Reductions in economic outcomes due to climate change today

James Rising[1], Muhammad Taky Tahmid[1]

[1] University of Delaware

Abstract:

The climate changes that are already being experienced today are expected to undermine both economic outcomes and the productive capacity in many regions[1,2,3]. A recent surge of research has developed empirical relationships that describe how economic growth is impacted by variation in weather and climate[4-5]. However, many disparate model assumptions and statistical approaches underlie this work, resulting in divergent impact estimates. Here we provide a first meta-analysis of econometrics models of climate impacts on macroeconomic growth, applying a machine learning approach to develop a “best estimate” from 85 statistical models from 15 key papers. We then combine this with other major dynamics by which climate change impacts and undermines economic outcomes: persistence of damages, sea-level rise, trade spill-overs, and additional capital loss. We find that the average person lives in a country that is 5.3% poorer today than it would have been without the warming since 1960. The greatest losses are in poor, tropical countries, with losses of 11% and 7% across Southeast Asia and Africa, respectively. Since 1993, these cumulative losses across low and middle-income countries total $26 trillion, with an additional loss of $2 trillion per year today. These results provide a crucial input to the Loss & Damage discussions under the Warsaw International Mechanism and the scale of adequate funding.

---

[1] Baarsch F, Granadillos JR, Hare W, Knaus M, Krapp M, Schaeffer M, Lotze-Campen H. The impact of climate change on incomes and convergence in Africa. *World Development* (2020).
[2] Burke M, Zahid M, Diffenbaugh N, Hsiang SM. Quantifying climate change loss and damage consistent with a social cost of greenhouse gases. (National Bureau of Economic Research, 2023).
[3] Newman R, Noy I. The global costs of extreme weather that are attributable to climate change. *Nat Commun.* (2023).
[4] Piontek F, Drouet L, Emmerling J, Kompas T, Méjean A, Otto C, Rising J, Soergel B, Taconet N, Tavoni M. Integrated perspective on translating biophysical to economic impacts of climate change. *Nature Climate Change* (2021).
[5] Kotz M, Levermann A, Wenz L. The economic commitment of climate change. *Nature* (2024).

Main:

Global temperatures in 2023 are reported to have been the hottest on record, with June-August temperatures 2.07°C hotter than the 1850 - 1900 average[6]. As the climate shifts, recent evidence has shown that the whole state of an economy and the growth of economic output can also be affected. Already today, we are likely to be poorer as a world because of climate change. Lower-income, tropical, and agriculturally dependent countries are expected to be particularly vulnerable to many impacts of climate change and most in need of development assistance.

With the development of the new Loss & Damage (L&D) Fund at COP28, impacted countries need high-quality estimates of the losses they are experiencing. Within the UNFCCC process, L&D refers to losses from climate impacts that remain after accounting for adaptation, including both market and non-market losses that result from both extremes and slow-onset changes[7-8]. While multiple working definitions are used in different contexts, losses and damages that have already occurred are synonymous with the economic valuation of all realized impacts that would not have occurred in the absence of climate change[9]. Attribution studies provide the core evidence of such impacts, and econometric studies which parse the causal effect of weather and climate variation from other drives have offered new evidence[10].

Macroeconomic growth studies, which study the effect of weather and climate on gross domestic product (GDP) are particularly useful in this regard. They exploit the economy itself to implicitly integrate the complexities of adaptive responses and sectoral interactions. However, the results of these studies vary widely, and key open questions concern the non-linearity of these relationships, the potential for populations to adapt, and the distinctness of poor and agriculturally dependent economies[4]. As a result, there is no current consensus on either the appropriate assumptions in the model or the resulting impacts.

---

[6] Esper, J., Torbenson, M. & Büntgen, U. 2023 summer warmth unparalleled over the past 2,000 years. *Nature* (2024).

[7] Mechler R, Thomas A, Huggel C, Boyd E, Muccione V, Wallimann-Helmer I, Bouwer L, Juhola S, Singh C, Adler C, Ebi K, Pinho P, Ara Begum R, Gemeda A, Nalau J, Frieler K, Jones R, Djalante R, Perez R, Lissner T, Wreford A, Pelling M, Gemenne F, Simpson N, Stabinsky D. Cross-Chapter Box LOSS | Loss and Damage. In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Pörtner H-O, Roberts DC, Tignor M, Poloczanska ES, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A, Rama B). Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 2563–2565 (2022).

[8] Markandya A, González-Eguino M. Integrated assessment for identifying climate finance needs for loss and damage: A critical review. *Loss and Damage from Climate Change* (2019).

[9] Warner K, Van der Geest K. Loss and damage from climate change: local-level evidence from nine vulnerable countries. *International Journal of Global Warming* (2013).

[10] Hope, P., Cramer, W., van Aalst, M., Flato, G., Frieler, K., Gillett, N., Huggel, C., Minx, J., Otto, F., Parmesan, C., Rogelj, J., Rojas, M., Seneviratne, S. I., Slangen, A., Stone, D., Terray, L., Vautard, R. & Zhang, X. Cross-Working Group Box ATTRIBUTION | Attribution in the IPCC Sixth Assessment Report. In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. & Rama, B.) 149–152 (Cambridge Univ. Press, 2022).

Significant questions also remain about the applicability of these empirical relationships to future long-term climate change, given the crucial roles of adaptation, new technology, and transformed economies. Here, we evaluate the projected losses during the historical period.

While future projections of damages are abundant, few analyses have attempted to evaluate how much poorer countries are today, because of existing climate change. African countries may have experienced total losses of 5 to 15% between 1986 - 2015[1], while global losses associated with the emissions of large producers of fossil fuels between 1988 and 2015 are estimated as $50 - 200B[2] and the attributable portion of extreme events from 2000 - 2019 amounted to $2.86T[3]. If one applies the results of an expert review[11] of forward-looking damages to the current warming level, it suggests that by 2023 annual losses may already be 2.05% of global gross domestic product (GDP) [0.9 - 3.4%], about $2.1 trillion (see SI 1.1).

This paper develops “best estimates” of the current macroeconomic losses from climate change, for each country across the globe, meta-analyzing the divergent econometric literature on macroeconomic losses. The main outcome is percent reductions in GDP and percent reductions in capital wealth today, relative to a world without the climate change experienced since 1960. As a measure of economic output, GDP is a useful, if incomplete, proxy for estimating government tax receipts and average personal income levels. At the same time, a reduction in GDP may imply the long-term destruction of productive human-built and natural capital. We develop an estimate of those capital losses, providing new evidence on the true losses borne by countries due to climate change. Recognizing that economic losses are not limited by national boundaries, we also estimate how climate-induced losses may affect other economies through trade networks.

Synthesis of gross domestic product (GDP) relationships

Weather variation has been shown to robustly affect economic growth. Broadly, the econometric literature on macroeconomic impacts from climate change posits a relationship

$$\Delta \log y_{it} \sim N(f(T_{it}) + g(P_{it}) + \alpha_i + h(X_{it}),\ \sigma_i)$$

Where y_{it} is the GDP per capita in country i in year t, and its growth rate is modeled as draws from a normal distribution, with a mean that accounts for temperature (T_{it}), precipitation (P_{it}), any static features of the country (α_i), and other controls (X_{it}). However, this basic setup has been widely varied, depending on different theoretical conclusions and observations from the data. There are questions about the appropriate statistical modeling decisions, including the appropriate controls, the modeling of background trends, and the resolution of the data.

We conduct a systematic literature review of the GDP impact literature to support a meta-analysis of these studies (see PRISMA criteria in SI 1.2). We identify 15 key studies and

[11] Howard P. H. & Sterner T. Few and not so far between: a meta-analysis of climate damage estimates. *Environmental and Resource Economics* (2017).

collect 85 econometric models from them. These represent all econometric studies using global panels of the GDP growth relationship with temperature published before 2023 which introduce a new main model. We then project them from 1960 to 2023, relative to a 1940 - 1959 climate. Here we report global population-weighted losses, which represent the impacts borne by the average person. Across the 85 studies, expected growth rates are 1.9% higher to 8.2% lower today (2014 - 2023) than without climate change, and across the preferred models from each paper, expected growth rate changes are from +0.2% to -1.1% today (Figure 1a). The greatest losses are generally in countries with the hottest temperatures and the lowest income levels (Figure 1c, top).

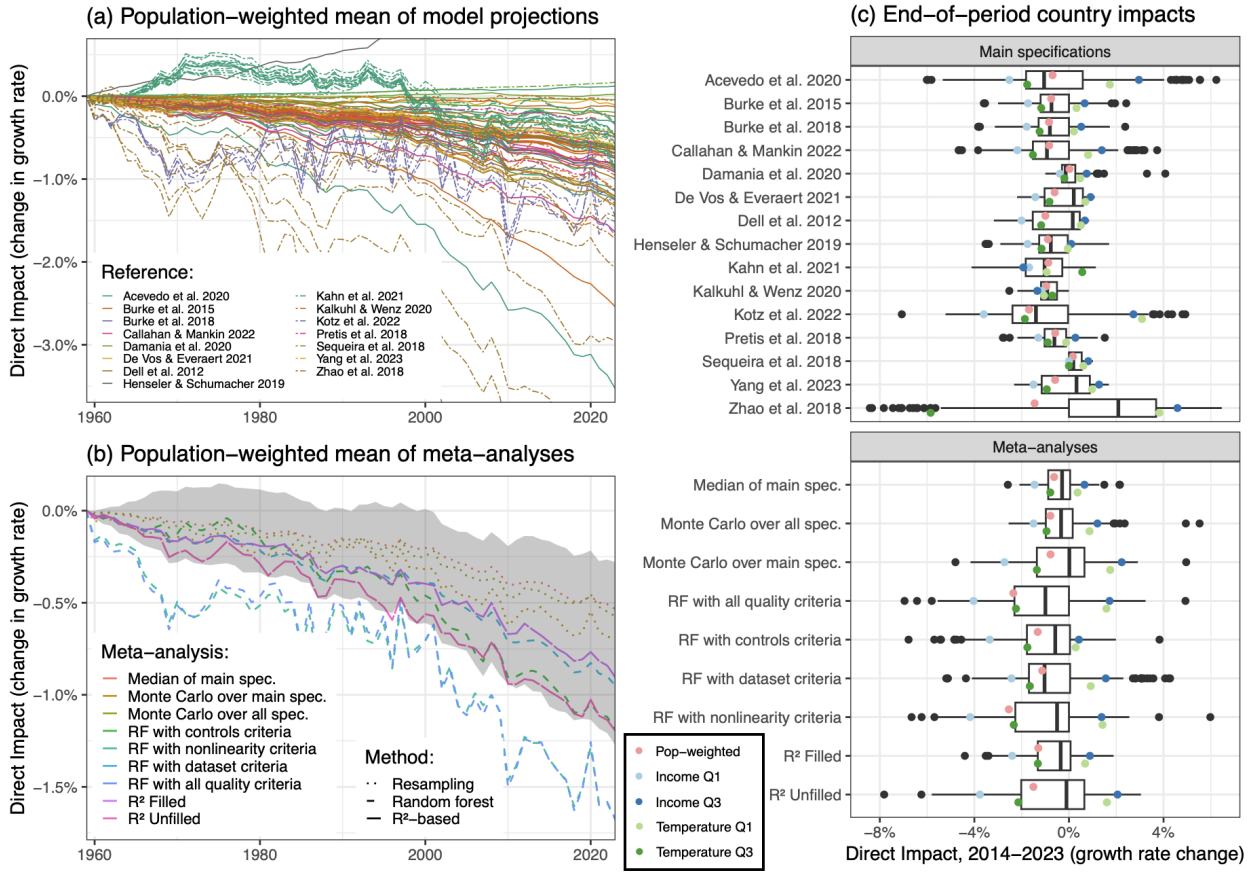


Figure 1: Projected losses by model and meta-analysis synthesis. (a) Econometric models drawn from 15 papers, projected under historical weather (N=85), aggregated globally by population and averaged in moving 10-year windows. (b) Models are combined at the country-year-draw level by either taking the median across paper-specified preferred model; randomly drawing a preferred model; randomly drawing from all models; using a random forest (RF) model accounting for attributes describing controls, nonlinearity, dataset coverage, or all features; or a weighted resampling using R^2, as reported (Raw) or imputed (Total). IQR is shown for the random forest with all features. (c) Boxplots show the distribution across all countries of the 2014 - 2023 average of the paper-specified preferred models (top) or meta-analyses (bottom). Colored points show the population-weighted mean (corresponding to a-b), the countries closest to the first and third quantiles (Q1 and Q3) of the income distribution (Lao and

Slovenia), and Q1 and Q3 of the temperature distribution (Bulgaria and India). Boxplots are shown with hinges at Q1 and Q3, whiskers at max/min points within 1.5 * IQR, and outliers plotted.

For each of the projected models, we record information about the spatial weighting of weather predictors, the including of a rich/poor distinction, the functional form representations of temperature and precipitation, the including of globally common shocks (econometric year fixed effects (FE)), country background trends, other controls including lags of growth and weather, and information about the span of data used.

Across all models, high impacts are found for models that use the longest time series (115 years) and the shortest (49 years), with these models showing an average present-day (2014 - 2023) annual growth loss of 0.8% and 1.0%, respectively (SI figure 9). On its own, the sophistication of the representation of temperature and precipitation is not shown to produce greater losses. Similarly, the inclusion of additional controls does not correspond to a consistent increase or decrease in estimated losses.

Generally, however, we expect more flexibility in the underlying statistical model to allow for a better representation of the complex data-generating process. Similarly, more extensive controls account for confounding variation, allowing the causal effect of weather to be identified. To develop a best-estimate, we assign quality values to each model attribute, with higher scores assigned to model attributes that support robust causal identification. Within each attribute, the available model decisions are ranked, according to flexibility for temperature and precipitation, the extent of controls and FE variables, and the recency and extent of data. A random forest (RF) model is used to generate predicted impacts on GDP growth collectively implied by model characteristics, which can be thought of as effectively assigning weights to each model based on its quality attributes.

The meta-analysis outcomes are fairly consistent across the approach used. Except for the median across the main model specification, all meta-analyses produce expected present-day annual growth losses between 0.8% and 1.1% (Figure 1b). The preferred meta-analysis, which applies quality weights for dataset coverage, weather functional form flexibility, and inclusion of controls, produces losses that grow to 1.1% in 2014 - 2023 [IQR 0.3 - 1.8%]. The largest losses are in poor countries, and rich countries generally see small losses or gains (Figure 1c, bottom).

Persistence, Coastal and Indirect Effects

A central question in this literature is the extent to which the estimated reductions in growth in a given year set the economy upon a permanently lower trajectory[12,13,14]. This is the “persistence”

[12] Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, *103*, 102360.
[13] Bastien-Olvera, B. A., Granella, F., & Moore, F. C. (2022). Persistent effect of temperature on GDP identified from lower frequency temperature variability. *Environmental Research Letters*, *17*(8), 084038.
[14] Nath, I. B., Ramey, V. A., & Klenow, P. J. (2024). *How much will global warming cool global growth?* (No. w32761). National Bureau of Economic Research.

of the temperature shocks. Our paper does attempt to contribute to this discussion, but we apply existing estimates of partial persistence to produce best-estimates of total losses. This results in population-weighted losses today (2014 - 2023) of 4.3% [2.1 - 6.1%]. Assuming full persistence would result in projected losses of 25.9% [15.2 - 33.9%].

The econometric models analyzed are calibrated using local temperature shocks, and use FE to remove the background trends. As a result, these models do not capture climate impacts that are not correlated with temperature shocks, and miss sea-level rise impacts in particular. We emulate the pyCIAM model[15] to capture these effects, including just the market damages for consistency, which describe inundation and storm surge losses to physical capital. Globally, market-based coastal impacts reduce GDP by 0.1%, although country-level losses can exceed 2%. We treat the level of historical adaptation as uncertain, but under optimal adaptation global losses are halved.

The econometric results also exclude spill-over effects. To account for these, we use the Eora Global MRIO model, applying a method based on Domar weights[16-17]. Spill-over effects under our preferred persistence result in an additional 1.4 percentage points (pp) in losses globally. Alternative spill-over assumptions, based on the same MRIO model and local impacts, produce additional losses of 0.1 pp (accounting for international final demand contributions only) to 14.4 pp (performing a Leontief inverse).

Finally, reductions in GDP are expected to go hand-in-hand with losses to stocks of manufactured capital. Manufactured capital refers to the human-produced physical entities that contribute to production and economic activity, such as roads, buildings, machines, and equipment[18]. Lower economic production will result in less funding available to invest in capital as it depreciates. We augment a Solow growth model with renewable and produced capital to study these effects[19]. The model is calibrated to reproduce the total loss estimates, to avoid double-counting persistence losses.

---

[15] Depsky N, Bolliger I, Allen D, Choi JH, Delgado M, Greenstone M, Hamidi A, Houser T, Kopp RE, Hsiang S. DSCIM-Coastal v1. 1: an open-source modeling platform for global impacts of sea level rise. *Geoscientific Model Development* (2023).

[16] Santini T, Araujo RA. Productivity growth and sectoral interactions under Domar aggregation: a study for the Brazilian economy from 2000 to 2014. Journal of Economic Structures. 2021 Dec;10:1-30.

[17] Lenzen, M., Moran, D., Kanemoto, K., Geschke, A. Building Eora: A Global Multi-regional Input-Output Database at High Country and Sector Resolution. *Economic Systems Research* (2013).

[18] Managi, S., & Kumar, P. Inclusive wealth report 2018. Taylor & Francis (2018).

[19] Gasmi F, Recuero Virto L, Couvet D. The impact of renewable versus non-renewable natural capital on economic growth. *Environmental and Resource Economics* (2020).

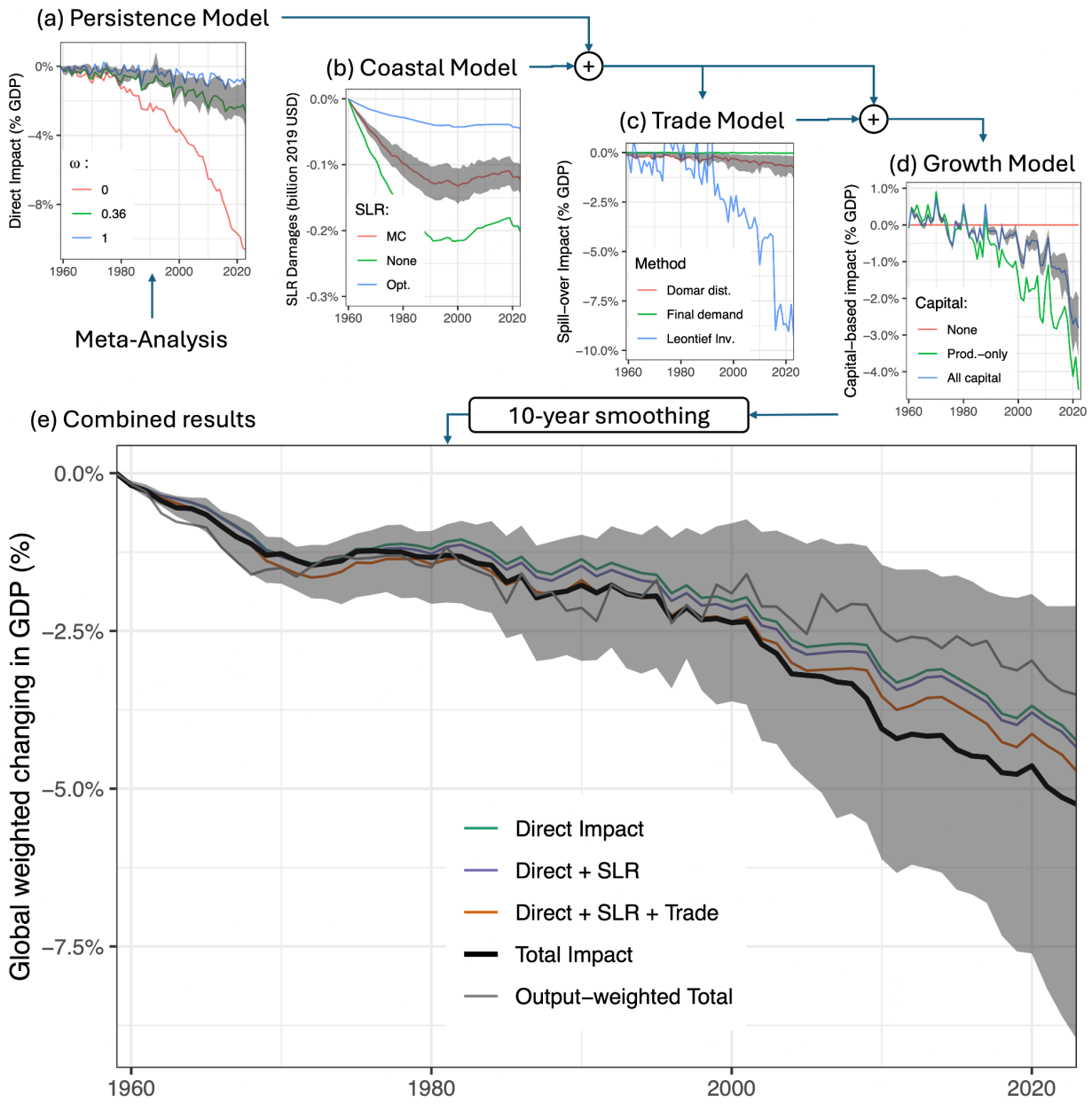


Figure 2: Components of losses and total losses since 1960. Top shows the results of contributing channels of impacts across steps in the calculation of total losses, including alternative models, with the IQR shown on the preferred model. (a) Single-year growth results are translated into persistent impacts ("direct impacts"), mediated by the persistence-decay parameter ω (preferred = 0.36) from a survey of the literature (SI 1.6) (b) Sea-level rise inundation and storm capital losses are emulated using pyCIAM[15] (preferred = Monte Carlo between "No adaptation" and "Optimal adaptation"). (c) Spill-over impacts from trade are estimated by applying the sum of direct impacts and coastal impacts to the Eora MRIO model[17] (preferred = Domar weight spill-overs). (d) All preceding impacts are combined into a capital growth model (preferred = All capital), based on the augmented Solow growth model[19]. (e) The population-weighted combined result of the preferred models, with an IQR band, as well as the output-weighted result.

Global and Regional Impacts Today

The climatic changes experienced since the mid-20th century have resulted in evident and significant economic impacts across the globe. Globally, the population-weighted GDP loss due to climate change in 2014 - 2023 is substantial at 5.3% [IQR 2 - 9%], taking into account the direct, coastal, spill-over, and capital losses related to climate (Figure 2e). Yet, the percentage of the global GDP lost is 3.5% [1 - 5%], about $3.7 trillion, as many wealthier nations have smaller impacts or benefits. That is, the world is estimated to be $3.7 trillion poorer than it would have been without climate change.

Positive and negative impacts vary widely by region and are largely dependent on the underlying economic structure and climatic vulnerability of each country (Figure 3). In contrast with the global average, the Global South and particularly tropical regions have borne the brunt of climate-related losses. African nations have experienced an average loss of 7% [4 - 12%] in GDP in 2014 - 2023 (Figure 3b). The most severely impacted region is Southeast Asia, which has suffered an average loss of 11% [8 - 18%] of GDP.

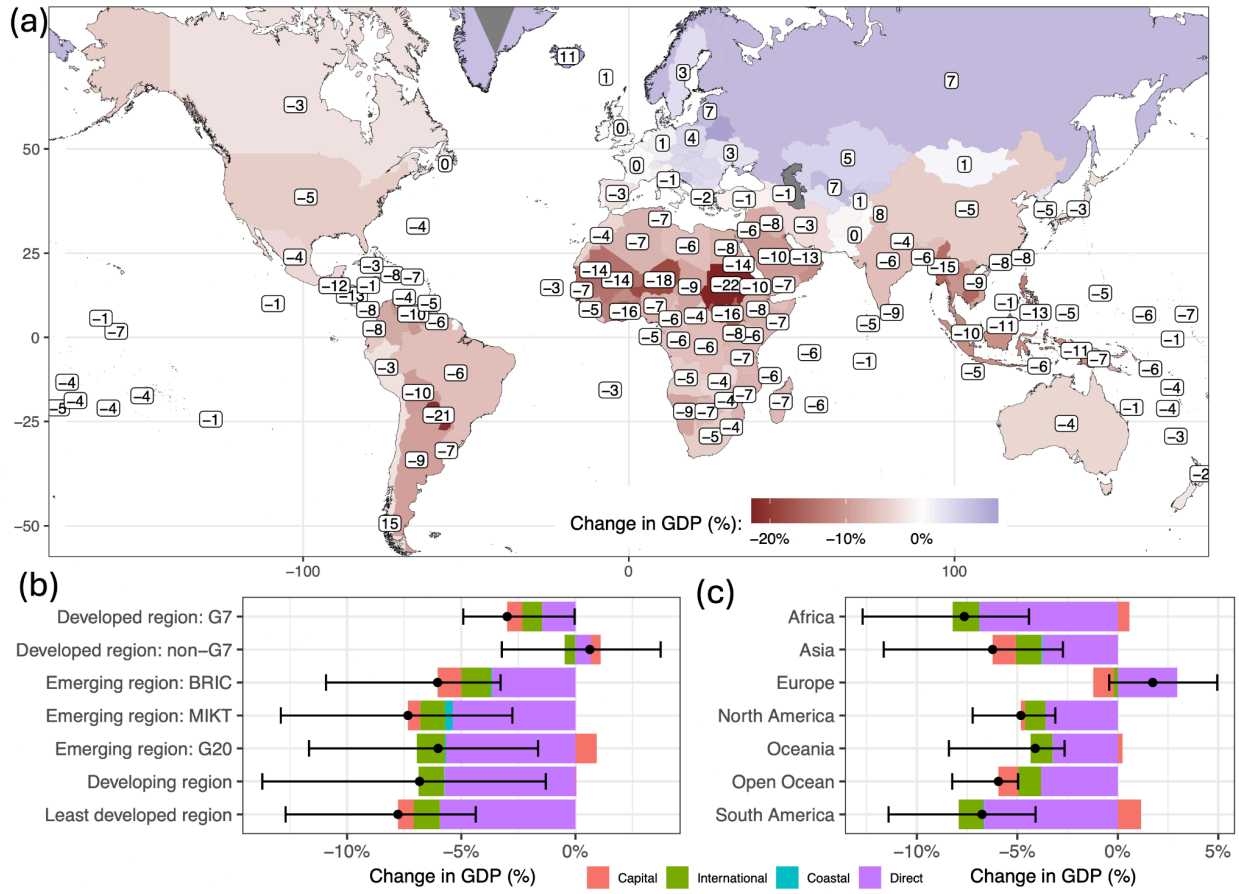


Figure 3: Distribution of GDP losses in 2014 - 2023, by country and group. (a) Total expected percent change in GDP due to climate change. (b) Population-weighted average change by economic group, split by contributing channel of impact. BRIC = Brazil, Russia, India,

China; MIKT = Mexico, Indonesia, South Korea, Turkey. Error bars show the IQR. (c) As b, split by continent.

Interestingly, some regions, particularly Europe and northern Asia, have experienced economic benefits from climate change. Europe is estimated to have a GDP that is 2% [0 - 5%] higher than they would have had without climate change. These benefits are expected to arise from reduced winter chill, which lowers energy consumption and mortality rates, among other factors. It is also expected that as the planet continues to warm, these benefits will erode for many regions and eventually turn negative, with the energy and health effects of hotter summers gradually offsetting the benefits from mild winters.

There is also considerable short-term variability. The impact on the median country varies by ±2 percentage point in the GDP effect of climate change from year to year as global climate change contributes not only to rising temperatures but also increased variability and extreme events.

The Erosion of Productive Capacity and Total Value Losses

Our analysis reveals significant heterogeneity in the magnitude of capital losses experienced across different income groups and geographic regions. OECD countries are estimated to have lost $2.3 trillion in manufactured capital by 2023, compared to their outcomes in the absence of climate change (SI Table 3). At the same time, climate change has reduced the value of their renewable natural capital by $130 billion.

In low- and middle-income countries, manufactured capital losses total $2.7 trillion in by 2023. The vast majority of these losses occur in middle-income countries, which typically have more produced capital.

Many of these countries also depend heavily on their natural capital, such as forest resources, fisheries, and agricultural land. Our models consider two factors that simultaneously exert opposing influences on renewable capital. Higher temperatures across the low- and middle-income countries produce a direct loss of renewable capital of $7.9 trillion. However, due to the negative GDP impact of climate change, lower demand for natural goods is projected in these countries. This counteracts the direct loss that is experienced due to climate change, reducing the impact on renewable capital to a loss of only $20 billion.

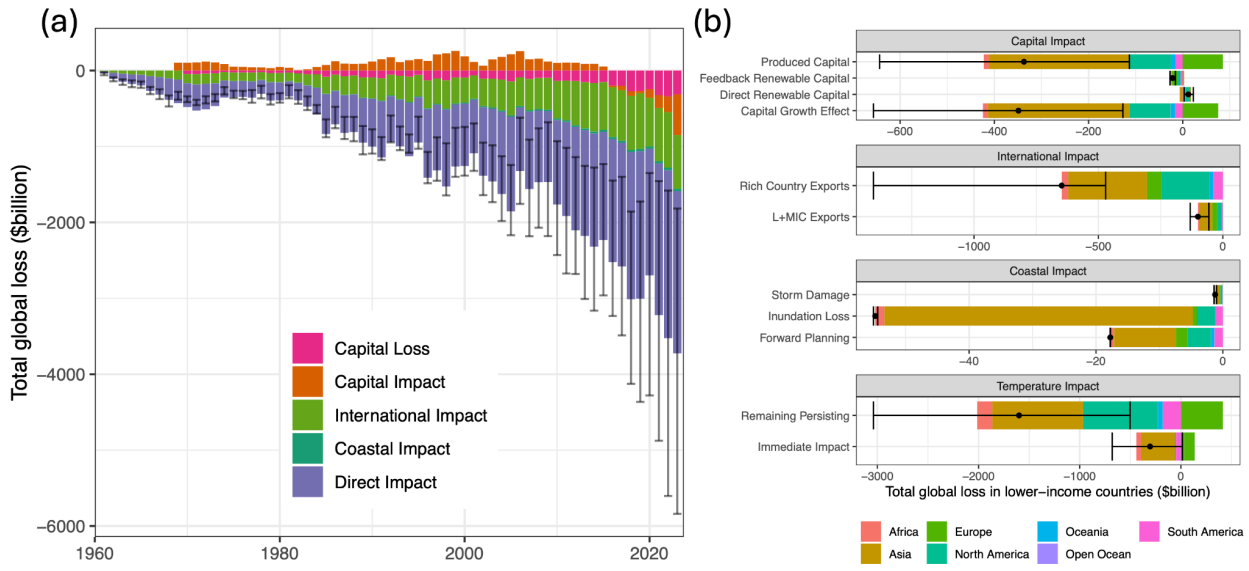


Figure 4: Total value of losses for low and middle-income countries and contributing channels. (a) Annual losses in billion 2019 USD. Components correspond to contributing channels in Figure 3, with Capital Loss additional showing the change in the total value of capital in each year. Error bars show IQR. (b) Value for subcomponents of each contributing channel, split by continent in billion 2019 USD.

GDP losses and capital losses both contribute to the total losses that countries have experienced. To compute this, we add all GDP losses from 1994 to 2023 to the capital losses in 2023. GDP losses cover the 30-year period since the Rio Convention, since the world was aware of climate risks by this time. These losses are not discounted, and standard discounting would further inflate the values. The capital losses are naturally cumulative, so we only include the final value of these at the end of the period.

We find that low- and middle-income countries have experienced a total loss of $26 trillion [$15 - 45 trillion], over half of the total 2023 GDP of the developing world ($44 trillion). In addition, between 2014 and 2023, additional losses of $2 trillion [$0.9 - 2.7 trillion] were incurred per year globally. As a comparison, OECD countries are estimated to be similarly $25 trillion poorer due to climate change, off of a $60 trillion combined GDP.

Discussion

Our study suggests a strong correlation between GDP losses attributable to climate change and rising temperatures. Since 1970, we have observed a nearly linear increase in global temperatures of 1°C, in pace with a corresponding reduction in global population-weighted GDP by approximately 5.3%. Incremental increases in temperature have consistently mapped to escalating losses in GDP, and these losses are expected to accelerate in the future, as long as temperatures keep rising.

There are significant disparities in the impacts of climate change across regions and economic groups. Low-income countries and tropical regions are particularly vulnerable, with double-digit losses to GDP. Meanwhile, many wealthier nations have seen smaller impacts or even benefited from climate change.

Multiple sectors and channels aid in understanding these effects, as well as the differences in results seen in different regions around the world. Agriculture and manufacturing are more sensitive to climate risks than service industries[20]. Outdoor workers are particularly vulnerable, such as those engaged in agriculture, fishing, forestry, mining, and construction[21]. High temperatures can also undermine health, while other extremes from climate change, such as flooding, can damage infrastructure[22]. Furthermore, poor countries have been shown to be more vulnerable to all of these effects[23], and those countries that are already hot are estimated to experience greater losses for each additional degree of warming[24].

The analysis also highlights some of the dynamics between climate change, economic outcomes, and capital investments. Low and middle-income countries face significant capital losses, posing challenges to their long-term economic resilience and growth. Low and middle-income countries have experienced $2.7 trillion in produced capital losses due to climate change.

Nevertheless, the approach used in this study has some significant limitations. As a top-down statistical estimate, it provides little information on the specific channels that result in the predicted GDP and capital losses. While individual events, such as newsworthy droughts and storms, have shaken economies across the globe, the hazards involved generally find a minor role in the empirical macroeconomic models[25].

GDP is also, by definition, an incomplete measure of climate impacts. Many kinds of climate impacts operate through non-market channels, such as increased risks of premature mortality and loss of welfare to outdoor workers. Other non-market channels are not human-centered, such as biodiversity loss. Finally, there is a range of missing channels, such as the consequences of climate tipping points, vector-borne disease, and human capital loss, which have not been included here and are more challenging to robustly quantify[26]. The risks associated with these missing risks are nonetheless an important policy concern.

---

[20] Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. The effects of weather shocks on economic activity: what are the channels of impact?. *Journal of Macroeconomics* (2020).
[21] Rode, A., Baker, R. E., Carleton, T., D'Agostino, A., Delgado, M., Foreman, T., ... & Yuan, J. Labor disutility in a warmer world: The impact of climate change on the global workforce. SSRN (2022).
[22] Carleton, T. A., & Hsiang, S. M. Social and economic impacts of climate. *Science* (2016).
[23] Dell, M., Jones, B. F., & Olken, B. A. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics* (2012).
[24] Burke, M., Hsiang, S. M., & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* (2015).
[25] Waidelich P, Batibeniz F, Rising J, Kikstra JS, Seneviratne SI. Climate damage projections beyond annual temperature. *Nature Climate Change* (2024).
[26] Rising, J., Tedesco, M., Piontek, F., & Stainforth, D. A. The missing risks of climate change. *Nature* (2022)

The 1960 starting point also removes a portion of the damages. As an approximation of these, consider that the FaIR simple climate model estimates that warming in 1960 was 0.28 °C, which is associated under the Howard & Sterner damage function with a 0.1% loss in global GDP.

Methods

Projection of econometric models

We collected temperature-related coefficients and standard errors (or covariance matrices, where available) for 85 econometric from 15 studies published in 2012 - 2022 which estimate the observed link between GDP and weather or climate (see SI 1.2). Temperature data from ERA5 (daily average, minimum, and maximum t2m) is aggregated by population using Gridded Population of the World v3 data for 1990 for each country and ADM1 region according to Natural Earth boundaries. Daily temperatures are further aggregated according to the model specifications.

Models are then projected with observed temperatures and with temperatures from resampled years from 1940 - 1959, and immediate impacts are defined as the difference. Monte Carlo projections are performed for each model, with draws from the multivariate uncertainty and from the historical resampling. Additional details in SI 1.3-1.4.

Coefficient of determination meta-analysis

The coefficient of determination (R^2) approach is described here, with other meta-analysis methods in SI 1.5. Each of the models is characterized by choices of the representation of the temperature and precipitation drivers, differential vulnerability, common year-specific shocks, background trends, the inclusion of additional controls and lags of the growth variable, and spans of the dataset. These attributes are recorded and then ranked according to their flexibility and exhaustiveness.

We collect total, adjusted, and within R^2 values from the study papers, and then use these multivariate imputation by chained expressions (mice in R) to input missing values. These values are then used as sampling weights (imputed are preferred, and reported values as an alterative), where each Monte Carlo draw selects all results from one model.

Partial persistence

The remaining calculation steps use the all-features RF result, which we refer to as $ImmediateImpact_{itm}$ for country *i*, year *t*, Monte Carlo draw *m*. Impacts are then assumed to have a partially persistent effect, parameterized by ω, so the cumulative impact is calculated as $CumulativeImpact_{itm} = \sum_{s \leq t} (1 - \omega)^{t-s} ImmediateImpact_{itm}$. We use ω = 0.36 (preffered) or ω = 0.21 or ω = 0.47 (alternative) for all results, based on a survey of the literature (SI 1.6).

Coastal impacts

We extract damages by adaptation case, cost type, SSP, quantile, and year, summed to the country level from Depsky et al. (2023): 10.5281/zenodo.10909655. For the main results, only cost types “inundation” and “stormCapital” are used, and these are summed. SSPs and quantiles are pooled to describe uncertainty. Values for years 2010 - 2023 are fit by the model $\log c_{itm} \sim N(\beta_{im} + \gamma_{im}(t - 1960),\ \eta_{im})$, and emulated damages are calculated as $SLRImpact_{itm} = -\left(\exp(\beta_{im} + \gamma_{im}(t - 1960)) - \exp(\beta_{im})\right) / GDP_{it}$, normalized by the World Bank 2019 USD PPP GDP, so that damages are 0 by construction in 1960.

Trade spill-overs

The Domar weights estimate is described here, with other approaches described in SI 1.8. Log-point impacts are translated into fractional changes with $LocalLevelImpact_{itm} = \exp(CumulativeImpact_{itm} + SLRImpact_{itm}) - 1$. The Eora26 MRIO transaction matrix for each year is aggregated nationally by summing within each 26x26 industry block, and summing across columns of the value added and final demand matrices. We then calculate total sales as the row sums of the transaction matrix plus the final demands, and GDP as the value added plus the final demand. The total global impact, accounting for spill-overs, is then $TotalDomarImpact_t = \sum_i (TotalSales_{it} LocalLevelImpact_{itm} / \sum_i GDP_{it})$, and the additional spill-over effect is $AdditionalDomarImpact_t = DomarImpact_t - \sum_i LocalLevelImpact_{itm} GDP_{it} / \sum_i GDP_{it}$. In each year, we also calculate the Free on board export value lost, assuming a direct relationship between losses in country *j* and its exports to all other countries, $ExportLoss_{it} = (\sum_j FOBValue_{ijt} LocalLevelImpact_{itm}) / \sum_j FOBValue_{ijt}$. We then find the factor that would scale the sum of $ExportLoss_{it}$ to equal the $AdditionalDomarImpact_t$, take the average scaling value across years, and apply this this $ExportLoss_{it}$ to get the trade loss.

Augmented Solow growth model

This describes the preferred all-capital growth model, with simplifications and additional details in SI 1.7. The growth model is fit to each country and Monte Carlo individually, and these indices are suppressed. The growth model responds to the total of the previous three impacts: $TotalImpact_t = CumulativeImpact_t + SLRImpact_t + AdditionalDomarImpact_t$. GDP is calculated as

$$Product_t = TFP_t\,(1 - ImmediateImpact_t - \alpha_t\,(TotalImpact_t - ImmediateImpact_t))$$

$$RenewableCapital_{t-1}^{s_{1t}}\ ProducedCapital_{t-1}^{s_{2t}}\ HumanCapital_{t-1}^{s_{3t}}\ Population_{t-1}^{s_{4t}}$$

Factor shares ($s_{\cdot t}$) and total factor productivity (TFP_t) follow linear trends across the period. Renewable capital follows a temperature-dependent Ricker growth function with extraction

driven by the renewable share of economic activity: $RenewableCapital_t = RenewableCapital_{t-1}(1 + (1 - \beta T_{t-1})\, r \exp(-b\, RenewableCapital_{t-1})) - (s_{1t}\, Product_t)/((1 + (s_{1t}\, Product_t)/RenewableCapital_{t-1})$. Produced capital follows a standard Solow capital dynamic: $ProducedCapital_t = ProducedCapital_{t-1} + SaveRate_t\, Product_t - DeprRate\, ProducedCapital_{t-1}$ where $SaveRate_t$ follows a linear trend. $HumanCapital_t$ follows an exponential growth. The model is fit to reproduce observed GDP (from the World Bank), renewable, produced, and human capital (from the Inclusive Wealth Report 2018), and $TotalImpact_t$ equals the log difference between observed GDP and no-climate-change counterfactual GDP (which is simultaneously modeled but without impacts), using Stan, a Bayesian MCMC.

Uncertainty
Throughout, we account for uncertainty arising from baseline conditions, model parameters, the machine learning synthesis, and the role of capital losses in explaining persistence in climate damages. This uncertainty is shown as the range of the middle 50% of the possible outcomes (the interquartile range or IQR).

Data Availability
Datasets, including reproduction input data and result data, are included in a Code Ocean associated with the paper as well as in the following Google Drive during peer review: https://drive.google.com/drive/folders/19ECb74P33p3fJwEaly3sbPTwmXZ60DeC?usp=sharing. The result data, including country-specific Monte Carlo results under multiple assumptions, will be provided as a Zenodo repository prior to publication.

Code Availability
All code necessary for reproduction of these results are included in a Code Ocean associated with the paper, and are available at https://github.com/openmodels/currentloss.

Acknowledgments

The author would like to acknowledge the helpful review of this work by A. R. Siders, Bob Ward, Leonie Wenz, and Benjamin Jullien. The University of Delaware Gerard J. Mangone Climate Change Science and Policy Hub also provided valuable input. An earlier version of these results has been shared as a public report by the Gerard J. Mangone Climate Change Science and Policy Hub.

Author Contributions
J.R. conceived the study and performed analysis for the study. M.T.T. developed the trade analysis and performed analysis. J.R. and M.T.T. jointly interpreted results and wrote the paper.

Competing Interests
The authors declare no competing interests.

Reductions in economic outcomes due to climate change today
Supplementary Information

James Rising, Muhammad Taky Tahmid

March 21, 2025

1 Supplementary Methods

1.1 Howard & Sterner comparison

The application of Howard and Sterner [2017] in the introduction is based on the climatological warming level of 1.34 °C above pre-industrial temperatures in 2023 produced by the FaIR simple climate model. For comparison, global mean surface air temperatures were estimated to be 1.48 °C in 2023 using ERA5, and the average over the previous 5 years comes to 1.28 °C [Copernicus, 2024]. We then apply the preferred model for total damages from Howard and Sterner [2017]. Global GDP is estimated to be $104.48 trillion in current prices in 2023, from the International Monetary Fund (IMF) 2023 World Economic Outlook report.

1.2 Literature Review

Our meta-analysis includes all macroeconometric impact estimates that satisfy the following criteria:

- Published before 2023.
- Uses a panel dataset (multiple observations at the national or ADM1 level).
- Data has global coverage.
- Uses GDP per capita growth rate (first-difference in log GDP per capita) as the dependent variable.
- Uses an econometric-based approach that accounts for spatial hetergeneity in the baseline (e.g., with unit-specific indicators).
- Reports coefficient estimates in a regression table in the main paper or supplementary information.

We take a three-pronged approach to identifying papers. First, we consider all references from the review performed by Piontek et al. [2021] and Chang et al. [2023] and the review presented in the Cross-Working Group Box ECONOMIC.1 from O'Neill et al. [2022]. Second, we used Google Scholar and reviewed all papers Google identified as "related to" Kahn et al. [2021] were considered (given its relevant title keywords).

Third, we performed a broad Scopus and Web of Science search to find relevant papers missed in the previous searches. The boolean search used on both services was `( "weather" OR "temperature*" OR climate OR "global warming" ) AND ( "GDP" OR "growth" OR "economic*" ) AND ( "global" OR "world*" OR "national" ) AND ( "panel" OR "time-series" OR "longitudinal" OR "long-term" OR "historical" )`. This retrieved 19 880 articles on Scopus and 35 782 articles on Web of Science, with 41 183 articles uniquely identified across the two services (based on their DOI).

Next we designed an automated process to filter out papers that did not meet our criteria, based on their abstract, title, and keywords. The approach was to perform a query for each paper on both OpenAI's GPT-4o model and Gemini's gemini-1.5-flash model. These models were observed to respond differently to the information, and so provided two evaluations of each article. The prompt used in both cases was:

I am performing a meta-analysis of econometric models of temperature on economic growth. These papers use regression-based techniques to understand how variation in weather results in variation in GDP growth rates. I am only interested in papers that do this globally, with at least national-level resolution.

The following is a paper identified by very general Scopus search: Title: ... Abstract: ... Keywords: ...

Based on this information, should this paper be included in the meta-analysis? Please classify this as (XG) Not GDP growth (studying a different dependent variable), (XE) Not econometric (using non-causal or non-statistical methods), (XW) Not global (region-specific), (XN) No new empirics (using previously-published work), or (P) Plausibly appropriate. You may use multiple restrictions (XG, XE, XW, XN), but do not combine them with P. If this abstract is not otherwise filtered (P), classify it as (PL) Unlikely, (PM) Somewhat likely, or (PH) Very likely. Provide a succinct explanation, and only mention codes identified for this paper.

We only drop articles if both services agree on a reason for their exclusion. The filtering results are shown in figure 1. We assess the eligibility of the remaining articles where there was disagreement or where either service specified that the article was plausibly appropriate.

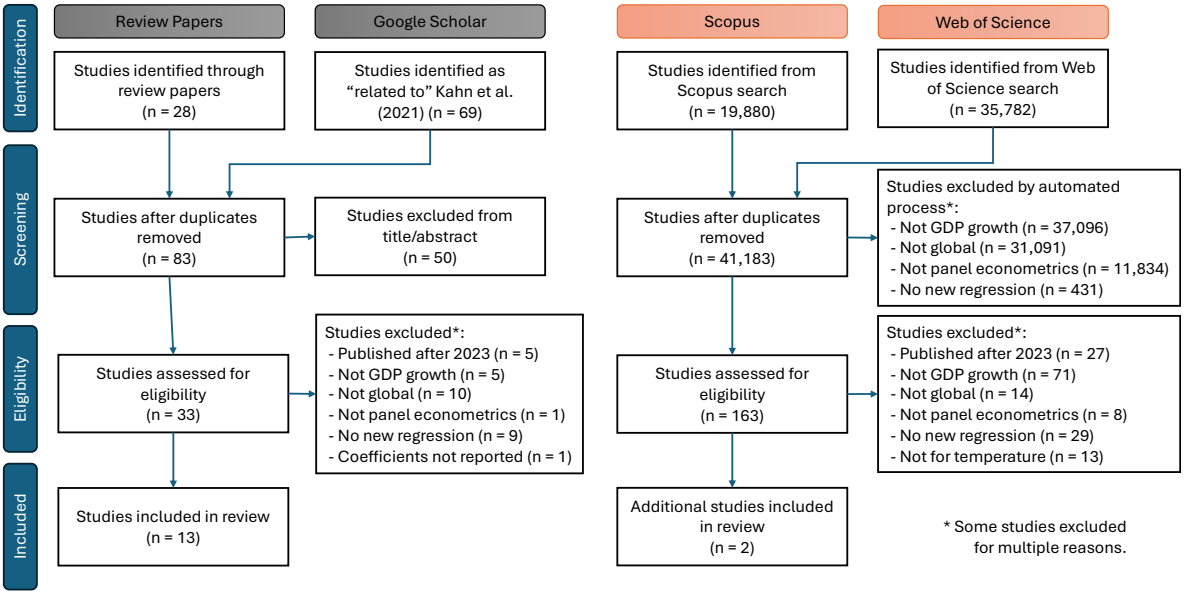


Figure 1: PRISMA 2020 flow diagram, showing the number of studies identified, included and excluded for this work.

Fifteen studies were identified: Acevedo et al. [2020], Burke et al. [2015, 2018], Callahan and Mankin [2022], Damania et al. [2020], De Vos and Everaert [2021], Dell et al. [2012], Henseler and Schumacher [2019], Kahn et al. [2021], Kalkuhl and Wenz [2020], Kotz et al. [2022], Pretis et al. [2018], Sequeira et al. [2018], Yang et al. [2023], Zhao et al. [2018]

These papers span a range of insights, from the differential vulnerability of low-income countries to the potential for adaptation and persistence of growth.

A total of 85 unique models from these papers were assessed and implemented. Meta-data was collected for each model under 11 distinct headings, representing various aspects of model sophistication and data quality. The dimensions are as follows:

- Weather aggregation weighting scheme
- Temperature variables representation
- Rainfall variables representation

- Handling of differential vulnerability for poor countries
- Treatment of unobserved heterogeneity by year
- Treatment of nonlinear socioeconomic trends
- Inclusion of additional heterogeneous factors
- Inclusion of additional controls
- Inclusion of lags of economic growth
- Recency of data
- Span of data

All of these models were estimated using econometric methods with high-quality weather and economic output data. The set of models and meta-data is available at DOI:10.5281/zenodo.10199433.

For instance, the main model developed by Dell et al. [2012] investigates the differential effect of climate change on low-income countries, but only includes linear representations of temperature and total rainfall. In contrast, the models detailed in Kahn et al. [2021], which incorporates an adaptive local climate optimum, includes linear splines for most of its models but do not include further consideration of trends and temporal heterogeneity.

The detailed ratings allow us to compare these models more objectively and to understand the relative strengths and weaknesses of each approach. This, in turn, helps to guide the subsequent machine learning-trained model integration and the assessment of current macroeconomic losses from climate change.

1.3 Model-specific additional details

Kalkuhl and Wenz [2020]: We do not include long-difference estimations since these are found to be insignificant or non-robust.

De Vos and Everaert [2021]: Table 5 reports results for models fit to data before 1983 and after 1983. Since the intention of this division to look for hetergeneity in the response over time, we combine both models into one projection, using column 1 (FE) or 3 (CCEPbc) for years boefore 1983, and column 4 or 6 for years after.

Yang et al. [2023]: FE-Naive results from Tables 4 - 6 are not projected, only FE-NLS models. In Table 6, only columns 2 and 6 are used because all coefficients are not reported for models with 5 and 10 lags.

Kotz et al. [2022]: The standard model includes persistence [Waidelich et al., 2024]. We therefore de-convolve this model against the persistence effect filters used later, so that the post-meta-analysis results will recover the persistent timeseries.

For Acevedo et al. [2020], Burke et al. [2015], and Callahan and Mankin [2022], coefficients and covariance are drawn from reproduction data provided by the authors; for the remaining papers, coefficients and standard errors are drawn from published tables.

1.4 Projections

The starting point for this analysis is the ERA5 reanalysis weather data available from 1940 to 2023. This dataset provides us with historical weather data, which we aggregate to the country and ADM1 levels using the `xagg` library.

Weighting temperature information by population is important, since in many regions people live in more moderate conditions (e.g., Canada and Bolivia). Figure 2 shows how temperatures are adjusted under population-weighting.

The population-weighted 2-meter air temperature for each country over the period is shown in figure 3.

We do not explicitly account for sub-annual temperatures or precipitation, although these are included in some of the underlying models. As a result, we implicitly assume that the effects of these additional factors remain unchanged.

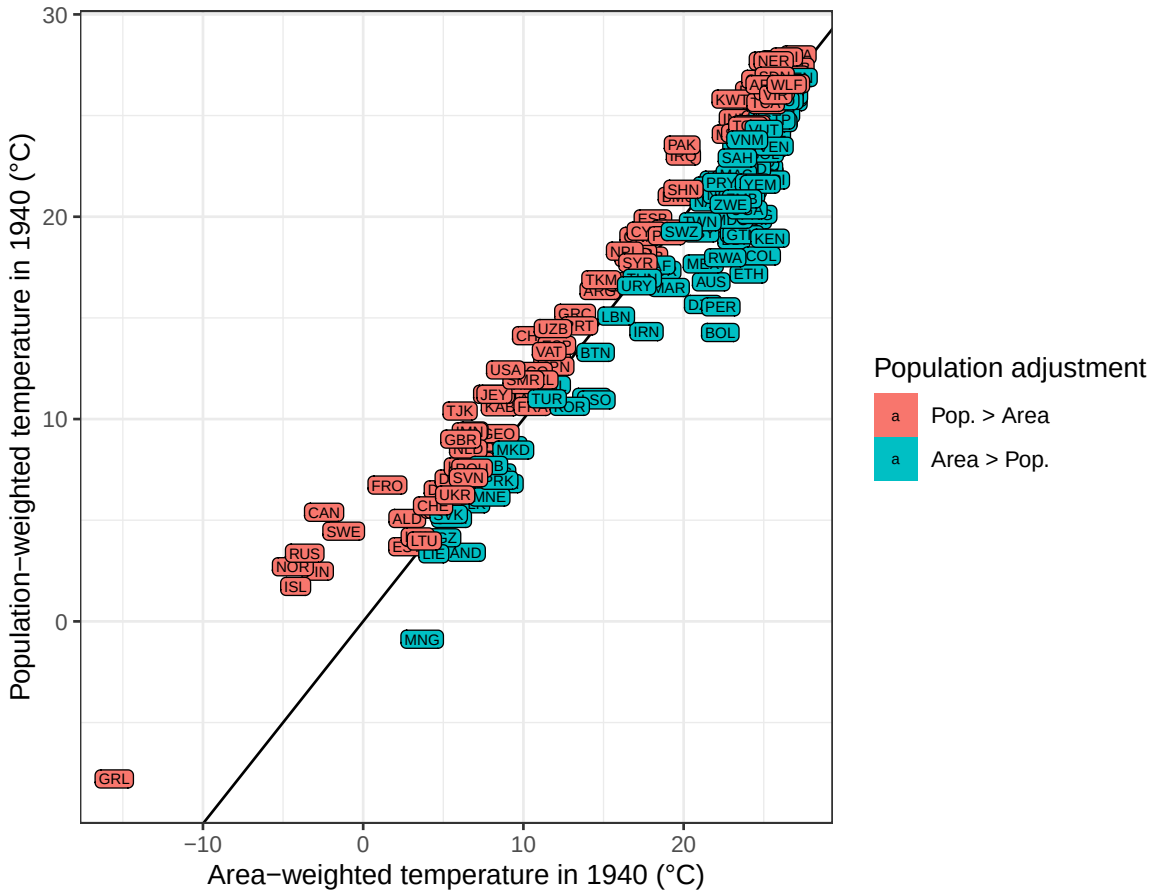


Figure 2: Comparison of population-weighted vs. area-weighted average temperatures in 1940. Colors denote if population-weighted temperatures are above or below area-weighted temperatures.

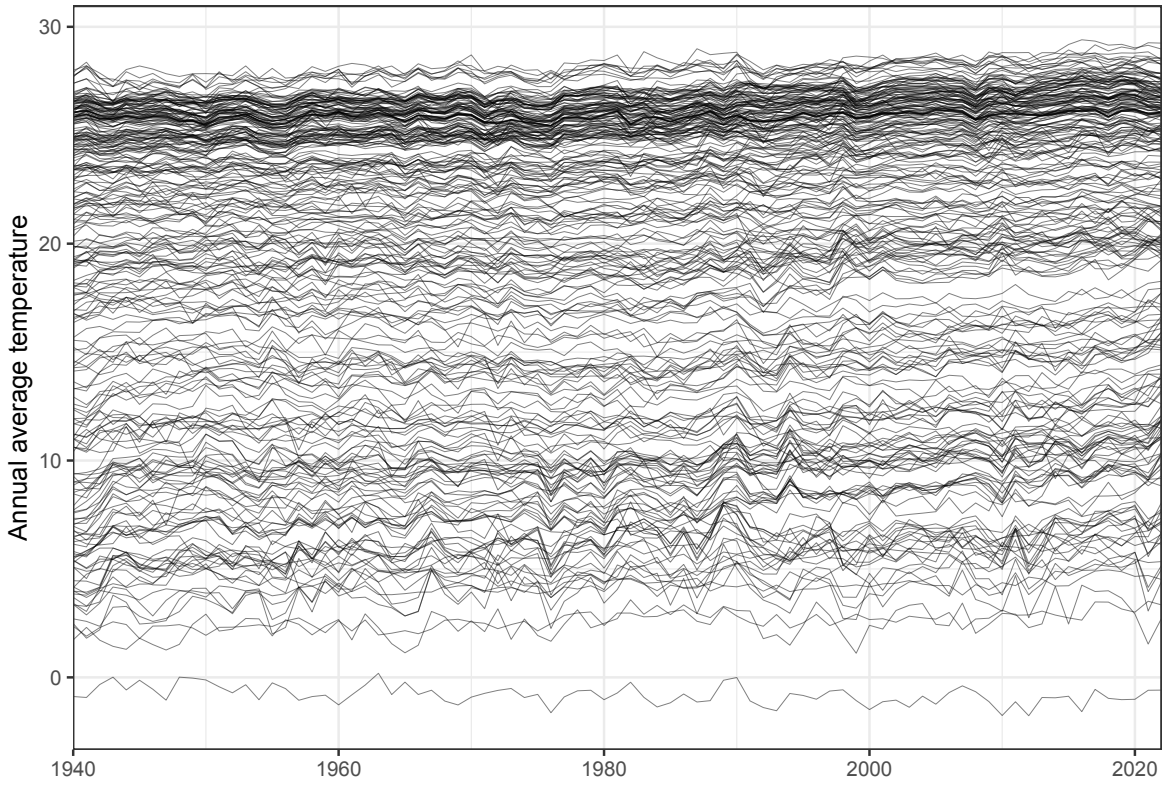


Figure 3: Population-weighted 2-meter air temperature for each country.

We only project the effects of temperature, even though measures of precipitation are included in almost all models. Recent work has shown that, at least for the model with the most sophisticated handling of precipitation (Kotz et al.), temperature is by far the dominant driver of damages [Waidelich et al., 2024].

The inherent uncertainty of the model parameters is accounted for by applying Monte Carlo (MC) simulations. For each of the MC simulations, we draw the model parameters from their respective probability distributions. After drawing the model parameters, we simulate our chosen models for every country under two conditions:

- Actual weather conditions, where we consider only the temperature variables,
- A hypothetical scenario where the climate didn't change, achieved by resampling the weather data from the baseline period of 1940 - 1959.

The difference in economic outcomes under these two conditions represents the immediate impact of climate change on the GDP of a country i in a year t, represented as the variable $ImmediateImpact_{it}$.

1.5 Meta-analysis approaches

1.5.1 Simple meta-analysis

The main results include three simple meta-analysis results:

1. Median across the main specifications of each paper.
2. Monte Carlo across the main specifications of each paper.
3. Monte Carlo across all specifications, weighted by paper.

The main specifications for each paper are as follows:

- Dell et al. [2012]: Table 2, column 3.
- Burke et al. [2015]: Extended Data Table 1, column 1.
- Callahan and Mankin [2022]: Short-run reproduction data file `Attribution_Coefficients_Bootstrap_BHMSR.csv`
- Pretis et al. [2018]: Table 1, column M2: within yr + IIS
- Sequeira et al. [2018]: Table 5, Spec. 1 & 2, 4 & 5.
- Baarsch et al. [2020]: Table 1, column 1.
- Acevedo et al. [2020]: Table 1, column 5.
- Kahn et al. [2021]: Table 2, Specification 1, m = 30, HPJ-FE.
- Kotz et al. [2022]: Extended Data Table 1, column 1.
- Kalkuhl and Wenz [2020]: Table 4, Spec. 5.
- Zhao et al. [2018]: Table 3, column 3.
- Damania et al. [2020]: Table 1, column 1.
- Henseler and Schumacher [2019]: Main specification.
- Burke et al. [2018]: Main specification.
- De Vos and Everaert [2021]: Table 5, CCEPbc specification.
- Yang et al. [2023]: Table 6, FE-NLS column 6.

For method 1, the median is computed for each year, country, and Monte Carlo draw, before any aggregation is done.

For method 2, a random paper is chosen for each Monte Carlo draw, and results for that draw reflect this paper. This treats the papers as model uncertainty.

For method 3, a random paper is chosen for each Monte Carlo draw, and then a random model from that paper. This treats individual models as model uncertainty, but weights their results by paper.

1.5.2 Random forest meta-analysis

To determine the impact and costs of climate change across nations, we leverage the insights provided by multiple research papers that have investigated the relationship between GDP growth, temperature, precipitation, and other factors. However, rather than taking a simple average of their results, we employ a machine learning approach to integrate their individual contributions, thus forming a single comprehensive model.

We proceed in two steps: First, for each instance, we assign quality values to the attributes of the models, ranging from 0 to 1, based on their assessed quality according to the criteria mentioned in the project proposal. A value of 1 corresponds to excellent quality model attribute and a value of 0 corresponds to poor quality modeling decision. The random forest outcomes only rely upon the ordering of these quality values, but the numerical calculations are relevant for determining that ordering in some cases.

To provide a level of objectivity to this analysis, the quality values are designed to provide higher values to more flexible specifications, irrespective of the different motivations behind the specifications.

The detail of each quality-related parameter specification is included in the following table: The Group column designates which attributes are included when only a subset of attributes are included in the Random Forest.

Secondly, these quality values are treated as parameters, upon which a random forest machine learning model is fitted for each country-year-Monte Carlo draw using the *ImmediateImpact* values.

The query is then made to the random forest model to infer the damages under the condition that all parameters are 1, hence indicating optimum conditions based on each attribute. The result is a robust estimate of the potential economic costs of climate change for each country.

Attribute	Quality Value Specification	Group
Weather Weight (Q.Weather)	1 if population-weighted, otherwise 0	Dataset
Rich/Poor Interaction (Q.Poverty)	1 if a subsetted model, 0.5 for an interaction effect, and otherwise 0	Nonlinear
Temperature (Q.Temp) and Precipitation (Q.Prec)	$1 - 0.5^A 0.75^B$ where A is the number of predictors, excluding those counted in B, minus 1; and B is the number of lagged instances of predictors that are also included in non-lagged form.	Nonlinear
Year Fixed Effects (Q.YearFE)	Fixed effects by region are given a value of 1, by continent a value of 0.75, global fixed effects are given a value of 0.5, and a lack of year fixed effects is given a value of 0.	Control
Trends (Q.Trends)	Quadratic trends by observed unit get a value of 1, linear trends by unit a value of 0.5, and missing trends get 0.	Control
Other Fixed Effects (Q.OtherFE)	IIS fixed effects get 1.0, year fixed effects interacted with poverty levels get 0.75, HPJ fixed effects get 0.5; poverty-level effects get 0.25, and no additional fixed effects get 0.	Control
Additional Controls (Q.Control)	$1 - 1/(C + 1)$ for C additional control variables	Control
Growth Lags (Q.GLags)	The number of growth lags included divided by 4.	Control
Data Recency (Q.YearLate)	The quality is calculated as 5 / (2020 - LatestYear)	Dataset
Data Span (Q.YearSpan)	The quality is calculated as (LatestYear - EarliestYear) / 65	Dataset

The impacts are then aggregated across time for each country, accounting for the possibility that the impacts of climate change persist over time and potentially put countries onto permanently lower growth trajectories. The aggregation formula is as follows:

$$CumulativeImpact_{it} = \sum_{s \leq t} (1 - \omega)^{t-s} ImmediateImpact_{is} \tag{1}$$

Where ω represents the rate of recovery from a climate shock. Following the work by Nath et al. [2023], we set $\omega = 0.21$, and use $\omega = 0.08$ as a robustness check.

1.5.3 Coefficient of Determination weighting

Where reported, we collected R^2 values for each model. Different papers reported different types of R^2, and we separately collected Total R^2, Adjusted R^2, and Within R^2. Total R^2 was most commonly reported.

To construct a meta-analysis by sampling across the papers weighted by their reported Total R^2 values. This is reported as `Raw R2` in the paper. We also use both the model attributes in the previous section and the set of available R^2 to fill in gaps in the Total R^2. This is performed with the R package `mice`. The resulting weightging is reported as `Total R2` in the paper.

1.5.4 Weights

All of the above meta-analysis methods can be represented as assigning a weight to each paper model, whether for Monte Carlo sampling or constructing an average. Figure **??** shows the weights assigned to each paper for the all-attribute Random Forest model, the Total R^2 approach, and the main model Monte Carlo.

1.6 Persistence

The level of persistence is a primary factor in determining the level of the total effect, with results differing by almost an order of magnitude.

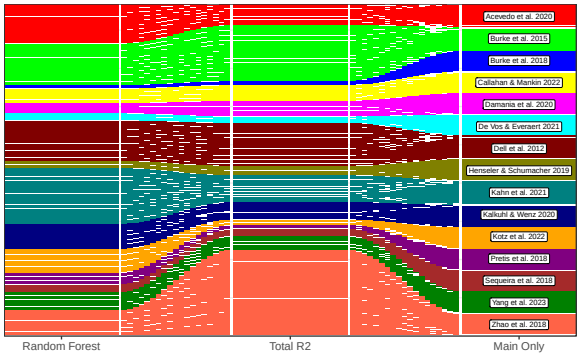


Figure 4: Proportional weights assigned to each model, colored by the source paper.

Paper	**Estimate**	**Methodology**
Nath et al. [2023]	0.08	Impulse response with year fixed-effects
Nath et al. [2023]	0.21	Impulse response with TFP controls
Kikstra et al. [2021]	0.47	Regression with 1 lagged quadratic
Kikstra et al. [2021]	0.79	Regression with 5 lagged quadratics
Bastien-Olvera et al. [2022]	0.11	3-year low-pass filter (recalculated by Kikstra et al. [2021])
Bastien-Olvera et al. [2022]	0.47	10-year low-pass filter (recalculated by Kikstra et al. [2021])

The average of these estimates is 0.36. Because of the long-term effects of lower values, using a distribution of these will provide a result greater than using the mean. We use the mean to be conservative.

1.7 Coastal Impacts

Coastal impacts are reported in dollar terms, and these generally increase over time. However, GDP also increases, and the ratio of these can vary year-by-year, as shown in figure 5.

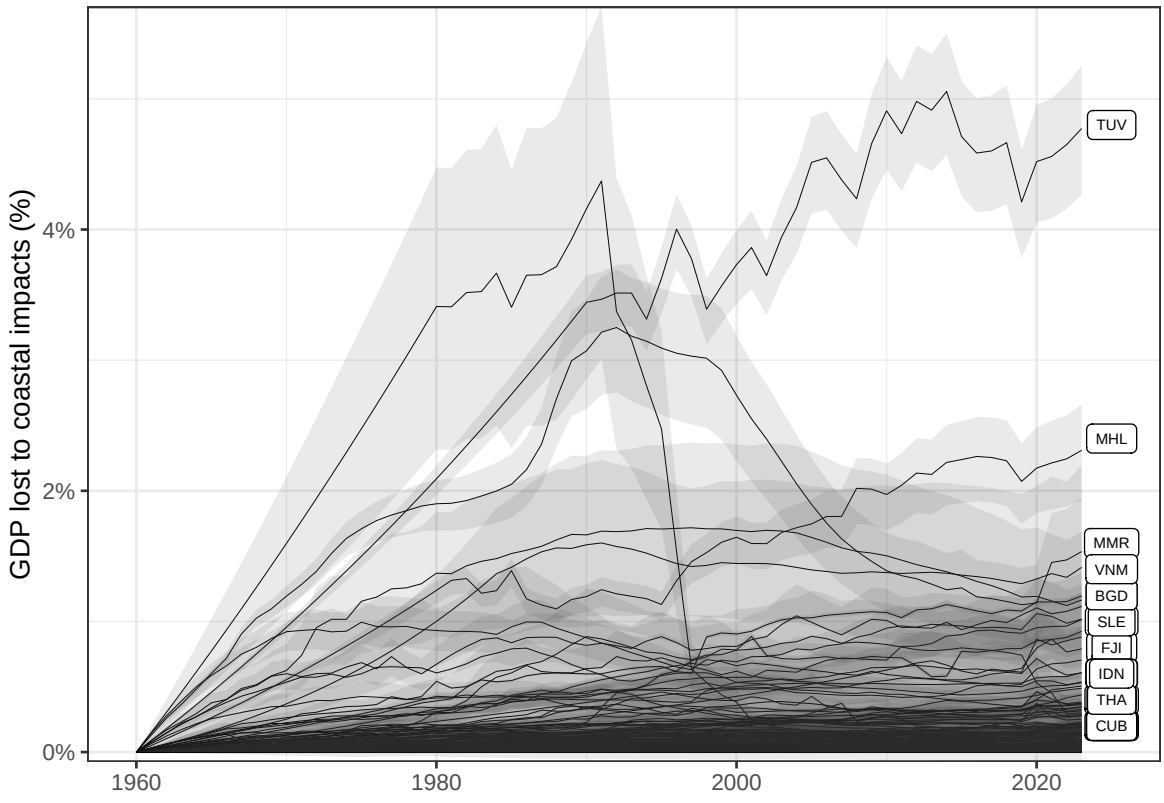


Figure 5: Emulated losses by country, as a fraction on contemporaneous GDP.

1.8 International Effects

The GDP-temperature literature uses local temperature shocks to estimate empirical relationships driving annual differences in GDPs, and as a result they structurally exclude international spill-over effects. The total market impact on each economy includes the spill-over effects of losses to other economies, as transmitted through international trade. We apply three methods to estimate this effect.

Three methods are explored. These provide different orders of magnitude of results, but the values are correlated (figure 6).

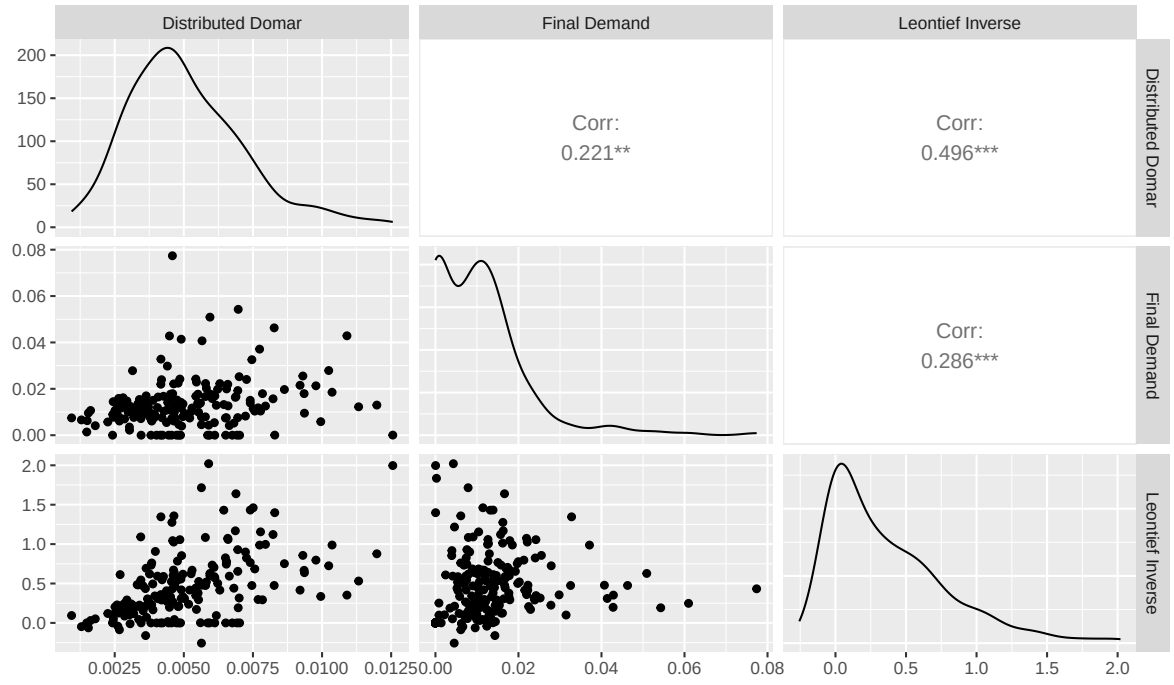


Figure 6: Scatterplot matrix of trade spill-overs (as a fraction of GDP) for each method, reporting trade losses in each country in 2015.

1.8.1 Leontief inverse method

Let Z be the international intermediate inputs, f be a vector of final demand, and v be a vector of value added by country. x is the total output of the economy, the row sums of Z plus each final demand value. T is the technical coefficient matrix, defined as $T_{ij} = Z_{ij}/x_j$. By the construction of an Input-Output matrix, we have that

$$\Delta x = (I - T)^{-1} \Delta f$$

For the Leontief Inverse trade effect, we assume that (1) final demand is reduced the same fraction as the GDP ($CumulativeImpact + SLRImpact$), and (2) that total GDP losses including trade spill-overs are reduced by the same fraction as total output according to the Leontief Inverse relationship. To get the additional trade effect, then, we calculate

$$TradeImpact = (I - T)^{-1}(CumulativeImpact + SLRImpact) - (CumulativeImpact + SLRImpact)$$

1.8.2 Final demand method

Eora26 provides a matrix of final demand inputs, so that entry F_ij describes the portion of final final demand of country j that is provided by country i. Under this approach, we assume that exports to final demand is reduced by the same fraction as the GDP ($CumulativeImpact + SLRImpact$), and calculate the resulting change in final demand. Under this method, we assume that there are no other mechanisms for trade spill-overs.

1.8.3 Domar weights additional details

The derivation of Domar weights is presented in Carvalho and Tahbaz-Salehi [2019]. However, the domar weights outcome only describes changes to global GDP. The challenge of this method is to decompose it by country.

For guidance, we use Brexit CGE studies to calibrate the international effect of impacts operating through the international trade network. The Brexit CGE results that form the basis of this relation-

ship are shown in Table 1, and the empirical relationship between import and export changes to GDP loss is shown in Table 2.

Source	Scenario	% GDP	% Exports	% Imports	Method
Latorre et al. 2019	Soft (Norway case)	-1.23	-7.54	-6.44	GAMS
Latorre et al. 2019	Hard (WTO case)	-2.53	-16.94	-14.42	GAMS
Dhingra et al. 2017	Soft Brexit scenario	-1.34	-9.00	-14.00	Eaton–Kortum
Dhingra et al. 2017	Hard Brexit scenario	-2.66	-16.00	-16.00	Eaton–Kortum

Table 1: Estimated losses to GDP, imports, and exports from selected Brexit studies. .

	Dependent variable:
	% GDP
% Exports	0.160**
	(0.027)
% Imports	−0.003
	(0.027)
Observations	4
R^2	0.997
Adjusted R^2	0.995
Residual Std. Error	0.151 (df = 2)
F Statistic	364.835*** (df = 2; 2)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression table based on the observations in Table 1.

We see that changes in exports are a strong predictor for changes in GDP. We assume that exports are reduced by the same fraction as the GDP ($CumulativeImpact + SLRImpact$), and look for a common value (in place of the 0.16 from table 2) that allows these impacts to be consistent with the Domar weights value.

1.9 Capital Dynamics

This analysis develops a model of capital dynamics based on the Solow growth model and the Inclusive Wealth capital framework. The model captures produced, human, and renewable capital dynamics for all countries.

The data includes country-level GDP, total Population, Savings Rates, and share of GDP from Agriculture from the World Bank, recorded in various years since 1960. Furthermore, estimates of produced, human, and renewable capital by country are sourced from the Inclusive Wealth Report 2018 [Managi and Kumar, 2018] for the years 1990, 1995, 2000, 2005, 2010, and 2014.

Our model includes the following equations, which suppress the country index since each country is fit and modeled independently:

1. GDP is produced by a Cobb-Douglas model, with the assumption that GDP impacts are applied fully to the total factor productivity (TFP).

$$\begin{aligned} Product_t =& (TFP_0 + dTFPdt \cdot t) \\ & (1 - ImmediateImpact_t - \alpha_t(CumulativeImpact_t - ImmediateImpact_t)) \\ & RenewableCapital_{t-1}^{s_{1t}} ProducedCapital_{t-1}^{s_{2t}} HumanCapital_{t-1}^{s_{3t}} Population_{t-1}^{s_{4t}} \end{aligned}$$

2. Shares (s_k) each follow a linear trend. Here, $0 \leq t \leq T$.

$$s_{kt} = s_{k0} + t \cdot \frac{s_{kT} - s_{k0}}{T}, \text{ where } \sum_k s_{k0} = 1 \text{ and } \sum_k s_{kT} = 1. \tag{2}$$

3. Renewable capital follow a Ricker growth function where growth rate is impacted by temperature. The extraction per year is deduced based on the renewable capital share of GDP.

$$\begin{aligned} RenewableCapital_t =& RenewableCapital_{t-1}(1 + (1 - \beta T_{t-1}) r \exp(-b RenewableCapital_{t-1})) - \\ & \frac{s_{1t} Product_t}{1 + \frac{s_{1t} Product_t}{RenewableCapital_{t-1}}} \end{aligned}$$

4. Produced capital follows a standard investment model including a trend in savings rate.

$$\begin{aligned} ProducedCapital_t =& ProducedCapital_{t-1} + (SavingsRate_0 + dSavingsRatedt \cdot t) Product_t - \\ & DepreciationRate \cdot ProducedCapital_{t-1} \end{aligned}$$

5. Human capital assumes a constant exponential growth rate.

$$HumanCapital_t = HumanCapital_{t-1}(1 + dlogHumanCapitaldt) \tag{3}$$

The model parameters above (those variables not directly drawn from data) are TFP_0, $dTFPdt$, s_{k0}, s_{kT}, $RenewableCapital_0$, β, r, b, $ProducedCapital_0$, $SavingsRate_0$, $dSavingsRatedt$, $DepreciationRate$, $HumanCapital_0$, and $dlogHumanCapitaldt$. We impose that $TFP_0 \geq 0$, $0 \leq \alpha_t \leq 1$, $0 \leq RenewableCapital_0 \leq MaximumObservedRenewableCapital$, $0 \leq \beta \leq .1$, $0 \leq r \leq 1$, $1 \leq b \leq 10$, $0 \leq ProducedCapital_0 \leq MaximumObservedProducedCapital$, $0 \leq SavingsRate_0 \leq 1$, $-0.1 \leq dSavingsRatedt \leq 0.1$, $0 \leq DepreciationRate \leq 1$, $0 \leq HumanCapital_0 \leq MaximumObservedHumanCapital$, $-0.1 \leq dlogHumanCapitaldt \leq 0.1$, $\sum_k s_{k0} = 1$, $\sum_k s_{kT} = 1$

The model parameters are calibrated using a Markov chain Monte Carlo (MCMC) computational Bayesian method, with the Stan software. The priors for the model are developed from a combination of theoretical assumptions, empirical observations, and as informed by various data sources, including World Bank data and the Inclusive Wealth Report.

$$\begin{aligned} \log ObservedGDP_t &\sim \mathcal{N}(\log Product_t, \sigma_{GDP}) \\ \log ObservedRenewableCapital_t &\sim \mathcal{N}(\log RenewableCapital_t, \sigma_{RenCap}) \\ \log ObservedProducedCapital_t &\sim \mathcal{N}(\log ProducedCapital_t, \sigma_{ProCap}) \\ \log ObservedHumanCapital_t &\sim \mathcal{N}(\log HumanCapital_t, \sigma_{HumCap}) \\ NaturalGDPShare &\sim \mathcal{N}(s_{1t}, \sigma_{RenCapShare}) \\ ObservedSavingsRate &\sim \mathcal{N}(SavingsRate_0 + dSavingsRatedt \cdot t), \sigma_{SavingsRate}) \\ CumulativeImpact_t &\sim \mathcal{N}\left(\log Product_t^{NoCC} - \log Product_t - (1 - \alpha_t) CumulativeImpact_t, \sigma_{GDP}\right) dSavingsR \\ s_{kT} - s_{k0} &\sim \mathcal{N}(0, \sigma_{Shares}) \\ \sigma_{Shares} &\sim \mathcal{N}(0, .1) \end{aligned}$$

GDP, Population, observed savings rate, and share of GDP from Agriculture, forestry, and fishing are taken from the World Bank.

We impose that $\sigma_{RenCap} > 0$, $\sigma_{RenCapShare} > 0$, $\sigma_{ProCap} > 0$, $\sigma_{SavingsRate} > 0$, $\sigma_{HumCap} > 0$, $\sigma_{Shares} > 0$, and $\sigma_{GDP} > 0$.

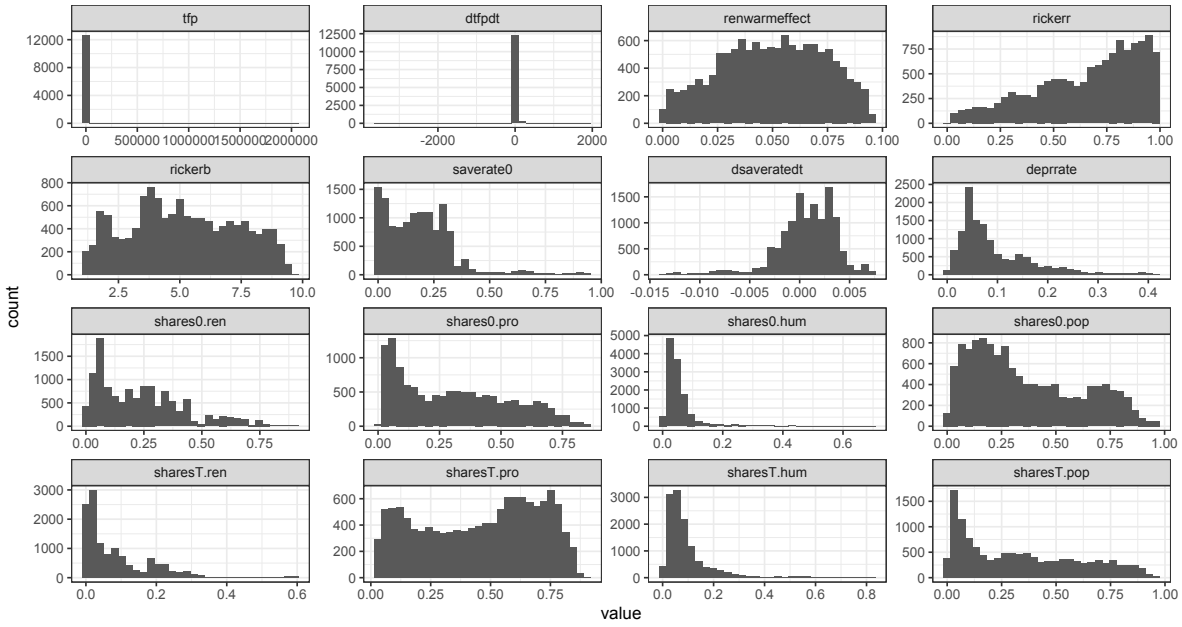


Figure 7: MCMC draws of growth model parameters, across all countries and underlying Monte Carlo draws.

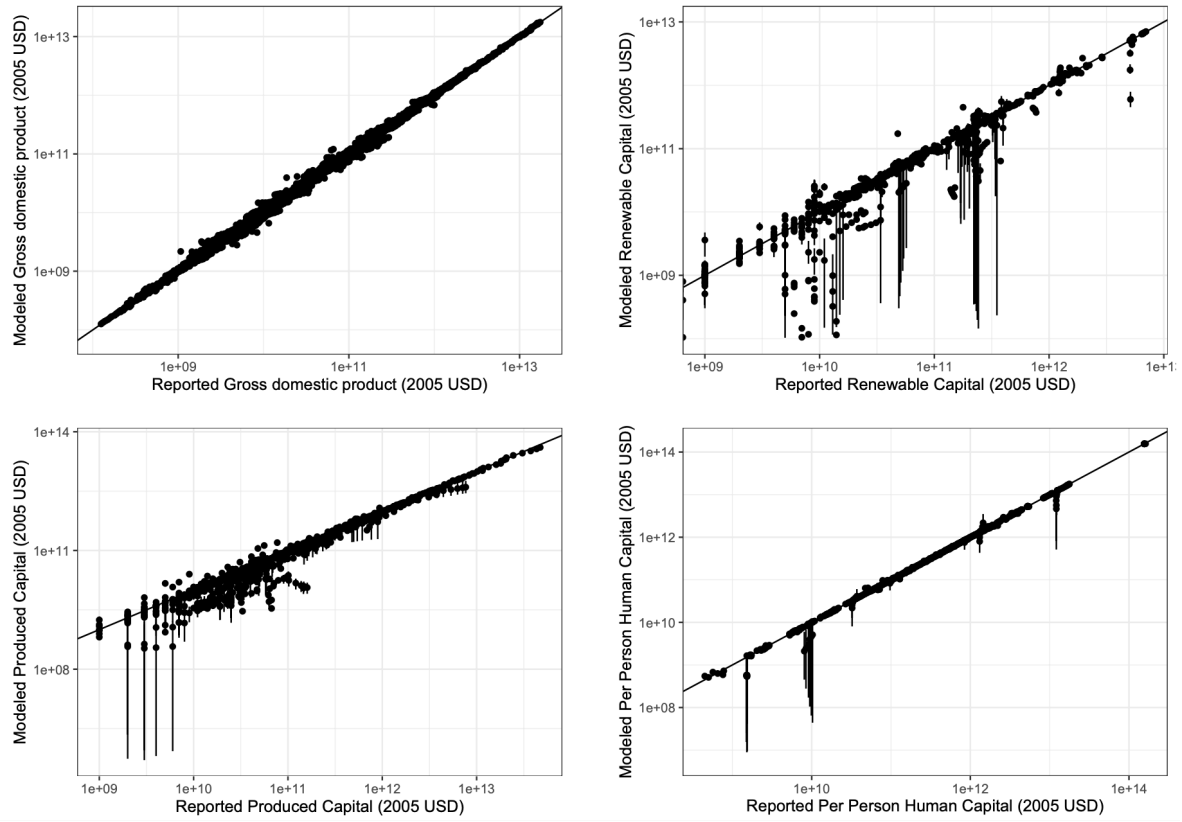


Figure 8: Model-predicted GDP and capital, compared to observed values, across all countries.

1.10 Reporting Results

Losses were reported as the population-weighted median across Monte Carlo draws, along with the interquartile range.

2 Additional results

2.1 Model choice effects

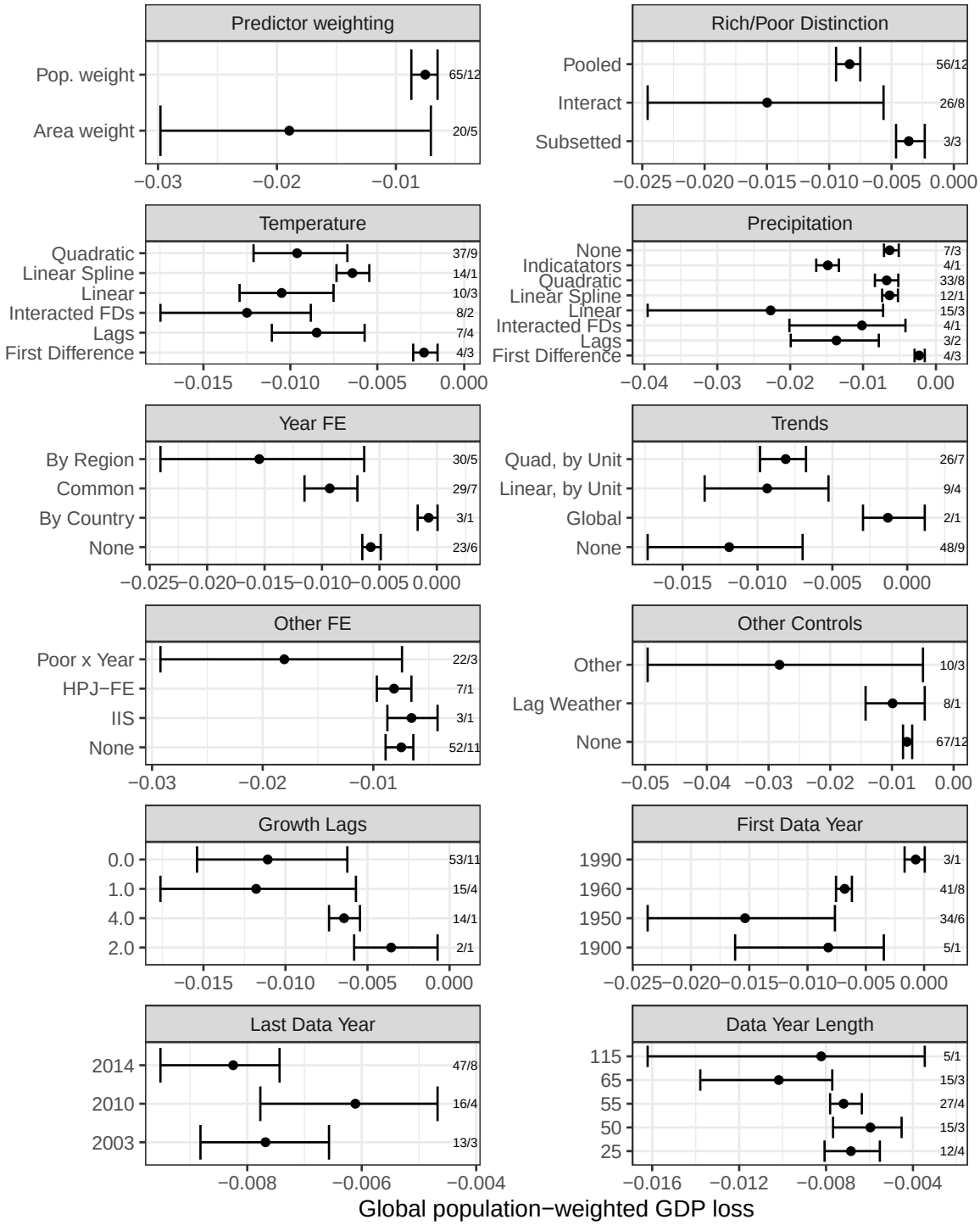


Figure 9: Range of outcome values (2014 - 2023) across model attributes. Each panel is a separate division of the data, and each bar shows the interquartile range of the mean for a given subset of the data, across the uncertainty in model parameters.

2.2 Country-level timeseries

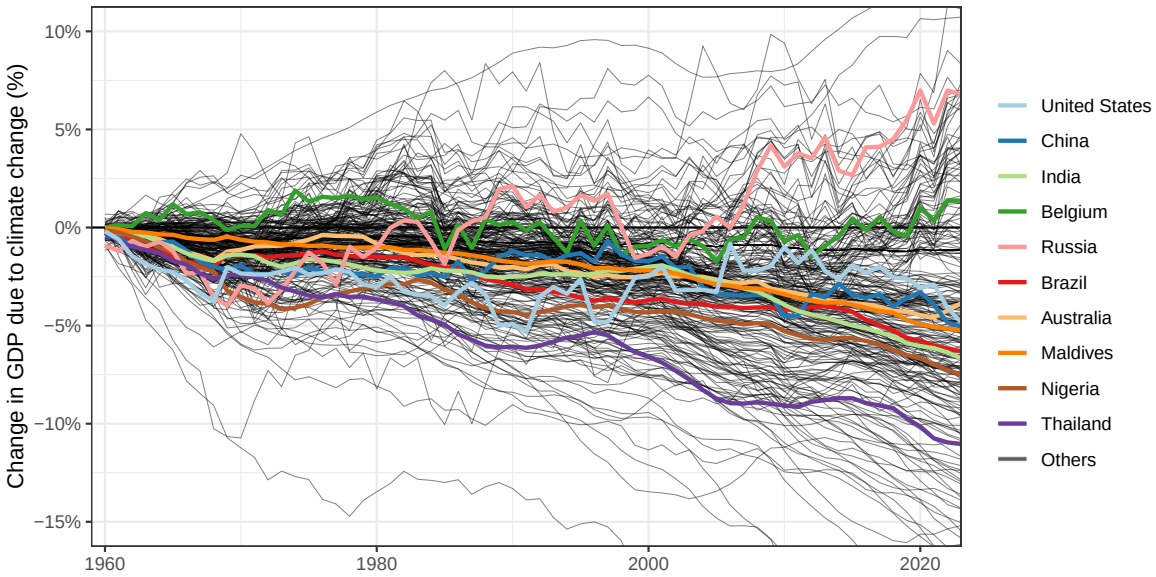


Figure 10: Total losses by year, for each country, with some countries highlighted.

2.3 Total by region

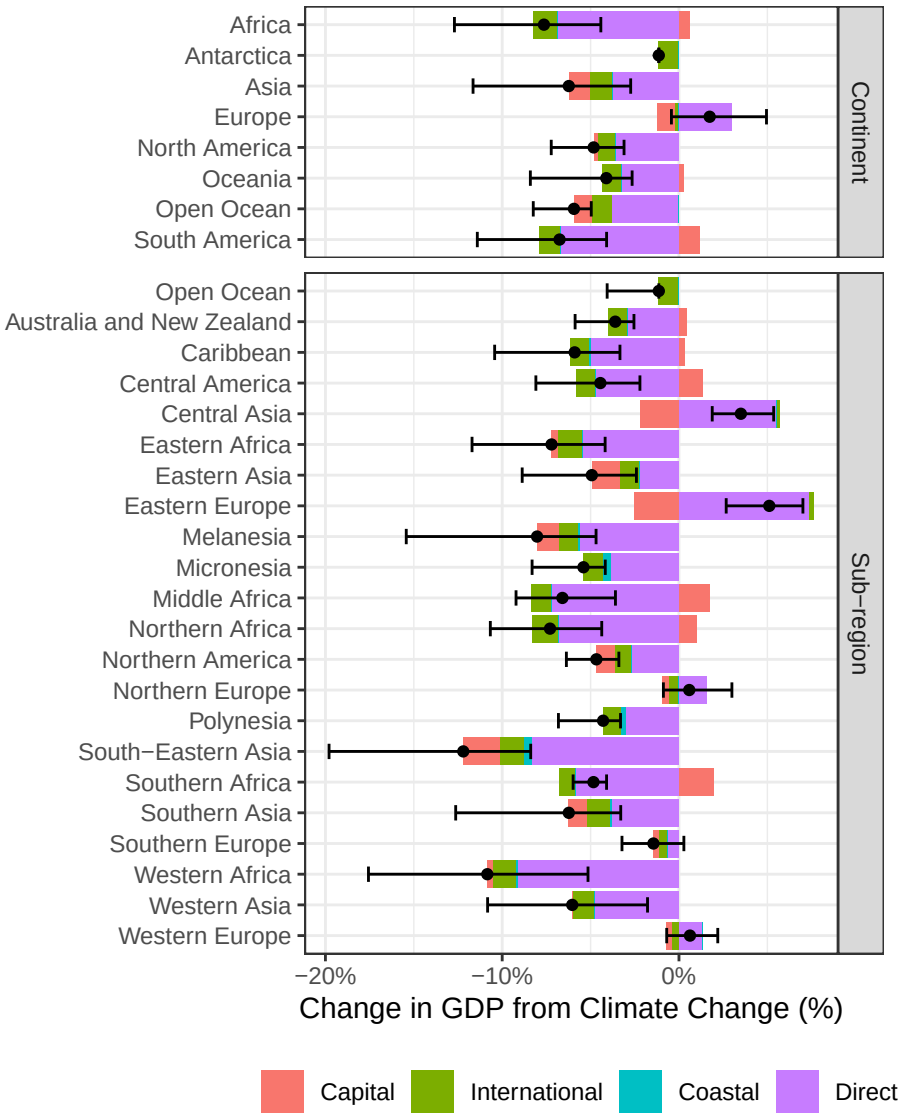


Figure 11: Percent GDP impact in 2014 - 2023 across regional groups. Direct, international, coastal, and capital impact combine to make the total GDP impact.

2.4 Total by income group

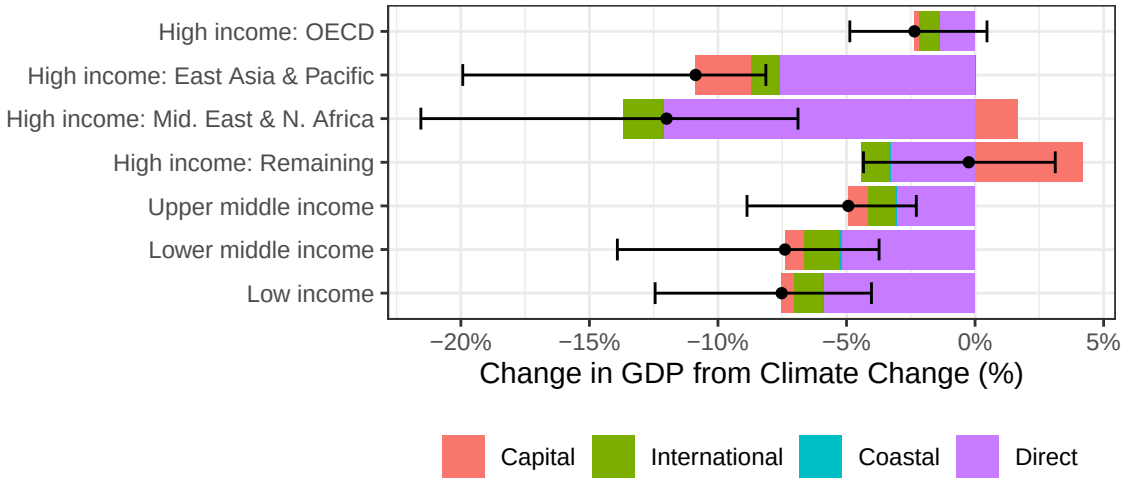


Figure 12: Percent GDP impact in 2022 across economic groups.

Income Group	2023 GDP Change ($billion)	30-year GDP Change ($billion)	Produced Capital Change ($billion)	Renewable Capital Direct Change ($billion)	Renewable Capital Feedback Change ($billion)	Total Loss ($billion)
1. High income: OECD	-1240	-22960	-2260	-370	240	25350
2. High income: nonOECD	-280	-4370	-420	-80	70	4800
3. Upper middle income	-1210	-15770	-1760	-6330	5900	17960
4. Lower middle income	-630	-8050	-840	-1380	1710	8560
5. Low income	-90	-1130	-70	-160	240	1120
High income (total)	-1520	-27330	-2680	-450	310	30150
Low and middle income	-1930	-24950	-2670	-7870	7850	27640

Table 3: Total changes to GDP and capital bases, reported in 2015 USD. GDP and capital changes are measured in 2015 USD in 2014 - 2023, and Total Loss & Damage equals the sum of GDP losses from 1993 to 2023 plus the capital losses in 2023.

2.5 Results by UNFCCC voting block

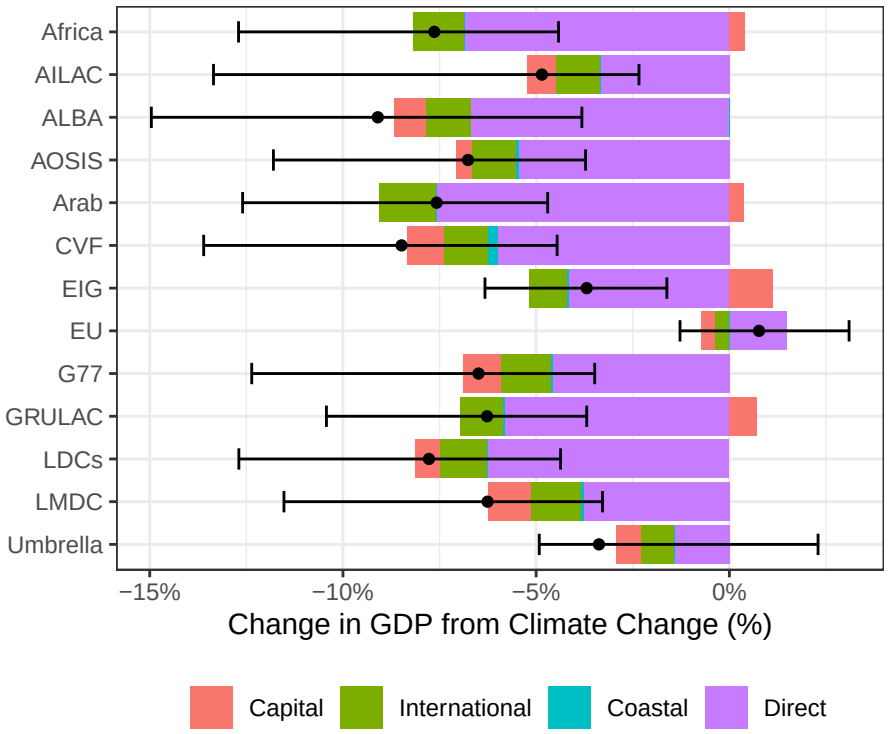


Figure 13: Percent GDP impact in 2022 across countries UNFCCC party groupings.

Party	2023 GDP Change ($billion)	30-year GDP Change ($billion)	Produced Capital Change ($billion)	Renewable Capital Direct Change ($billion)	Renewable Capital Feedback Change ($billion)	Total Loss ($billion)
Africa	-240	-3450	-240	-370	420	3640
AILAC	-80	-1140	-110	-40	40	1250
ALBA	-10	-140	-100	-50	50	240
AOSIS	-60	-870	-110	-10	10	980
Arab	-310	-4710	-450	-560	700	5020
CVF	-150	-1770	-150	-300	370	1850
EIG	-120	-2160	-290	-60	50	2460
EU	120	-3360	-150	-130	70	3570
G77	-2260	-28610	-3190	-7720	7800	31720
GRULAC	-350	-6160	-700	-210	220	6850
LDCs	-120	-1670	-70	-440	660	1520
LMDC	-1540	-17500	-2130	-6920	6710	19840
Umbrella	-1140	-16610	-1640	-370	240	18380

Table 4: Total changes to GDP and capital bases, reported in 2015 USD. GDP and capital changes are measured in 2015 USD in 2014 - 2023, and Total Loss & Damage equals the sum of GDP losses from 1993 to 2023 plus the capital losses in 2023.

2.6 Comparison of alternatives

Persistence	SLR	Trade	Growth	Impact	Range
0.00				-8.7%	-31.5 - 0.4%
0.36				-2.3%	-3.1 - -1.1%
1.00				-0.9%	-1.2 - -0.4%
	Market-only			0.1%	0.1 - 0.1%
	All Damages			0.2%	0.2 - 0.2%
	Optimal Adapt.			0%	0 - 0%
	No Adaptation			0.2%	0.2 - 0.2%
0.36	Market-only	Final demand	None	-2.4%	-3.3 - -1.2%
0.36	Market-only	Domar dist.	None	-3%	-3.6 - -1.4%
0.36	Market-only	Leontief Inv.	None	-9.6%	-13.6 - -4.2%
0.36	Market-only	Domar dist.	All capital	-5.1%	-8.5 - -2.1%
0.36	Market-only	Domar dist.	Prod.-only	-10.9%	-15.7 - -5.9%

Table 5: Alternative population-weighted estimates. Each row shows a different set of model choices, and resulting global population-weighted estimate across 2014 - 2023.

3 Country-level estimates

Results for each country are shown below. The first set of columns, under "GDP Change (%)", reports direct, international, and capital-based percent changes to GDP in 2022, along with their total effect and the interquartile range. The second set of columns, under "Capital Change (%)", reports percent changes to produced capital, renewable capital stock (direct and through economic feedbacks), and total capital stock with its interquartile range in 2022. The total capital stock includes only renewable and produced capital. The third set of columns, under "Total Change ($billion)", reports losses as billions of 2015 USD, for produced capital, renewable capital (direct and through economic feedbacks), all in 2022, and total GDP losses since 1992 under the "GDP (30-yr)" column and its interquartile range.

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
							Renewable							GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
Afghanistan	1%	-0.4%	0%	-1.2%	-0.5%	-2 - 1%	2.7%	-7.5%	4.8%	-0.1%	-1 - 0%	0	-1	0	-10 - 10
Akrotiri Sovereign Base Area	-5.4%	-1.1%	0%		-6.5%	-9 - -4%								0	0 - 0
Aland	2.1%	-1.1%	0%		1%	-1 - 2%								0	0 - 0
Albania	-0.1%	-0.1%	-0.1%	-0.7%	-1%	-3 - 1%	3.4%	-5.7%	2.2%	-0.6%	-1 - 0%	0	0	-3	-10 - 10
Algeria	-7.2%	-0.8%	0%	0.5%	-7.5%	-10 - -4%	9.7%	-35.2%	21.1%	-6.3%	-7 - -6%	-41	-3	-255	-290 - -140
American Samoa	-3.5%	-1.1%	-0.1%		-4.7%	-8 - -3%								-1	-10 - 0
Andorra	6.6%	-0.5%	0%		6.1%	2 - 8%								1	-10 - 10
Angola	-4.1%	-0.9%	0%		-5%	-8 - -3%								-62	-90 - -40
Anguilla	-2.8%	-1%	0%		-3.7%	-6 - -3%								0	0 - 0
Antarctica	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Antigua and Barbuda	-2.7%	-0.9%	-0.1%		-3.7%	-6 - -2%								-1	-10 - 0
Argentina	-9.3%	-1.4%	0%	1.5%	-9.2%	-12 - -8%	-5%	-0.1%	1.5%	-3.7%	-4 - -3%	-106	14	-1279	-1400 - -1200
Armenia	2.9%	-0.2%	0%	-2.1%	0.6%	-2 - 2%	8.5%	-10.5%	2.6%	0%	0 - 1%	0	0	0	-10 - 10
Aruba	-3.4%	-1.7%	0%		-5.1%	-9 - -3%								-3	-10 - 0
Ashmore and Cartier Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Australia	-3.1%	-1.1%	0%	0.4%	-3.8%	-6 - -3%	-2.9%	-0.9%	1.1%	-2.7%	-3 - -2%	-176	3	-1198	-1540 - -850
Austria	5.6%	0.3%	0%	-1.9%	3.9%	2 - 5%	3.7%	-6.5%	2.9%	0%	-1 - 0%	11	-3	-95	-190 - 30
Azerbaijan	-0.3%	-0.6%	0%		-0.8%	-3 - 2%								-4	-20 - 10
Bahrain	-5.1%	-2%	0%	1.3%	-5.7%	-8 - -4%	-4.4%	-1.9%	2.1%	-4.2%	-5 - -4%	-4	0	-30	-40 - -20
Bajo Nuevo Bank (Petrel Is.)	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Bangladesh	-4.2%	-0.6%	-0.8%	-0.1%	-5.7%	-10 - -4%	1.7%	-15.5%	9.9%	-5.1%	-6 - -5%	-17	-3	-212	-330 - -160
Barbados	-3.2%	-1.3%	0%	1.3%	-3.2%	-5 - -2%	-0.6%	-7.9%	6.9%	-1.5%	-2 - -1%	0	0	-4	-10 - 0
Baykonur Cosmodrome	9.9%	-1.1%	0%		8.7%	6 - 12%								0	0 - 0
Belarus	10.5%	1.1%	0%		11.8%	7 - 16%								59	40 - 100
Belgium	2.6%	-0.2%	0%	-1%	1.4%	-1 - 3%	7.8%	-11.2%	4.3%	0.3%	0 - 1%	10	-1	-35	-130 - 50
Belize	-12.1%	-1.1%	-0.2%	-5.2%	-17.7%	-25 - -12%	-2.4%	-1.6%	2.5%	-1.6%	-2 - -1%	-1	0	-8	-20 - 0
Benin	-9.4%	-1.7%	-0.1%	-2.2%	-13%	-23 - -9%	-5.8%	-4.1%	5.8%	-4.5%	-5 - -4%	-3	0	-32	-60 - -20
Bermuda	-3.4%	-1%	0%		-4.4%	-6 - -3%								-6	-10 - 0
Bhutan	-3.3%	-1.4%	0%		-4.7%	-8 - -2%								-2	-10 - 0
Bir Tawil	-13.1%	-1.1%	0%		-14.1%	-20 - -10%								0	0 - 0
Bolivia	-5.1%	-1.5%	0%	-3.3%	-9.6%	-13 - -3%	-0.5%	-1%	1%	-0.5%	-1 - 0%	-4	-1	-61	-90 - -30
Bosnia and Herzegovina	5.7%	0.6%	0%		6.3%	2 - 10%								1	-10 - 20
Botswana	-5.9%	-1.4%	0%	0.8%	-6.5%	-9 - -5%	-1.4%	-0.2%	0.6%	-1.1%	-2 - -1%	-4	0	-19	-30 - -10
Brazil	-5.6%	-1.2%	0%	0.7%	-6.1%	-9 - -4%	-1.3%	-0.8%	0.8%	-1.4%	-2 - -1%	-229	3	-2201	-2720 - -1590
Brazilian Island	0.9%	-1.1%	0%		-0.2%	-1 - 1%								0	0 - 0
British Indian Ocean Territory	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
British Virgin Islands	-2.8%	-1.1%	0%		-3.9%	-6 - -3%								0	0 - 0
Brunei	-8.5%	-1.4%	-0.1%		-9.8%	-17 - -8%								-33	-60 - -20
Bulgaria	5.5%	0.1%	0%	-2.3%	3.2%	1 - 6%	4.2%	-6%	2.3%	0.4%	0 - 1%	3	-1	12	0 - 30
Burkina Faso	-11%	-0.8%	0%		-11.7%	-17 - -8%								-28	-50 - -20
Burundi	-4.7%	-2.1%	0%	0.8%	-6%	-8 - -3%	0.4%	-19.2%	15.6%	-3.7%	-4 - -3%	0	0	-3	-10 - 0
Cabo Verde	-2.1%	-0.7%	-0.3%		-3%	-5 - -2%								-1	-10 - 0

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
								Renewable						GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
Cambodia	-13.8%	-1.3%	-0.1%	0.1%	-14.9%	-26 - -9%	-4.7%	-2%	4.4%	-1.2%	-2 - -1%	-4	11	-56	-100 - -30
Cameroon	-6.5%	-0.8%	0%	1.9%	-5.6%	-9 - -3%	-1.2%	-1.4%	1.5%	-1%	-2 - -1%	-3	0	-33	-50 - -10
Canada	0.1%	-0.9%	0%	-1.8%	-2.5%	-5 - -1%	-0.6%	-0.6%	0.5%	-0.8%	-1 - 0%	-59	-4	-799	-1000 - -620
Cayman Islands	-3.6%	-1.1%	0%		-4.8%	-7 - -3%								-4	-10 - 0
Central African Rep.	-4.8%	-1.2%	0%	1.6%	-4.5%	-7 - -2%	0%	-0.1%	0.1%	0%	0 - 1%	0	0	-1	-10 - 0
Chad	-7.7%	-1.1%	0%		-8.8%	-14 - -7%								-16	-30 - -10
Chile	-1.3%	-0.9%	0%	-0.5%	-2.6%	-4 - -1%	-2%	-0.3%	0.6%	-1.7%	-2 - -1%	-14	1	-126	-170 - -110
China	-2%	-1.1%	0%	-1.9%	-4.9%	-9 - -2%	-7%	-48.2%	52.1%	-4%	-5 - -4%	-979	-350	-8425	-14190 - -4070
Clipperton Island	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Colombia	-6%	-1.1%	0%	-1.5%	-8.4%	-19 - -1%	-2.6%	-5.3%	4.4%	-3.7%	-4 - -3%	-53	-2	-410	-980 - -50
Comoros	-4.1%	-1.4%	-0.3%		-5.7%	-10 - -4%								-1	-10 - 0
Cook Islands	-2.7%	-0.9%	0%		-3.6%	-7 - -2%								0	0 - 0
Coral Sea Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Costa Rica	-2%	-1%	-0.1%	0.3%	-2.8%	-5 - -1%	-1%	-3%	2.2%	-1.8%	-2 - -1%	-2	0	-33	-60 - -10
Croatia	3.3%	0.4%	0%	-0.9%	2.9%	1 - 4%	2%	-4.6%	2.1%	-0.6%	-1 - 0%	0	0	-16	-40 - 0
Cuba	-3.4%	-0.7%	-0.2%	1.1%	-3.2%	-5 - -2%	6%	-1.7%	1.1%	-2.1%	-3 - -2%	-4	4	-46	-60 - -30
Curaçao	-3.2%	-1.1%	0%		-4.3%	-7 - -3%								-3	-10 - 0
Cyprus	-5.2%	-1.2%	0%	1%	-5.4%	-8 - -2%	1.5%	-11.2%	7.2%	-3.3%	-4 - -3%	-3	0	-29	-40 - -20
Cyprus No Mans Area	-6.2%	-1.1%	0%		-7.2%	-10 - -4%								0	0 - 0
Czechia	5.9%	0.5%	0%	-2.1%	4.1%	1 - 6%	18.3%	-47.4%	32.5%	0.9%	0 - 1%	10	0	3	-60 - 40
DR Congo	-7.9%	-1.6%	0%	3.2%	-6.4%	-9 - -3%	-0.2%	-0.3%	0.3%	-0.1%	-1 - 0%	-4	1	-44	-60 - -20
Denmark	2.4%	-0.1%	0%	-0.6%	1.6%	0 - 3%	4.6%	-7.5%	3.7%	0.4%	0 - 1%	9	-1	19	-70 - 70
Dhekelia Sovereign Base Area	-6%	-1.1%	0%		-7%	-9 - -4%								0	0 - 0
Djibouti	-8.1%	-1.1%	0%		-9.2%	-16 - -6%								-6	-10 - 0
Dominica	-2.8%	-1.3%	0%		-4.1%	-7 - -3%								0	-10 - 0
Dominican Republic	-5.7%	-1.1%	0%	-1.6%	-8.2%	-15 - -4%	-5.5%	-2.4%	3.3%	-5.2%	-6 - -5%	-14	0	-102	-160 - -50
East Timor	-4.6%	-1.3%	-0.2%		-6.1%	-10 - -4%								-2	-10 - 0
Ecuador	-5%	-0.9%	-0.1%	0.6%	-5.4%	-10 - -2%	-1.8%	-3.5%	2.5%	-2.7%	-3 - -2%	-10	-2	-79	-150 - -30
Egypt	-5.9%	-1.7%	0%	0.1%	-7.5%	-11 - -4%	11.9%	-29.8%	15.5%	-6.9%	-7 - -6%	-32	-2	-398	-490 - -200
El Salvador	-8.2%	-1.4%	-0.1%	-0.7%	-10.2%	-20 - -7%	-2.9%	-18.2%	14.5%	-6.8%	-7 - -6%	-5	0	-54	-100 - -40
Equatorial Guinea	-7.5%	-1.1%	-0.1%		-8.7%	-13 - -5%								-18	-30 - -10
Eritrea	-8.9%	-1.1%	0%		-10%	-16 - -6%								-5	-10 - 0
Estonia	9%	1%	-0.1%	-2.6%	7%	5 - 9%	5.3%	-3.1%	0.8%	2.8%	2 - 3%	3	-1	13	0 - 20
eSwatini	-4.5%	-1.8%	0%	2.4%	-4%	-7 - -3%	-1.1%	-3.2%	2.8%	-1.7%	-2 - -1%	0	0	-3	-10 - 0
Ethiopia	-6.2%	-1.5%	0%		-7.6%	-13 - -3%								-108	-160 - -40
Falkland Islands	-1.2%	-1.1%	0%		-2.3%	-4 - -1%								0	0 - 0
Faroe Islands	1.3%	-0.1%	0%		1.2%	0 - 3%								0	-10 - 0
Federated States of Micronesia	-4.6%	-1.1%	-0.4%		-6.1%	-10 - -4%								0	-10 - 0
Fiji	-4.9%	-1%	-0.6%	-0.5%	-6.9%	-12 - -5%	-3%	-1.5%	1.8%	-2.7%	-3 - -2%	-1	0	-5	-10 - 0
Finland	10.5%	0.2%	0%	-3.3%	7.1%	5 - 9%	4.3%	-3.3%	1.1%	1.9%	1 - 2%	31	-4	81	40 - 120
France	0.4%	-0.5%	0%	-0.1%	-0.2%	-2 - 1%	1.8%	-5.2%	2.6%	-0.9%	-1 - 0%	-83	-8	-1009	-1640 - -630
French Polynesia	-2.7%	-1%	-0.3%		-4%	-7 - -3%								-6	-10 - 0
French Southern and Antarctic Lands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Gabon	-6.5%	-1.4%	0%	2.5%	-5.5%	-9 - -3%	-0.2%	-0.1%	0.1%	-0.3%	-1 - 0%	-3	0	-15	-30 - 0
Gambia	-6.6%	-2.7%	-0.9%	-1.9%	-11.6%	-20 - -8%	-4.4%	-1.8%	4.3%	-2.6%	-3 - -2%	0	0	-3	-10 - 0
Georgia	-1.4%	-0.3%	-0.1%		-1.8%	-4 - 3%								-1	-10 - 10
Germany	2.3%	-0.3%	0%	-0.6%	1.4%	0 - 3%	4.7%	-7.2%	3.3%	0.1%	0 - 1%	32	-9	-465	-1040 - 600
Ghana	-11.1%	-1.5%	-0.1%	-4.2%	-16.1%	-24 - -11%	-12.3%	-9.1%	15.9%	-7.3%	-8 - -7%	-18	9	-144	-220 - -90
Gibraltar	-2.2%	-1.1%	0%		-3.3%	-5 - -1%								0	0 - 0
Greece	-1.3%	-0.5%	0%	0.2%	-1.6%	-3 - 0%	1.2%	-3.1%	1.8%	-0.2%	-1 - 0%	-1	-3	-40	-90 - -10
Greenland	6.3%	0.3%	0%		6.6%	2 - 11%								1	-10 - 10
Grenada	-3.4%	-1.1%	0%		-4.5%	-7 - -3%								-1	-10 - 0

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
								Renewable						GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
Guam	-3.7%	-1.1%	0%		-4.8%	-7 - -3%								-5	-10 - 0
Guatemala	-8%	-1.6%	0%	-2.6%	-11.8%	-17 - -5%	-4.7%	-5.4%	5.6%	-4.6%	-5 - -4%	-12	0	-139	-210 - -60
Guernsey	-0.2%	-1.1%	0%		-1.3%	-3 - 0%								0	0 - 0
Guinea	-6.7%	-0.5%	-0.1%		-7.3%	-12 - -5%								-15	-30 - -10
Guinea-Bissau	-5.8%	-1.1%	-1.1%		-7.9%	-12 - -6%								-2	-10 - 0
Guyana	-4.4%	-1.4%	-0.3%	-0.2%	-6.2%	-10 - -3%	-0.1%	-0.8%	0.7%	-0.2%	-1 - 0%	0	0	-7	-10 - 0
Haiti	-7.4%	-1.6%	-0.1%	0.6%	-8.4%	-12 - -5%	-1.7%	-10.2%	8.9%	-4.7%	-5 - -4%	-2	-1	-21	-40 - -10
Heard Island and McDonald Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Honduras	-7.3%	-0.8%	-0.1%	-0.4%	-8.5%	-18 - -3%	-3%	-1.6%	1.8%	-2.9%	-3 - -2%	-4	2	-34	-70 - -10
Hong Kong S.A.R.	-7.2%	-1%	0%		-8.2%	-11 - -6%								-563	-690 - -480
Hungary	5.8%	0.5%	0%	-2.2%	3.9%	3 - 6%	5.8%	-7.2%	1.9%	0.2%	0 - 1%	5	-2	-16	-30 - 10
Iceland	17.6%	0.3%	0%	-5.5%	11.3%	10 - 13%	2.4%	-0.5%	-0.3%	1.5%	1 - 2%	4	-1	29	20 - 40
India	-4%	-1.5%	-0.1%	-1%	-6.4%	-13 - -4%	-6.7%	-33.9%	36%	-4.9%	-5 - -4%	-348	103	-2165	-4300 - -1490
Indian Ocean Territories	-3.5%	-1.1%	0%		-4.6%	-7 - -3%								0	0 - 0
Indonesia	-7.9%	-1.5%	-0.4%	-1.5%	-11%	-18 - -7%	-4.4%	-3.6%	5.5%	-3.2%	-4 - -3%	-220	41	-1913	-3080 - -1270
Iran	-3.3%	-1%	0%	1.2%	-3.1%	-6 - -1%	-0.8%	-4.9%	2.9%	-2.8%	-3 - -2%	-44	-11	-291	-500 - -220
Iraq	-7.5%	-1.7%	-0.1%	1.6%	-7.8%	-13 - -6%	-0.9%	-27.5%	21.3%	-7.5%	-8 - -7%	-8	-1	-289	-360 - -200
Ireland	1%	-0.5%	0%	0%	0.5%	-1 - 1%	0.5%	-0.4%	0%	0.1%	0 - 1%	-1	0	-8	-50 - 20
Isle of Man	0.3%	-1.1%	0%		-0.8%	-2 - 0%								-2	-10 - 0
Israel	-5.5%	-0.8%	0%	1.4%	-4.9%	-7 - -2%	10.8%	-33.6%	20.9%	-4.5%	-5 - -4%	-28	-1	-303	-400 - -240
Italy	-0.3%	-0.5%	0%	-0.3%	-1.1%	-3 - 1%	1.4%	-5.1%	2.7%	-1.1%	-2 - -1%	-84	-10	-769	-1510 - -440
Ivory Coast	-10.8%	-1.6%	0%	-0.1%	-12.3%	-19 - -8%	-2.7%	-4.1%	5.4%	-1.6%	-2 - -1%	-11	1	-118	-180 - -70
Jamaica	-5.6%	-0.8%	-0.1%	1.6%	-5%	-8 - -3%	-1.8%	-2.2%	1.9%	-2.1%	-3 - -2%	-2	0	-14	-20 - 0
Japan	-2.9%	-1%	0%	1.1%	-2.8%	-5 - 0%	1.3%	-7.7%	4.6%	-1.9%	-2 - -1%	-509	-19	-2497	-4240 - -440
Jersey	-0.1%	-1.1%	0%		-1.3%	-3 - 0%								0	0 - 0
Jordan	-5.1%	-1.8%	0%	0.6%	-6.3%	-8 - -2%	-0.9%	-13.5%	9.4%	-5%	-5 - -4%	-4	0	-42	-50 - -20
Kazakhstan	6.5%	-0.1%	0%	-1.6%	4.6%	2 - 6%	11.8%	-7.1%	0.3%	3.9%	3 - 4%	15	-1	114	70 - 150
Kenya	-5%	-1.3%	0%	-0.1%	-6.4%	-11 - -3%	0.2%	-15.8%	12.7%	-6.1%	-7 - -6%	-5	-1	-90	-150 - -40
Kiribati	-4.2%	-1.4%	-1%		-6.5%	-11 - -5%								0	-10 - 0
Kosovo	4.6%	-1.1%	0%		3.4%	0 - 6%								0	0 - 0
Kuwait	-8.6%	-2.2%	0%	-2.5%	-12.8%	-19 - -7%	-9.5%	-15.4%	17.1%	-8.7%	-9 - -8%	-24	0	-241	-310 - -160
Kyrgyzstan	5.4%	0.6%	0%	-1.1%	4.9%	3 - 8%	3.9%	-3.7%	1.1%	1.1%	1 - 2%	0	0	2	0 - 10
Laos	-8%	-2.5%	0%	-2%	-12.1%	-21 - -7%	-1.5%	-1.7%	2.7%	-0.8%	-1 - 0%	-2	3	-32	-60 - -10
Latvia	9.9%	1.1%	0%	-3.5%	7.3%	6 - 11%	6%	-4.3%	1.4%	2.9%	2 - 3%	4	-1	22	10 - 30
Lebanon	-4.3%	-1.9%	0%		-6.1%	-9 - -4%								-60	-80 - -40
Lesotho	-6.1%	-1.3%	0%	1.6%	-5.8%	-7 - -5%	16.5%	-40.7%	22.8%	-5%	-5 - -4%	-1	0	-3	-10 - 0
Liberia	-5.7%	-1.1%	-0.1%	1.7%	-5.3%	-8 - -4%	-0.8%	-2.1%	1.7%	-0.6%	-1 - 0%	0	0	-3	-10 - 0
Libya	-5.4%	-1.1%	0%		-6.5%	-9 - -4%								-97	-130 - -60
Liechtenstein	6.6%	-1.1%	0%		5.4%	2 - 8%								0	0 - 0
Lithuania	9%	0.8%	0%	-2.9%	6.6%	5 - 9%	7.1%	-5.4%	1.5%	2.8%	2 - 3%	4	-1	29	20 - 50
Luxembourg	2.1%	0%	0%	-0.8%	1.2%	0 - 3%	2.9%	-4.1%	1.6%	0.3%	0 - 1%	1	0	-11	-30 - 10
Macao S.A.R	-7.3%	-2%	0%		-9.1%	-12 - -7%								-75	-100 - -60
Madagascar	-5.9%	-0.8%	-0.2%		-6.9%	-10 - -3%								-19	-30 - -10
Malawi	-5.4%	-1%	0%	-0.9%	-7.3%	-11 - -5%	-3.2%	-1.3%	3.3%	-1.6%	-2 - -1%	-1	1	-11	-20 - 0
Malaysia	-9.4%	-1.2%	-0.3%	-0.7%	-11.4%	-16 - -6%	-4.6%	-14.9%	13.4%	-6.4%	-7 - -6%	-74	-2	-668	-1000 - -400
Maldives	-4.8%	-1.7%	-0.1%	1.5%	-5.1%	-8 - -3%	-4%	-2.7%	4%	-3.1%	-4 - -3%	0	0	-4	-10 - 0
Mali	-11%	-1.7%	0%	-1.6%	-14%	-22 - -11%	-4.6%	-6.5%	8.8%	-2.6%	-3 - -2%	-2	3	-36	-70 - -20
Malta	-1.4%	-0.9%	0%	0.7%	-1.5%	-4 - 0%	36.1%	-64.2%	37.3%	-1.1%	-2 - -1%	0	0	-3	-10 - 0
Marshall Islands	-3.9%	-1.1%	-2.2%		-7.1%	-10 - -5%								0	-10 - 0
Mauritania	-10.6%	-0.8%	0%	-3.3%	-14.3%	-22 - -10%	-8%	-7.1%	8.3%	-6.9%	-7 - -6%	-2	0	-20	-40 - -10
Mauritius	-3.7%	-0.8%	0%	-2%	-6.4%	-8 - -5%	-4.1%	-2.8%	3.2%	-3.6%	-4 - -3%	-2	0	-13	-20 - -10
Mexico	-4.1%	-1%	0%	1.5%	-3.6%	-7 - -1%	-1%	-5.1%	3.4%	-2.8%	-3 - -2%	-114	-17	-1000	-1540 - -490

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
							Renewable							GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
Moldova	3.2%	0.4%	0%	-1.8%	1.7%	0 - 4%	5.9%	-10%	4.1%	-0.5%	-1 - 0%	0	0	-2	-10 - 10
Monaco	-1.8%	-1.1%	0%		-2.9%	-5 - -1%								-4	-10 - 0
Mongolia	2.2%	-0.5%	0%	-0.9%	0.8%	-2 - 2%	0%	-0.2%	0.1%	-0.2%	-1 - 0%	0	0	-3	-10 - 0
Montenegro	3.7%	0.4%	0%		4.1%	1 - 7%								1	-10 - 10
Montserrat	-2.7%	-0.9%	0%		-3.5%	-6 - -3%								0	0 - 0
Morocco	-3.3%	-0.6%	0%	0.1%	-3.8%	-7 - -1%	-0.1%	-9.5%	6.8%	-3.4%	-4 - -3%	-11	-2	-98	-130 - -50
Mozambique	-4%	-0.9%	-0.4%	-1.8%	-7%	-11 - -5%	-0.6%	-0.2%	1%	0.2%	0 - 1%	-2	2	-17	-30 - -10
Myanmar	-10.4%	-1.5%	-1%	-2.3%	-14.6%	-24 - -9%	-10.8%	-6.3%	14.2%	-2.6%	-3 - -2%	-5	35	-171	-270 - -110
Namibia	-6.7%	-1.1%	0%	-1.1%	-8.7%	-11 - -6%	-0.9%	-0.6%	0.8%	-0.8%	-1 - 0%	-2	1	-13	-20 - -10
Nauru	0%	-1.1%	-0.2%		-1.3%	-2 - -1%								0	-10 - 0
Nepal	-3.2%	-1.3%	0%	0%	-4.4%	-10 - -2%	-1.1%	-2.9%	2.6%	-1.2%	-2 - -1%	-1	1	-21	-50 - -10
Netherlands	0.4%	-0.3%	-0.1%	0%	0%	-2 - 1%	5.4%	-11.1%	5.2%	-0.8%	-1 - 0%	-22	-3	-190	-370 - -110
New Caledonia	-3.3%	-0.8%	0%		-4%	-6 - -2%								0	0 - 0
New Zealand	-1.4%	-1%	-0.1%	0.4%	-2%	-3 - 0%	-0.1%	-1.1%	0.9%	-0.4%	-1 - 0%	-5	-6	-42	-90 - 20
Nicaragua	-8.9%	-1.7%	-0.1%	-2.5%	-12.7%	-20 - -7%	-1.7%	-2.2%	3.4%	-1.3%	-2 - -1%	-4	1	-31	-50 - -20
Niger	-12.1%	-1.7%	0%	-5.7%	-18.5%	-27 - -14%	-13.8%	-17.2%	19.6%	-10.2%	-11 - -10%	-4	0	-42	-80 - -30
Nigeria	-6.8%	-1%	-0.1%	0.6%	-7.2%	-12 - -4%	-2.5%	-10.7%	7.9%	-4.7%	-5 - -4%	-22	-4	-627	-1030 - -360
Niue	-3.1%	-1.1%	0%		-4.2%	-6 - -3%								0	0 - 0
Norfolk Island	-1.9%	-1.1%	0%		-3%	-4 - -2%								0	0 - 0
North Korea	3.6%	-1.1%	0%		2.4%	0 - 5%								0	0 - 0
North Macedonia	2.4%	0.2%	0%		2.7%	0 - 6%								3	-10 - 10
Northern Cyprus	-6.6%	-1.1%	0%		-7.6%	-9 - -4%								0	0 - 0
Northern Mariana Islands	-3.3%	-1.1%	-0.1%		-4.5%	-6 - -3%								-1	-10 - 0
Norway	10.3%	0.2%	0%	-3%	7.1%	4 - 9%	6.5%	-3.8%	1.3%	3.8%	3 - 4%	56	-3	304	220 - 410
Oman	-9.3%	-2%	0%		-11.1%	-18 - -8%								-174	-270 - -120
Pakistan	1.1%	-1%	-0.1%	-0.4%	-0.4%	-2 - 2%	0.1%	0.3%	-0.2%	0.1%	0 - 1%	0	0	45	-10 - 80
Palau	-3.9%	-1%	-0.4%		-5.2%	-9 - -3%								0	-10 - 0
Palestine	-5.7%	-1.1%	0%		-6.8%	-9 - -5%								0	0 - 0
Panama	-5.9%	-1.3%	-0.3%	-0.4%	-7.7%	-13 - -4%	-4.5%	-1.9%	2.2%	-4.3%	-5 - -4%	-5	0	-61	-100 - -30
Papua New Guinea	-5.7%	-1%	-0.1%	-0.6%	-7.4%	-14 - -4%	-0.5%	-1.2%	1.2%	-0.4%	-1 - 0%	-1	1	-30	-60 - -10
Paraguay	-16.2%	-1.9%	0%	-4.1%	-21.2%	-23 - -18%	-5.7%	-0.7%	3.8%	-2.7%	-3 - -2%	-10	3	-216	-250 - -200
Peru	-2%	-0.7%	0%	-0.2%	-2.9%	-5 - -1%	-0.5%	-1%	0.9%	-0.7%	-1 - 0%	-9	-2	-117	-190 - -80
Philippines	-7.1%	-1.6%	-0.3%	-4.5%	-12.9%	-19 - -10%	-15.4%	-9.9%	16.1%	-11.2%	-12 - -11%	-68	18	-677	-1010 - -480
Pitcairn Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Poland	5.8%	0.4%	0%	-2%	4.1%	2 - 7%	8.1%	-9.7%	2.9%	1.1%	1 - 2%	17	-5	7	-90 - 130
Portugal	-0.5%	-0.4%	0%	0.3%	-0.6%	-2 - 1%	-0.6%	-1.7%	1.1%	-1.2%	-2 - -1%	-11	0	-102	-150 - -70
Puerto Rico	-5.7%	-1.1%	0%		-6.8%	-11 - -5%								-148	-220 - -110
Qatar	-9%	-1.2%	0%	1.3%	-9%	-13 - -6%	-9.2%	-12.2%	15%	-6.9%	-7 - -6%	-42	0	-204	-280 - -140
Republic of Serbia	5.4%	0.5%	0%	-1.9%	4%	2 - 6%	2.4%	-4.4%	1.8%	-0.2%	-1 - 0%	1	-1	-4	-10 - 10
Republic of the Congo	-5.2%	-0.8%	0%	0.4%	-5.6%	-8 - -3%	-0.5%	-0.1%	0.1%	-0.5%	-1 - 0%	-2	0	-8	-20 - 0
Romania	5.8%	0.3%	0%	-2%	3.9%	2 - 6%	3.3%	-4.9%	2%	0.3%	0 - 1%	11	-6	32	-10 - 70
Russia	10.2%	0.3%	0%	-3.1%	7%	4 - 9%	2.2%	-1.6%	0.8%	1.4%	1 - 2%	193	-59	973	550 - 1410
Rwanda	-5.5%	-2.1%	0%	0.2%	-7.3%	-9 - -4%	3.1%	-22.2%	14.9%	-5.4%	-6 - -5%	-1	0	-10	-20 - 0
Saint Barthelemy	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Saint Helena	-1.7%	-1.1%	0%		-2.8%	-5 - -1%								0	0 - 0
Saint Kitts and Nevis	-2.8%	-1.1%	-0.1%		-4%	-7 - -3%								-1	-10 - 0
Saint Lucia	-5.1%	-1.2%	0%		-6.3%	-10 - -4%								-2	-10 - 0
Saint Martin	-2.7%	-1.1%	0%		-3.8%	-6 - -3%								0	0 - 0
Saint Pierre and Miquelon	0.8%	-1.1%	0%		-0.4%	-2 - 1%								0	0 - 0
Saint Vincent and the Grenadines	-3.5%	-1.3%	-0.1%		-4.9%	-8 - -3%								-1	-10 - 0
Samoa	-3.2%	-0.9%	0%		-4.1%	-7 - -3%								-1	-10 - 0
San Marino	0.5%	-1.1%	0%		-0.6%	-3 - 1%								-1	-10 - 0

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
							Renewable							GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
São Tomé and Principe	-4.5%	-0.5%	-0.3%		-5.2%	-10 - -4%								0	-10 - 0
Saudi Arabia	-12.5%	-1.5%	0%	4.4%	-9.9%	-19 - -5%	-3.1%	-2.6%	2.3%	-3.4%	-4 - -3%	-166	-9	-1359	-2480 - -800
Scarborough Reef	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Senegal	-5.5%	-1.6%	-0.1%	0.3%	-6.9%	-13 - -5%	-2.5%	-0.9%	1.5%	-2%	-2 - -1%	-3	1	-27	-50 - -20
Serranilla Bank	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Seychelles	-3.5%	-1.2%	-1%		-5.6%	-10 - -4%								-2	-10 - 0
Siachen Glacier	8.9%	-1.1%	0%		7.7%	3 - 10%								0	0 - 0
Sierra Leone	-4%	-1.3%	-0.8%	1.5%	-4.6%	-7 - -4%	-0.4%	-3.4%	3.2%	-1.1%	-2 - -1%	0	0	-3	-10 - 0
Singapore	-8.3%	-2%	0%	-0.2%	-10.3%	-19 - -7%	18.4%	-79.6%	55.6%	-9%	-10 - -9%	-80	0	-564	-1040 - -420
Sint Maarten	-2.7%	-1.1%	0%		-3.8%	-6 - -3%								-1	-10 - 0
Slovakia	6.2%	0.4%	0%	-2%	4.6%	3 - 6%	10.2%	-13.3%	5.3%	1.2%	1 - 2%	6	-1	18	-20 - 40
Slovenia	5%	0.5%	0%	-1.9%	3.5%	2 - 5%	3%	-5.4%	2.7%	0.3%	0 - 1%	2	0	-4	-20 - 10
Solomon Islands	-5.1%	-1%	-0.3%		-6.4%	-11 - -4%								-1	-10 - 0
Somalia	-6.1%	-1.1%	0%		-7.2%	-11 - -5%								-8	-20 - 0
Somaliland	-5.3%	-1.1%	0%		-6.4%	-10 - -4%								0	0 - 0
South Africa	-5.6%	-0.9%	0%	2%	-4.7%	-6 - -3%	-2.5%	-1.8%	1.5%	-2.8%	-3 - -2%	-41	-1	-333	-420 - -290
South Georgia and the Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
South Korea	-4.1%	-1.2%	0%	0.6%	-4.8%	-8 - -2%	-3%	-1.1%	1.2%	-2.8%	-3 - -2%	-211	1	-1092	-1450 - -500
South Sudan	-14.7%	-1.1%	0%		-15.7%	-23 - -11%								0	0 - 0
Southern Patagonian Ice Field	16%	-1.1%	0%		14.7%	11 - 17%								0	0 - 0
Spain	-3%	-0.7%	0%	1.1%	-2.6%	-4 - -1%	-0.4%	-6.7%	5.4%	-1.9%	-2 - -1%	-125	-5	-851	-1150 - -610
Spratly Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
Sri Lanka	-8.2%	-1%	-0.1%	0.1%	-9.1%	-20 - -5%	-10.2%	-4.9%	9.7%	-7.8%	-8 - -7%	-13	5	-147	-330 - -70
Sudan	-19.3%	-3.8%	0%		-22.4%	-29 - -15%								-428	-580 - -250
Suriname	-6%	-1.3%	-0.4%		-7.6%	-12 - -5%								-8	-20 - 0
Sweden	4.1%	0%	0%	-0.9%	3.2%	2 - 5%	2.2%	-2.5%	1%	0.7%	0 - 1%	19	-2	42	-40 - 110
Switzerland	4.7%	-0.6%	0%	-1.7%	2.3%	0 - 5%	3.9%	-5.9%	2.8%	0.6%	0 - 1%	34	-3	-68	-250 - 140
Syria	-6.2%	-1%	0%	-1%	-8.1%	-12 - -5%	3.7%	-48.3%	43.3%	-2.4%	-3 - -2%	-3	-2	-21	-30 - -10
Taiwan	-7.3%	-1.1%	0%		-8.4%	-11 - -5%								0	0 - 0
Tajikistan	2.3%	-0.1%	0%	-1.1%	1.1%	0 - 3%	7.3%	-6.7%	1.4%	0.8%	0 - 1%	0	0	1	0 - 10
Thailand	-8.2%	-1.3%	-0.2%	-1%	-10.4%	-13 - -7%	-7.8%	-2.6%	3.3%	-7.1%	-8 - -7%	-116	6	-892	-1230 - -690
The Bahamas	-3.2%	-1.1%	-0.3%		-4.6%	-7 - -3%								-9	-20 - 0
Togo	-7.9%	-2.1%	0%	-2.6%	-12.2%	-17 - -6%	-6.2%	-17.5%	16.3%	-7.4%	-8 - -7%	-1	0	-14	-20 - 0
Tonga	-3.5%	-1%	-0.3%		-4.7%	-7 - -3%								0	-10 - 0
Trinidad and Tobago	-4.9%	-1%	0%	1.1%	-4.9%	-7 - -3%	-2.6%	-2%	1.7%	-2.9%	-3 - -2%	-2	0	-21	-30 - -10
Tunisia	-5.9%	-0.6%	0%	-0.6%	-7%	-10 - -4%	7.5%	-93.9%	83.5%	-4.4%	-5 - -4%	-8	16	-67	-90 - -30
Turkey	0.1%	-0.8%	0%	-0.4%	-1.1%	-3 - 1%	2.3%	-6.2%	2.6%	-1.3%	-2 - -1%	-19	-14	-192	-430 - 120
Turkmenistan	4.3%	-1.1%	0%		3.1%	0 - 5%								26	10 - 40
Turks and Caicos Islands	-2.9%	-1.2%	-0.7%		-4.7%	-7 - -3%								-1	-10 - 0
Tuvalu	0%	-1.2%	-4.6%		-5.7%	-7 - -5%								0	-10 - 0
Uganda	-6%	-1.9%	0%	-0.5%	-8.2%	-20 - -6%	-3.8%	-22.7%	21.8%	-6.3%	-7 - -6%	-5	-2	-47	-110 - -20
Ukraine	5.9%	0.2%	0%	-2.9%	3%	1 - 5%	7.2%	-10.6%	3.7%	-0.2%	-1 - 0%	6	-5	1	-40 - 20
United Arab Emirates	-11.3%	-1.7%	0%	-0.6%	-13.3%	-22 - -10%	8%	-48.4%	33%	-9.2%	-10 - -9%	-98	0	-843	-1310 - -660
United Kingdom	0.5%	-0.6%	0%	0.3%	0.1%	-2 - 1%	2.7%	-5.8%	2.9%	-0.2%	-1 - 0%	-33	-4	-411	-1100 - 90
United Rep. of Tanzania	-4.5%	-1.2%	0%	-1.1%	-6.7%	-10 - -4%	-6.2%	-16.6%	20%	-3.3%	-4 - -3%	-7	33	-55	-80 - -30
United States Minor Outlying Islands	0%	-1.1%	0%		-1.1%	-2 - -1%								0	0 - 0
USA	-2.8%	-0.9%	0%	-1.1%	-4.7%	-7 - -3%	-1.6%	-2.1%	1.7%	-2.1%	-3 - -2%	-1166	-34	-13466	-20680 - -8860
United States Virgin Islands	-2.6%	-1.1%	0%		-3.8%	-6 - -3%								-4	-10 - 0
Uruguay	-4.8%	-1.7%	0%	-0.5%	-6.9%	-8 - -5%	-5.7%	-0.2%	1.9%	-4%	-5 - -4%	-6	1	-103	-120 - -90
US Naval Base Guantanamo Bay	-5.4%	-1.1%	0%		-6.4%	-10 - -5%								0	0 - 0
Uzbekistan	6.5%	0.4%	0%		6.9%	5 - 11%								111	90 - 150
Vanuatu	-2.8%	-1.1%	-0.1%		-4%	-6 - -3%								-1	-10 - 0

	GDP Change (%)						Captial Change (%)					Total Change ($billion)			
									Renewable					GDP	
Country	Direct	Trade	SLR	Capital	Total	IQR	Produced	Direct	Feedback	Total	IQR	Prod.	Ren.	(30-yr)	IQR
Vatican	-2.2%	-1.1%	0%		-3.3%	-5 - -2%								0	0 - 0
Venezuela	-8.1%	-0.9%	0%	-1.6%	-10.4%	-17 - -6%	-5.3%	-6.4%	5.9%	-6%	-6 - -5%	-91	-1	0	0 - 0
Vietnam	-6.1%	-1%	-0.9%	-1.2%	-9%	-13 - -6%	-8.8%	-39.9%	42.3%	-7%	-8 - -7%	-35	14	-386	-570 - -280
Wallis and Futuna	-3.4%	-1.1%	0%		-4.5%	-7 - -3%								0	0 - 0
Western Sahara	-6.4%	-1.1%	0%		-7.5%	-10 - -6%								0	0 - 0
Yemen	-5%	-1.2%	0%	-0.9%	-7%	-12 - -3%	0.9%	-87.4%	84%	-4.8%	-5 - -4%	-5	144	-68	-150 - -20
Zambia	-4.4%	-0.6%	0%	1.3%	-3.7%	-8 - -2%	0%	-0.4%	0.5%	-0.4%	-1 - 0%	-2	0	-15	-30 - -10
Zimbabwe	-4.7%	-2%	0%	3.1%	-3.7%	-7 - -2%	-0.3%	-0.6%	1.2%	0.3%	0 - 1%	0	1	-17	-30 - -10

References

S. Acevedo, M. Mrkaic, N. Novta, E. Pugacheva, and P. Topalova. The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics*, 65:103207, 2020.

F. Baarsch, J. R. Granadillos, W. Hare, M. Knaus, M. Krapp, M. Schaeffer, and H. Lotze-Campen. The impact of climate change on incomes and convergence in africa. *World Development*, 126: 104699, 2020.

B. A. Bastien-Olvera, F. Granella, and F. C. Moore. Persistent effect of temperature on gdp identified from lower frequency temperature variability. *Environmental Research Letters*, 17(8):084038, 2022.

M. Burke, S. M. Hsiang, and E. Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239, 2015.

M. Burke, W. M. Davis, and N. S. Diffenbaugh. Large potential reduction in economic damages under un mitigation targets. *Nature*, 557(7706):549–553, 2018.

C. W. Callahan and J. S. Mankin. National attribution of historical climate damages. *Climatic Change*, 172(3-4):40, 2022.

V. M. Carvalho and A. Tahbaz-Salehi. Production networks: A primer. *Annual Review of Economics*, 11:635–663, 2019.

J.-J. Chang, Z. Mi, and Y.-M. Wei. Temperature and gdp: A review of climate econometrics analysis. *Structural Change and Economic Dynamics*, 66:383–392, 2023.

Copernicus. 2023 is the hottest year on record, with global temperatures close to the 1.5°c limit, 2024. https://climate.copernicus.eu/copernicus-2023-hottest-year-record.

R. Damania, S. Desbureaux, and E. Zaveri. Does rainfall matter for economic growth? evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102: 102335, 2020.

I. De Vos and G. Everaert. Bias-corrected common correlated effects pooled estimation in dynamic panels. *Journal of Business & Economic Statistics*, 39(1):294–306, 2021.

M. Dell, B. F. Jones, and B. A. Olken. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95, 2012.

M. Henseler and I. Schumacher. The impact of weather on economic growth and its production factors. *Climatic change*, 154(3):417–433, 2019.

P. H. Howard and T. Sterner. Few and not so far between: a meta-analysis of climate damage estimates. *Environmental and Resource Economics*, 68(1):197–225, 2017.

M. E. Kahn, K. Mohaddes, R. N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang. Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, 104:105624, 2021.

M. Kalkuhl and L. Wenz. The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103:102360, 2020.

J. S. Kikstra, P. Waidelich, J. Rising, D. Yumashev, C. Hope, and C. M. Brierley. The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. *Environmental Research Letters*, 16(9):094037, 2021.

M. Kotz, A. Levermann, and L. Wenz. The effect of rainfall changes on economic production. *Nature*, 601(7892):223–227, 2022.

S. Managi and P. Kumar. *Inclusive wealth report 2018*. Taylor & Francis, 2018.

I. B. Nath, V. A. Ramey, and P. J. Klenow. How much will global warming cool global growth? Technical report, Working paper, 2023.

B. O'Neill, M. van Aalst, Z. Z. Ibrahim, L. B. Ford, S. Bhadwal, H. Buhaug, D. Diaz, K. Frieler, M. Garschagen, A. Magnan, G. Midgley, A. Mirzabaev, A. Thomas, and R. Warren. Key risks across sectors and regions. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, and B. Rama, editors, *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 2411–2538. Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022. doi: 10.1017/9781009325844.025.

F. Piontek, L. Drouet, J. Emmerling, T. Kompas, A. Méjean, C. Otto, J. Rising, B. Soergel, N. Taconet, and M. Tavoni. Integrated perspective on translating biophysical to economic impacts of climate change. *Nature Climate Change*, 11(7):563–572, 2021.

F. Pretis, M. Schwarz, K. Tang, K. Haustein, and M. R. Allen. Uncertain impacts on economic growth when stabilizing global temperatures at 1.5 c or 2 c warming. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2119):20160460, 2018.

T. N. Sequeira, M. S. Santos, and M. Magalhães. Climate change and economic growth: a heterogeneous panel data approach. *Environmental Science and Pollution Research*, 25:22725–22735, 2018.

P. Waidelich, F. Batibeniz, J. Rising, J. S. Kikstra, and S. I. Seneviratne. Climate damage projections beyond annual temperature. *Nature Climate Change*, pages 1–8, 2024.

Y. Yang, F. Jia, and H. Li. Estimation of panel data models with mixed sampling frequencies. *Oxford bulletin of economics and statistics*, 85(3):514–544, 2023.

X. Zhao, M. Gerety, and N. V. Kuminoff. Revisiting the temperature-economic growth relationship using global subnational data. *Journal of environmental management*, 223:537–544, 2018.