Country-level social cost of carbon

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The social cost of carbon (SCC) is a commonly employed metric of the expected economic damages from carbon dioxide (CO_2) emissions. Although useful in an optimal policy context, a world-level approach obscures the heterogeneous geography of climate damage and vast differences in country-level contributions to the global SCC, as well as climate and socio-economic uncertainties, which are larger at the regional level. Here we estimate country-level contributions to the SCC using recent climate model projections, empirical climate-driven economic damage estimations and socio-economic projections. Central specifications show high global SCC values (median, US$417 per tonne of CO_2 (tCO_2); 66% confidence intervals, US$177–805 per tCO_2) and a country-level SCC that is unequally distributed. However, the relative ranking of countries is robust to different specifications: countries that incur large fractions of the global cost consistently include India, China, Saudi Arabia and the United States.

The social cost of carbon (SCC) represents the economic cost associated with climate damage (or benefit) that results from the emission of an additional tonne of carbon dioxide (tCO_2). One way to compute it is by taking the net present value of the difference between climate change damages along with a baseline climate change pathway and the same pathway with an additional incremental pulse release of CO_2. The SCC provides an economic valuation of the marginal impacts of climate change. It has been estimated hundreds of times in the past three decades[1] using a range of assumptions about uncertain parameters (such as social discount rate, economic growth and climate sensitivity). Recent estimates[2–7] of SCC range from approximately US$10 per tCO_2 to as much as US$1,000 per tCO_2. A recent report issued by the US National Academies highlighted the many challenges and opportunities associated with improving estimates of SCC[8].

Among the state-of-the-art contemporary estimates of the SCC are those calculated by the US Environmental Protection Agency. The latest figures equal to US$12, US$42 and US$62 per tCO_2 emitted in 2020 for 5, 3 and 2.5% discount rates, respectively[2]. These estimates are used, among other purposes, to inform US environmental rule-making. Various alternative approaches to estimate the SCC have been employed over the years, and include more sophisticated treatments of time, risk and equity preferences[9–14], as well as those that incorporate more recent representations of climate damage and feedback[15–18]. A recent expert elicitation of climate scientists and economists[3] found a mean SCC of approximately US$150–200 per tCO_2.

The global SCC (GSCC) captures the externality of CO_2 emissions, and is thus the right value to use from a global welfare perspective. Nonetheless, country-level contributions to the SCC are important for various reasons. Mapping domestic impacts can allow us to quantify non-cooperative behaviour, and thus better understand the determinants of international cooperation. The governance of climate agreements[19,20] is a key issue for climate change. The nationally determined architecture of the Paris climate agreement—and its vulnerability to changing national interests—is one important example. Country-level estimates can also allow us to better understand regional impacts, which are important for adaptation and compensation measures. Finally, a higher spatial resolution estimation of climate damage and benefits can impact estimates of net global climate damage[21,22] and its sensitivity to climate and socio-economic drivers.

Existing studies agree on the significant gap between domestic and global values of the SCC, but provide limited agreement on the distribution of the SCC by region[23]. Due to limitations on the availability of country-level climate and economic inputs, no previous analysis has partitioned GSCC into country-level contributions from each individual nation. In this article, we draw upon recent developments in physical and economic climate science to estimate country-level SCC (CSCC) and aggregate SCC and quantify the associated uncertainties. The CSCC captures the amount of marginal damage (or, if negative, the benefit) expected to occur in an individual country as a consequence of additional CO_2 emission. Although marginal impacts do not capture all the information relevant to climate decision-making, the distribution of the CSCC provides useful insights into distributional impacts of climate change and national strategic incentives.

A modular framework
Following the recommendations of the recent report by the US National Academies, we executed our calculations of the social cost of carbon through a process with four distinct components[8]: a socio-economic module wherein the future evolution of the economy, which includes the projected emissions of CO_2, is characterized without the impact of climate change; a climate module wherein the earth system responds to emissions of CO_2 and other anthropogenic forcings; a damages module, wherein the economy's response to changes in the Earth system are quantified; and a discounting module, wherein a time series of future damages is compressed into a single present value. In our analysis, we explored uncertainties associated with each module at the global and country level. We focused only on climate impacts, and did not carry out a fully fledged cost–benefit analysis, which would require modelling mitigation costs.

We developed a method to calculate SCC that is oriented towards partitioning and quantifying uncertainties. Although it follows the same module structure as the integrated assessment models that are conventionally used to calculate SCC, rather than build reduced-form

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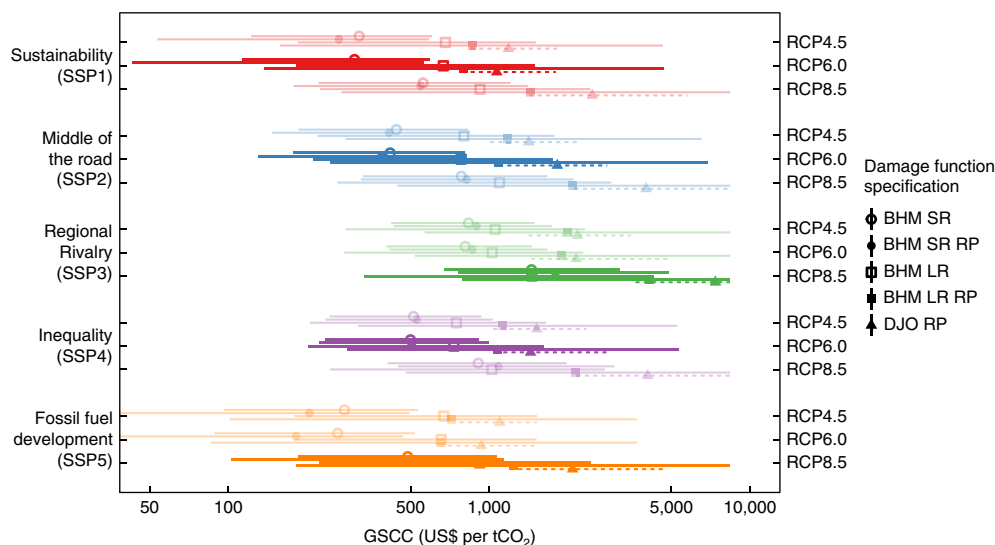
Fig. 1 | GSCC in 2020 under various assumptions and scenarios. Median estimates and 16.7% to 83.3% quantile bounds for GSCC under SSPs 1–5, and RCPs 4.5, 6.0 and 8.5. For each SSP, the darker colours indicate the SSP–RCP pairing with a superior consistency (Methods and Supplementary Table 4). The five specifications of damage function are four BHM models (short run (SR) and long run (LR) pooled and with the rich and poor (RP) distinction) and the DJO model. The values displayed assume growth-adjusted discounting with a pure rate of time preference of 2% per year and elasticity of marginal utility substitution (μ) of 1.5. Supplementary Fig. 2 compares these results with fixed discounting (rate of 3%). Coloured bars represent the 66% CIs.

models of the climate or economy, we used country-level climate projections taken directly from gridded ensemble climate model simulation data as well as country-level economic damage relationships taken directly from empirical macroeconomic analyses. As climate and economic quantities are empirical in this analysis, these uncertainties are probabilistic in our output. Socio-economic and discounting uncertainties are assessed parametrically using five socio-economic scenarios and twelve discounting schemes.

Socio-economic module. For the socio-economic projections, we used the shared socio-economic pathway scenarios (SSPs)[24]. The SSPs provide five different storylines of the future (Supplementary Table 1). We used the GDP and population assumptions of the SSPs as well as subsequent work to estimate the emissions associated with each SSP without the climate mitigation policies[25].

Climate module. We matched emission profiles of the SSPs to those of the representative concentration pathways (RCPs)[26] modelled in the Fifth Coupled Model Intercomparison Project (CMIP5)[27] to estimate baseline warming (Methods).To estimate the response of the climate system to a pulse release of CO_2, we combined results from CMIP5 and a carbon cycle model intercomparison project[28] (Supplementary Tables 2 and 3). Carbon cycle uncertainty is represented by using the global-scale decay of atmospheric CO_2 after a pulse release of CO_2 into the present-day atmosphere. The climate system response uncertainty is calculated at the population-weighted country level using gridded output from the CMIP5 abrupt4×CO_2 experiment in which atmospheric CO_2 is instantaneously quadrupled from the preindustrial level. By convoluting the results from these experiments (as in Ricke and Caldeira[29], but at the population-weighted country-mean level), we derived a range of country-specific transient warming responses to an incremental emission of CO_2. To test the sensitivity of our results to the uncertain feedbacks between economic growth and emissions, we performed the calculations for RCPs 4.5, 6.0 and 8.5 for all the SSPs.

Damages module. We converted country-level temperature and precipitation changes into country-level damages using empirical

macroeconomic relationships derived by Burke et al.[30] and Dell et al.[31]. Their econometric approaches exploit interannual climate variability in historical observations to estimate the impact of climate on economic growth. Estimating the economic damages associated with a given level of warming is a notoriously challenging problem for which there is no perfect state-of-the-art solution[8,32]. Gross domestic product (GDP) is an informative, but highly imperfect measure of welfare[33]. Among its advantages, an empirical macroeconomic approach captures the interactions and feedbacks among sectors of the economy, captures the effects of climate on the economy that have been neglected or are difficult to partition and quantify, has a higher geographical resolution (country level) than existing alternatives, is empirically validated and has confidence intervals that allow uncertainty analysis, and is completely transparent and replicable. As results are sensitive to the econometric specifications, for example, whether lags are included to capture long-run effects, and countries are distinguished between rich and poor to account for different capabilities to adapt[30], we compared all the existing empirical specifications (Methods and Supplementary Information).

Discounting module. We applied these damage functions to our country-level temperature pulse response, SSP and RCP projections, including associated climate and damage function uncertainty bounds (Methods and Supplementary Fig. 1) and then compressed the time series of output into country-level contributions to the SCC (CSCCs) using discounting. Discounting assumptions are consistently one of the biggest determinants of differences between estimations of the SCC[10,34]. Although intuitive, the use of a fixed discounting rate is not appropriate, particularly when applied universally to countries with highly disparate growth rates and with significant economic losses due to climate change. We thus used growth-adjusted discounting determined by the Ramsey endogenous rule[35], with a range of values for the elasticity of marginal utility (μ) and the pure rate of time preference (ρ), but we also report fixed discounting results to demonstrate the sensitivity of SCC calculations to discounting methods.
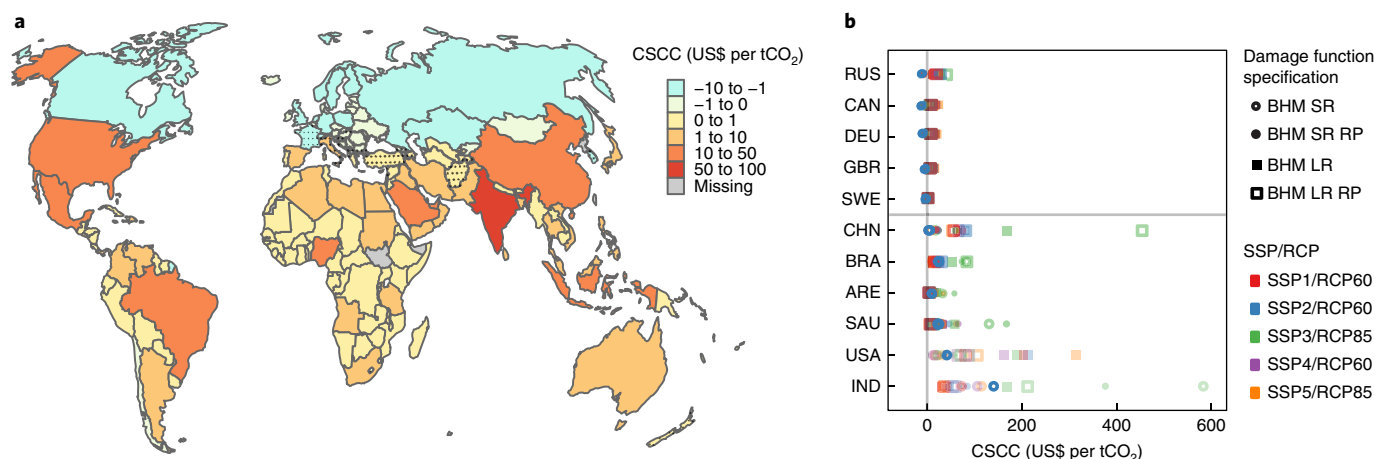
Fig. 2 | CSCCs. a, Spatial distribution of median estimates of the CSCCs computed for the reference case of scenario SSP2/RCP6.0, BHM-SR and a growth-adjusted discount rate ($\rho = 2\%$, $\mu = 1.5$). Stippling indicates countries in which BHM damage function is not statistically robust[30]. **b**, CSCCs for alternative scenarios and damage function specification combinations for the five smallest and six largest CSCCs in the reference case (blue open circles). RUS, Russia; CAN, Canada; DEU, Germany, GBR, Great Britain; SWE, Sweden; CHN, China; BRA, Brazil; ARE, United Arab Emirates; SAU, Saudi Arabia; USA, United States; IND, India.

Global results

The GSCC is the sum of the CSCC values. We calculated CSCC for each set of scenario, parameter and model specification assumptions, and established an uncertainty range based on a bootstrap resampling method (Methods and Supplementary Information) and then aggregated to the global level. The median estimates of the GSCC (Fig. 1) are significantly higher than the Inter-agency Working Group estimates, primarily due to the higher damages associated with the empirical macroeconomic production function[30], although similar SCC values have been estimated in the past using other methodologies[11,18]. Under the 'middle-of-the-road' socio-economic scenario (SSP2) and its closest corresponding climate scenario (RCP6.0), and with the central specification of Burke–Hsiang–Miguel (BHM) damage function (short run, no income differentiation) we estimated a median GSCC of US$417 per tCO$_2$ (ρ, 2%; μ, 1.5).

The choice of both socio-economic and climate scenario has an impact on the estimated GSCC (Fig. 1 and Supplementary Fig. 2). For a given RCP, scenarios with strong economic growth and reduced cross-country inequalities (SSP1 and SSP5) have a smaller GSCC than do scenarios with low productivity and persistent or even increasing global inequality (SSP3 and SSP4). For a given SSP, higher emission scenarios lead to a higher GSCC. When fixed time discounting is used (Supplementary Fig. 2), the results are significantly different. In particular, the GSCC values are lower across the scenarios, and the ranking to SSPs and RCPs is often reversed. This highlights the importance of using the appropriate endogenous discounting rules to capture the feedback of climate on the economy.

Figure 1 also shows the sensitivity to the impact function specification. Under most socio-economic scenarios, the GSCC is significantly higher and more uncertain when calculated with a long-run (lagged) damage model specification (BHM-LR). This somewhat counterintuitive result indicates that whether climate's primary impact on the economy is through growth or level effects, the negative cumulative effect of climate change on long-term growth is substantial and robust. The GSCC tends to be similar in both pooled and rich/poor specifications of the damages model, with the exception of SSP3, in which the estimated GSCC is much higher in the rich/poor specifications. The DJO specification of the economic impact function[31] yields significantly higher GSCC values.

The confidence intervals (CIs, 66%) illustrated in Fig. 1 emphasize the large degree of empirical uncertainty that surrounds SCC estimates, even if scenario and structural uncertainties are disregarded. These stem from both the uncertainties of the climate system response to CO$_2$ (climate sensitivity) and uncertainties in the economic harm expected from climate change (damage function). The latter are especially significant for the long-run specifications, which, by construction, have larger confidence intervals.

Country-level results

These global estimates conceal substantial heterogeneity in CSCCs. Figure 2a shows the spatial distribution of CSCCs under a reference scenario (SSP2-RCP6, standard BHM specification). All the fixed discounting, alternative scenario, parameterization and specification results are available as part of the database included in the Supplementary Information.

India's CSCC is the highest (US$86 per tCO$_2$ (49–157); 21% of the GSCC (20–30%); CIs are given in parentheses), followed by the United States (US$48 per tCO$_2$ (1–118); 11% of the GSCC (0–15%)) and Saudi Arabia (US$47 per tCO$_2$ (27–86); 11% of the GSCC (11–16%)) of the GSCC. Three countries follow at above US$20 per tCO$_2$: Brazil (US$24 (14–41) per tCO$_2$), China (US$24 (4–50) per tCO$_2$) and the United Arab Emirates (US$24 (14–48) per tCO$_2$). Northern Europe, Canada and the Former Soviet Union have negative CSCC values because their current temperatures are below the economic optimum. These results are among the most sensitive in the analysis, as under the BHM long-run and DJO damage model specifications all countries have positive CSCC. Under the reference case and other short-run model specifications, about 90% of the world population has a positive CSCC. Although the magnitude of CSCC varies considerably depending on the scenario and discount rate, the relative distribution is generally robust to these uncertainties. Damage function uncertainty is a larger contributor to the overall uncertainty, but at the country level, either climate or damages uncertainty may be larger. The alternative economic damage functions confirm the broad heterogeneity of CSCCs and relative country ranking (Fig. 2b and Supplementary Fig. 5).

Consistent with past work on the geography of climate damages[5,30,36], we found that the international distribution of SCC is inequitable (Lorenz curves in Fig. 3). The magnitude of the inequality is sensitive to the model specification of the economic impact function. As discussed above and in the Supplementary Discussion, there is an unsettled debate as to whether empirical evidence points toward the influence of climate on the economy operating primarily via growth
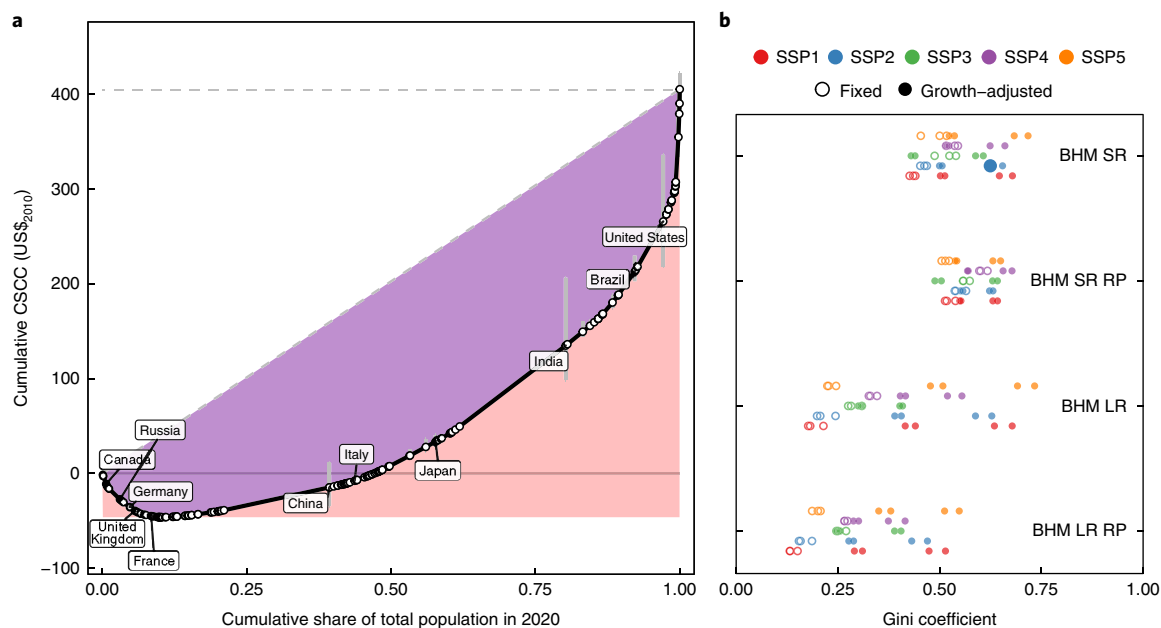
Fig. 3 | Lorenz curve and Gini coefficients for the country-level contributions to the GSCC in 2020. a, Cumulative global population plotted against cumulative SCC, with countries ranked by CSCC per capita, produces a Lorenz curve for the reference case of scenario SSP2/RCP60, BHM-SR and a growth adjusted discount rate with $\rho = 2\%$ and $\mu = 1.5$. The red and purple areas illustrate the quantities required to calculate the Gini coefficient, a synthetic metric of heterogeneity, or inequality, which is equal to the purple area divided by the sum of the purple and red areas. **b**, Gini coefficients for all four damage model specifications. SSPs are distinguished by colour for both three fixed discounting rates; 2.5%, 3% and 5%), and four growth-adjusted discounting with $\rho = (1\%, 2\%)$ and $\mu = (0.7, 1.5)$. The reference case illustrated in **a** (Gini coefficient, 0.62) is shown with a large solid blue circle.

or level effects, something that has been analysed without definitive conclusion in BHM and follow-up work[37]. Our results indicate that this uncertainty is consequential from a strategic perspective (that is, in determining the relative gains and losses to particular countries). In particular, with long-run and Dell–Jones–Olken (DJO) specifications, all countries have a positive CSCC. This results in higher (almost twice as much) global values of the SCC (as already observed in Fig. 1) and lower inequality with respect to the short-term specification. The distinction between income groups in the impact function (rich and poor countries) has smaller impacts, reducing GSCC and either leaving inequality unchanged (for the short-term specification) or lowering it (for the long-term specification).

Figure 3b summarizes the inequality of the CSCC across all scenarios through Gini coefficients[38,39], a synthetic measure of global heterogeneity. Under the short-run pooled BHM impact function (BHM-SR) specification, Gini values are slightly higher for SSP1 and SSP5, and significantly lower for SSP3, which is also the socioeconomic scenario with the highest GSCC value. Damage model specification is the most important uncertainty factor to future outcomes, as under long-run economic impact models, inequality (Gini value) is considerably lower (where GSCCs are higher), whereas the rich/poor distinction plays a smaller role. The discounting method also plays an important role—fixed discounting leads to significantly lower inequality (Gini coefficients) in the distribution of CSCC for most specifications.

Figure 4 highlights a mapping of the winners and losers from climate change among the G20 nations. Although the magnitude of the CSCC is subject to considerable uncertainty, the shares of the GSCC allocated among world powers remains relatively stable (Supplementary Figs. 7–9) in all short-run impact model specifications. Russia dominates all the other nations in gains from emissions, whereas India is consistently dominated by all the other large economies with large losses. Other developing economies, such as Indonesia and Brazil, will accrue a significantly greater share of the

GSCC than their current share of global emissions. The world's biggest emitters (China and the United States) both stand to accrue a smaller share of the GSCC than their share of emissions, but are consistently dominated by the European Union, Canada, South Korea and—in the case of the United States—Japan.

The relative ranking of the SCC is highly consistent among most of the 276 scenario-impact-discounting uncertainty cases with the notable exception of the change in relative positions of major world powers that occurs under the long-run impact model specifications (Supplementary Figs. 7–9). Countries like Russia, Canada, Germany and France that have negative CSCC under the reference case switch to having among the highest positive CSCCs (Supplementary Fig. 9). After the short- and long-run differences, the largest shifts in country order relative to our reference case occur under the high-emissions SSP5 scenario and in the transition between growth-adjusted and fixed discounting (Supplementary Fig. 8).

Discussion

The discord between country-level shares in CO_2 emissions and country-level shares in the SCC illustrates an important reason why significant challenges persist in reaching a common climate agreement. If countries were to price their own carbon emissions at their own CSCC, approximately 5%, a small amount, of the global climate externality would be internalized. At the same time, our results consistently show that the three highest-emitting countries (China, the United States and India) also have the among the highest country-level economic impacts from a CO_2 emission. These high-emitter CSCCs are on a par with carbon prices foreseen by detailed process integrated assessment models for climate stabilization scenarios (Supplementary Fig. 10). That is, internalizing the domestic SCC in some major emitters could result in emissions pathways for those countries that are consistent with the 1.5–2 °C temperature pathways. Fully internalizing the CO_2 externality (that is, pricing carbon at the GSCC) would allow the Paris Agreement goal to be met, and beyond.
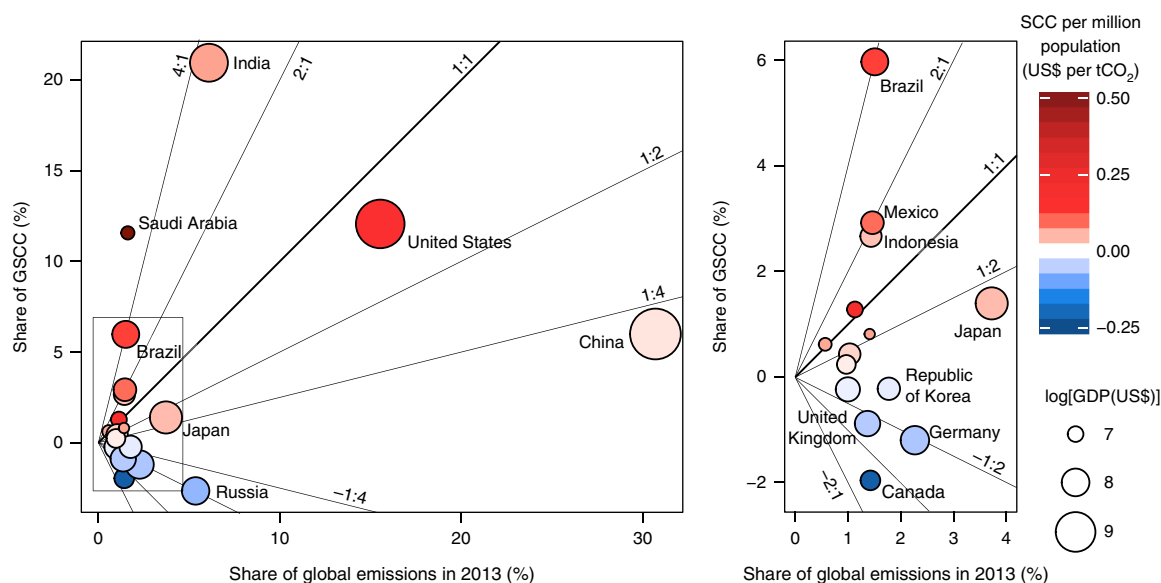
Fig. 4 | Winners and Losers of climate change among the G20 nations. Country-level shares of the GSCC (that is, CSCC/GSCC) versus shares of the 2013 CO2 emissions. The CSCC is the median estimate with growth adjusted discounting ($\rho = 2\%$, $\mu = 1.5$) for SSP2/RCP6.0 and BHM-SR. Points are shaded by CSCC per capita and sized according to country GDP in 2015. Diagonal lines show the ratio of the GSCC share to the emissions share. Ratios greater than 1:1 indicate that a country's share of the GSCC exceeds its share of global emission. The box in the left panel indicates the bounds of the detail shown in the right panel.

Empirical macroeconomic damage functions have advantages and disadvantages compared to the approaches typically used to estimate the SCC in the past. The strengths include transparency, a strong empirical basis and the capacity to account for interactions among all the sectors of the economy as well as for impacts that are difficult to isolate and quantify. However, a number of long-term effects of climate change are not captured by this type of relationship. We present a number of these excluded contributors in Supplementary Table 5, along with an indication of the likely sign of impacts on the CSCCs and the GSCC. For example, adjustment costs associated with adaptation are not accounted for in this model. Such costs could be high or, given that climate change is not a surprise, could be modest compared to the type of effects that are represented (and which are demonstrably large). Already in our analysis, impacts from climate change are large enough in some countries to lead to negative discount rates (Supplementary Fig. 11). Most of these additional contributors would be expected to increase the GSCC.

Globalization and the many avenues by which the fortunes of countries are linked mean that a high CSCC in one place may result in costs as the global climate changes even in places where the CSCC is nominally negative. For many countries, the effects of climate change may be felt more greatly through transboundary effects, such as trade disruptions[40], large-scale migration[41] or liability exposure[42] than through local climate damage. Although the CSCC in 2020 is negative for many rich northern countries, if the non-linear climate damages hold over time, the CSCC will become positive in most countries as the planet continues to warm. Furthermore, reducing greenhouse gas emissions can yield positive synergies on other environmental goals, such as improving air quality, which already have large welfare impacts[43]. These considerations suggest that country-level interests may be more closely aligned to global interests than indicated by contemporary country-level contributions to the SCC. Furthermore, climate decision-making does not occur in a vacuum. Some countries, such as northern Europe and Canada, are leaders on climate policy despite potentially negative SCCs, whereas other countries with the highest CSCCs, like the United States and India, lag behind. Clearly, a host of other strategic

and ethical considerations factor into the international relations of climate change mitigation.

In the recent US National Academy of Sciences report on SCC, the Working Group cites three essential characteristics for future SCC estimates: scientific basis, uncertainty characterization and transparency[8]. Our work includes improvements upon past estimates of SCC on all three counts. Past estimates of SCC were based on reduced form climate modules and damage function calibration with limited empirical support[44], whereas ours uses output from an ensemble of state-of-the-art coupled climate model simulations and two independently generated empirical damage functions. Past estimates of the SCC have included limited uncertainty analysis focused mostly on a limited set of parameters such as the social discount rate, whereas our estimates include quantified uncertainty bounds for carbon cycle, climate, economic and demographic uncertainties, and also provide disaggregation to the national level. In addition, past estimates of the SCC were often generated using opaque models and/or proprietary software. We provide all of our source code and the full output of our analysis for complete transparency (Supplementary Data).

The high values and profound inequalities highlighted by the country-level estimates of the social costs of carbon provide a further warning of the perils of unilateral or fragmented climate action. We make no claim here regarding the utility of the CSCC in setting climate policies. CO_2 emissions are a global externality. Despite 'deep uncertainty'[45] about discounting, socio-economic pathways and appropriate models of coupling between climate and economy, by all accounts the estimates of the GSCC made by the Interagency Working Group on Social Cost of Greenhouse Gases[2] appear much too low. More research is needed to estimate the geographical diversity of climate change impacts and to help devise policies that align domestic interests to the global good. However, large uncertainties in the precise magnitudes of the SCC, both national and global, cannot overshadow the robust indication that some of the world's largest emitters also have the most to lose from their effects.

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Author contributions

M.T. conceived the study. K.R. performed the climate data analysis. L.D. replicated the economic damage functions and performed the CSCC calculations and uncertainty analysis. K.R., M.T. and L.D. analysed the results. K.R. and M.T. wrote the manuscript. All authors discussed the results and provided input on the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

We combine socio-economic, climate and impact data to estimate the CSCC, that is, the marginal damages from CO_2 emissions, for each of the possible scenarios SSP–RCP using exogenous and endogenous discounting. Lemoine and Kapnick uses a similar methodology to calculate growth rate impacts[36] rather than the CSCCs based on SSPs and damage estimates in Dell et al.[31]. The sequential process for calculating each CSCC is summarized in Supplementary Fig. 1. The GSCC is calculated by summing the CSCCs.

Supplementary Table 1 summarizes the underlying narratives, which cover different challenges to mitigation and adaptation. Several integrated assessment models have recently completed the implementation of the SSPs, computing for each of them future emissions as well as climate outcomes based on the medium complexity MAGICC6 model[25]. This allows us to map the SSPs onto four different CO_2 emission pathways, the RCPs.

Data. The SSP database provided the socio-economic projections at country level for the five SSP narratives (https://tntcat.iiasa.ac.at/SspDb/dsd). The GDP projections were produced by the Organisation for Economic Co-operation and Development and the population projections were generated by the International Institute for Applied Systems Analysis. We computed annual GDP per capita growth rates for each country. The population-weighted average temperature increase at country level was calculated for three RCPs (RCP4.5, RCP6.0 and RCP8.5) using the gridded temperature projections provided by a total of 26 global climate models that contribute to CMIP5 (Supplementary Table 2). GDP per capita growth rates and temperature increases cover the period 2020–2100. The population-weighted average temperature response over time at country level to the addition of 1 $GtCO_2$ in the atmosphere was obtained by combining the results from the CMIP5 model's outcomes and a total of 15 carbon cycle models from a carbon cycle modelling project[29] (http://climatehomes.unibe.ch/~joos/IRF_Intercomparison/). Additionally, baseline temperature at the country level was computed as the annual population-weighted average temperature increases from 1980 to 2010 from the Willmott and Matsuura gridded observational temperature data set[46].

Climate projections. Population-weighted country-level temperature time series were calculated for all the RCP warming scenarios as well as for the abrupt4× CO2 experiment. Projections were bias corrected using a 1980-2010 observational baseline[46]. To remove the influence of interannual variability, for the purposes of the SCC calculations, RCP scenario time series were represented as a quadratic polynomial fit and the abrupt4×CO2 time series were represented as a three-exponential fit. The carbon cycle response to a CO_2 pulse was also represented with a three-exponential fit.

Impact projections. We followed the procedure described in Burke et al.[30] to project the economic impacts from the temperature increase. GDP per capita in country i at year t is $G_{i,t} = G_{i,t-1}(1 + \eta_{i,t} + \delta(T_{i,t}))$, where $\eta_{i,t}$ is the growth rate coming from the data in which no climate change occurs and $\delta(T_{i,t})$ is a response function of the temperature increase at year t. The projected warming effect is adjusted by the baseline temperature effect[30]. When a BHM rich/poor model is applied, we specified the impact function recursively. As a number of countries transition from poor to rich within the course of a given century-long simulation, for each year simulated, if a country is 'rich' the rich-country impact function is applied and if it is 'poor' the poor-country impact function is applied.

(Supplementary Information gives more details about the application of the alternative climate impact functions).

The CSCC. The difference in GDP per capita, including the temperature change impacts, between the scenario with and without pulse, provided the yearly compound of the CSCC until 2100 (Supplementary Fig. 12). After 2100, the compound was kept constant at its value in 2100 until 2200 (or set to zero (the sensitivity analysis is given in Supplementary Table 6)). The CSCC is the net present value of the yearly compound multiplied by the population projection.

Discounting. CSCCs were calculated using both exogenous and endogenous[9] discounting. For conventional exogenous discounting, two discount rates were used, 3 and 5%. the results under endogenous discounting were calculated using two rates of pure time preference ($\rho = 1$, 2%) and two values of elasticity of marginal utility of consumption ($\mu = 0.7$, 1.5) for four endogenous discounting parameterizations.

Reference scenarios. Recent work[26] calculated the forcing paths associated with SSPs by five marker models. For each SSP, we considered the RCP forcing scenario with the minimum Euclidian distance between the SSP as a reference scenario (Supplementary Fig. 13 and Supplementary Table 4).

Uncertainty. The uncertainty analysis used a full ensemble of carbon and climate model combinations to represent climate uncertainty (210–345 model combinations, varying according to the scenarios). Damage function uncertainty was analysed via bootstrapping (1,000 sets of parameter values). The combined uncertainty was obtained by convolution. At the end, a Bayesian bootstrap resampling analysis was conducted to provide the estimates of the median and the quantiles, along with their confidence interval.

Lorenz curves and Gini coefficients. Lorenz curves were generated using the classical approach[38]. The Gini coefficients were generated using the method of Raffinetti et al.[39], which developed a coherent approach to incorporating negative income into the measurement of inequality that adhered to the principle that 0 designates perfect equality and 1 maximum inequality.

Code availability. All of the scripts used to calculate the CSCCs and GSCC are available at https://github.com/country-level-scc/cscc-paper-2018.

Methods. Methods, including statements of data availability and any associated accession codes and references, are available at https://doi.org/10.1038/s41558-018-0282-y.

Data availability

The database of the CSCCs with uncertainty bounds under all scenarios, model specifications and discounting schemes is available as a part of the Supplementary Information and via https://country-level-scc.github.io/.

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