocated into experimental groups, state so OR describe how participants were allocated to groups, and if allocation was not random, describe how covariates were controlled.*

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Simulation study
Research sample	NA
Sampling strategy	Sample size determined by availability of climate model runs.
Data collection	NA
Timing and spatial scale	NA
Data exclusions	NA
Reproducibility	NA
Randomization	NA
Blinding	NA

Did the study involve field work? ☐ Yes ☒ No

Field work, collection and transport

Field conditions	*Describe the study conditions for field work, providing relevant parameters (e.g. temperature, rainfall).*
Location	*State the location of the sampling or experiment, providing relevant parameters (e.g. latitude and longitude, elevation, water depth).*
Access & import/export	*Describe the efforts you have made to access habitats and to collect and import/export your samples in a responsible manner and in compliance with local, national and international laws, noting any permits that were obtained (give the name of the issuing authority, the date of issue, and any identifying information).*
Disturbance	*Describe any disturbance caused by the study and how it was minimized.*

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Antibodies

Antibodies used	*Describe all antibodies used in the study; as applicable, provide supplier name, catalog number, clone name, and lot number.*
Validation	*Describe the validation of each primary antibody for the species and application, noting any validation statements on the manufacturer's website, relevant citations, antibody profiles in online databases, or data provided in the manuscript.*

Eukaryotic cell lines

Policy information about [cell lines and Sex and Gender in Research]

Cell line source(s)	*State the source of each cell line used and the sex of all primary cell lines and cells derived from human participants or vertebrate models.*
Authentication	*Describe the authentication procedures for each cell line used OR declare that none of the cell lines used were authenticated.*
Mycoplasma contamination	*Confirm that all cell lines tested negative for mycoplasma contamination OR describe the results of the testing for mycoplasma contamination OR declare that the cell lines were not tested for mycoplasma contamination.*
Commonly misidentified lines (See ICLAC register)	*Name any commonly misidentified cell lines used in the study and provide a rationale for their use.*

Palaeontology and Archaeology

Specimen provenance	*Provide provenance information for specimens and describe permits that were obtained for the work (including the name of the issuing authority, the date of issue, and any identifying information). Permits should encompass collection and, where applicable, export.*
Specimen deposition	*Indicate where the specimens have been deposited to permit free access by other researchers.*
Dating methods	*If new dates are provided, describe how they were obtained (e.g. collection, storage, sample pretreatment and measurement), where they were obtained (i.e. lab name), the calibration program and the protocol for quality assurance OR state that no new dates are provided.*

☐ Tick this box to confirm that the raw and calibrated dates are available in the paper or in Supplementary Information.

Ethics oversight	*Identify the organization(s) that approved or provided guidance on the study protocol, OR state that no ethical approval or guidance was required and explain why not.*

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Animals and other research organisms

Policy information about studies involving animals; ARRIVE guidelines recommended for reporting animal research, and Sex and Gender in Research

Laboratory animals	*For laboratory animals, report species, strain and age OR state that the study did not involve laboratory animals.*
Wild animals	*Provide details on animals observed in or captured in the field; report species and age where possible. Describe how animals were caught and transported and what happened to captive animals after the study (if killed, explain why and describe method; if released, say where and when) OR state that the study did not involve wild animals.*
Reporting on sex	*Indicate if findings apply to only one sex; describe whether sex was considered in study design, methods used for assigning sex. Provide data disaggregated for sex where this information has been collected in the source data as appropriate; provide overall numbers in this Reporting Summary. Please state if this information has not been collected. Report sex-based analyses where performed, justify reasons for lack of sex-based analysis.*
Field-collected samples	*For laboratory work with field-collected samples, describe all relevant parameters such as housing, maintenance, temperature, photoperiod and end-of-experiment protocol OR state that the study did not involve samples collected from the field.*
Ethics oversight	*Identify the organization(s) that approved or provided guidance on the study protocol, OR state that no ethical approval or guidance was required and explain why not.*

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Clinical data

Policy information about clinical studies

All manuscripts should comply with the ICMJE guidelines for publication of clinical research and a completed CONSORT checklist must be included with all submissions.

Clinical trial registration	*Provide the trial registration number from ClinicalTrials.gov or an equivalent agency.*
Study protocol	*Note where the full trial protocol can be accessed OR if not available, explain why.*
Data collection	*Describe the settings and locales of data collection, noting the time periods of recruitment and data collection.*
Outcomes	*Describe how you pre-defined primary and secondary outcome measures and how you assessed these measures.*

Dual use research of concern

Policy information about dual use research of concern

Hazards

Could the accidental, deliberate or reckless misuse of agents or technologies generated in the work, or the application of information presented in the manuscript, pose a threat to:

No	Yes	
☒	☐	Public health
☒	☐	National security
☒	☐	Crops and/or livestock
☒	☐	Ecosystems
☒	☐	Any other significant area

Experiments of concern

Does the work involve any of these experiments of concern:

No	Yes	
☒	☐	Demonstrate how to render a vaccine ineffective
☒	☐	Confer resistance to therapeutically useful antibiotics or antiviral agents
☒	☐	Enhance the virulence of a pathogen or render a nonpathogen virulent
☒	☐	Increase transmissibility of a pathogen
☒	☐	Alter the host range of a pathogen
☒	☐	Enable evasion of diagnostic/detection modalities
☒	☐	Enable the weaponization of a biological agent or toxin
☒	☐	Any other potentially harmful combination of experiments and agents

ChIP-seq

Data deposition

☐ Confirm that both raw and final processed data have been deposited in a public database such as GEO.

☐ Confirm that you have deposited or provided access to graph files (e.g. BED files) for the called peaks.

Data access links *May remain private before publication.*	*For "Initial submission" or "Revised version" documents, provide reviewer access links. For your "Final submission" document, provide a link to the deposited data.*
Files in database submission	*Provide a list of all files available in the database submission.*
Genome browser session (e.g. UCSC)	*Provide a link to an anonymized genome browser session for "Initial submission" and "Revised version" documents only, to enable peer review. Write "no longer applicable" for "Final submission" documents.*

Methodology

Replicates	*Describe the experimental replicates, specifying number, type and replicate agreement.*
Sequencing depth	*Describe the sequencing depth for each experiment, providing the total number of reads, uniquely mapped reads, length of reads and*

Sequencing depth | *whether they were paired- or single-end.*

Antibodies | *Describe the antibodies used for the ChIP-seq experiments; as applicable, provide supplier name, catalog number, clone name, and lot number.*

Peak calling parameters | *Specify the command line program and parameters used for read mapping and peak calling, including the ChIP, control and index files used.*

Data quality | *Describe the methods used to ensure data quality in full detail, including how many peaks are at FDR 5% and above 5-fold enrichment.*

Software | *Describe the software used to collect and analyze the ChIP-seq data. For custom code that has been deposited into a community repository, provide accession details.*

Flow Cytometry

Plots

Confirm that:

- [ ] The axis labels state the marker and fluorochrome used (e.g. CD4-FITC).
- [ ] The axis scales are clearly visible. Include numbers along axes only for bottom left plot of group (a 'group' is an analysis of identical markers).
- [ ] All plots are contour plots with outliers or pseudocolor plots.
- [ ] A numerical value for number of cells or percentage (with statistics) is provided.

Methodology

Sample preparation | *Describe the sample preparation, detailing the biological source of the cells and any tissue processing steps used.*

Instrument | *Identify the instrument used for data collection, specifying make and model number.*

Software | *Describe the software used to collect and analyze the flow cytometry data. For custom code that has been deposited into a community repository, provide accession details.*

Cell population abundance | *Describe the abundance of the relevant cell populations within post-sort fractions, providing details on the purity of the samples and how it was determined.*

Gating strategy | *Describe the gating strategy used for all relevant experiments, specifying the preliminary FSC/SSC gates of the starting cell population, indicating where boundaries between "positive" and "negative" staining cell populations are defined.*

- [ ] Tick this box to confirm that a figure exemplifying the gating strategy is provided in the Supplementary Information.

Magnetic resonance imaging

Experimental design

Design type | *Indicate task or resting state; event-related or block design.*

Design specifications | *Specify the number of blocks, trials or experimental units per session and/or subject, and specify the length of each trial or block (if trials are blocked) and interval between trials.*

Behavioral performance measures | *State number and/or type of variables recorded (e.g. correct button press, response time) and what statistics were used to establish that the subjects were performing the task as expected (e.g. mean, range, and/or standard deviation across subjects).*

Acquisition

Imaging type(s) | *Specify: functional, structural, diffusion, perfusion.*

Field strength | *Specify in Tesla*

Sequence & imaging parameters | *Specify the pulse sequence type (gradient echo, spin echo, etc.), imaging type (EPI, spiral, etc.), field of view, matrix size, slice thickness, orientation and TE/TR/flip angle.*

Area of acquisition | *State whether a whole brain scan was used OR define the area of acquisition, describing how the region was determined.*

Diffusion MRI ☐ Used ☐ Not used

Preprocessing

Preprocessing software	*Provide detail on software version and revision number and on specific parameters (model/functions, brain extraction, segmentation, smoothing kernel size, etc.).*
Normalization	*If data were normalized/standardized, describe the approach(es): specify linear or non-linear and define image types used for transformation OR indicate that data were not normalized and explain rationale for lack of normalization.*
Normalization template	*Describe the template used for normalization/transformation, specifying subject space or group standardized space (e.g. original Talairach, MNI305, ICBM152) OR indicate that the data were not normalized.*
Noise and artifact removal	*Describe your procedure(s) for artifact and structured noise removal, specifying motion parameters, tissue signals and physiological signals (heart rate, respiration).*
Volume censoring	*Define your software and/or method and criteria for volume censoring, and state the extent of such censoring.*

Statistical modeling & inference

Model type and settings	*Specify type (mass univariate, multivariate, RSA, predictive, etc.) and describe essential details of the model at the first and second levels (e.g. fixed, random or mixed effects; drift or auto-correlation).*
Effect(s) tested	*Define precise effect in terms of the task or stimulus conditions instead of psychological concepts and indicate whether ANOVA or factorial designs were used.*

Specify type of analysis: ☐ Whole brain ☐ ROI-based ☐ Both

Statistic type for inference (See Eklund et al. 2016)	*Specify voxel-wise or cluster-wise and report all relevant parameters for cluster-wise methods.*
Correction	*Describe the type of correction and how it is obtained for multiple comparisons (e.g. FWE, FDR, permutation or Monte Carlo).*

Models & analysis

n/a	Involved in the study
☒	☐ Functional and/or effective connectivity
☒	☐ Graph analysis
☒	☐ Multivariate modeling or predictive analysis

Functional and/or effective connectivity	*Report the measures of dependence used and the model details (e.g. Pearson correlation, partial correlation, mutual information).*
Graph analysis	*Report the dependent variable and connectivity measure, specifying weighted graph or binarized graph, subject- or group-level, and the global and/or node summaries used (e.g. clustering coefficient, efficiency, etc.).*
Multivariate modeling and predictive analysis	*Specify independent variables, features extraction and dimension reduction, model, training and evaluation metrics.*