Persistent effect of El Niño on global economic growth

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El Niño-Southern Oscillation (ENSO) shapes extreme weather globally, causing myriad socioeconomic impacts, but whether economies recover from ENSO events and how anthropogenic changes to ENSO will affect the global economy are unknown. Here we show that El Niño persistently reduces country-level economic growth, attributing $4.1T and $5.7T in global income losses to the 1982-83 and 1997-98 events, respectively. Increased ENSO amplitude and teleconnections from warming cause $84T in 21st-century economic losses in an emissions scenario consistent with current mitigation pledges, but these effects are shaped by stochastic variation in the sequence of El Niño and La Niña events. Our results highlight the sensitivity of the economy to climate variability independent of warming and the potential for future losses due to anthropogenic intensification of such variability.

As the leading mode of interannual climate variability, El Niño-Southern Oscillation (ENSO) integrates a wide range of Earth system processes (*1*). El Niño events shift deep convection from the western to the eastern Pacific, shaping global weather through "teleconnections" (*2*, *3*). The resulting temperature and hydroclimate extremes have many well-documented impacts, including flooding (*4*, *5*), crop losses (*6*, *7*), and civil conflict (*8*). Many climate models project that warming will increase El Niño amplitude (*9*, *10*) and frequency (*11*), with potentially devastating socioeconomic impacts (*12*).

Despite ENSO's global impacts, however, empirical climate-economy studies have generally focused on temperature and rainfall averages (*13–16*) or variability (*17*), leaving the costs of changes in modes of climate variability unquantified. While studies have shown that El Niño reduces contemporaneous economic growth (*18–20*) and drives commodity price fluctuations (*21–23*), it remains unclear if and for how long its impacts persist. Distinguishing between transient and persistent impacts on economic growth is essential. Transient impacts ("level effects") are quickly recovered, as an economy rebounds to its original trajectory. Persistent impacts ("growth effects") reduce an economy's ability to grow, compounding exponentially in time. Poor observational constraints on growth effects limit our understanding of the economic costs of ENSO and climate damages broadly (*24–26*).

Here we estimate the effect of ENSO on past and future economic growth, accounting for the spatiotemporal heterogeneity of ENSO teleconnections. We define ENSO by the E-index and C-index (*27*) (Fig. S1). These metrics of El Niño and La Niña, respectively, capture the nonlinear feedbacks that drive ENSO (Methods). We define country-level teleconnections for each index (τ^E and τ^C) using correlations between the indices and country-level temperature and rainfall (Methods, Fig. S2). Teleconnections are strongest in tropical countries and weaker in the midlatitudes (Fig. 1a), consistent with the physical responses of regional climate to tropical variability (*28*).

We use a distributed lag regression model to quantify the effect of ENSO on growth in national Gross Domestic Product per capita (GDPpc) from 1960-2019. Departing from previous work (*8*, *19*, *20*), we interact the E- and C-indices with teleconnections to allow the economic effect of ENSO to vary smoothly as a function of teleconnection strength (*29*) (Methods). Our model compares economic growth before and after El Niño events to assess their cumulative effects over time and distinguish growth from level effects (Methods). We focus on the five years following El Niño events, but also evaluate effects for more than ten years as well as for La Niña. We then couple these empirical estimates with climate model projections to assess the future economic effects of changes to ENSO amplitude and teleconnections.

El Niño persistently reduces economic growth

El Niño events persistently decrease economic growth (Fig. 1b). The magnitude of this effect is determined by the strength of each country's E-index teleconnection. In Peru ($\tau^E = 1.18$), for example, a 1-standard-deviation (s.d.) El Niño event decreases growth by 1.3 percentage points (p.p.) in the year of the event (95% confidence interval [CI]: 0.9 – 1.7 p.p.). After five years, growth in Peru has declined by 6.2 p.p. (CI: 4.7 – 8.2) (Fig. 1b). By contrast, weakly teleconnected countries experience small and uncertain effects (Fig. 1b). Interacting El Niño and teleconnections allows us to calculate marginal effects for each country based on their τ^E value (Fig. 1c) and allows statistical significance to be determined by uncertainty in the distributed lag model (Fig. 1c hatching), rather than prescribing "teleconnected" and "non-teleconnected" countries. 56% of countries experience significant declines in growth 5 years after El Niños, averaging 2.3 p.p., not simply level effects from which they recover immediately (Fig. 1d).

These negative effects are robust to using alternative ENSO indices, growth data, standard error clustering, or teleconnection metrics, as well as excluding the most strongly teleconnected countries (SM

Text, Figs. S3-S5). They also vary little over the 1960-2019 period, indicating little effect heterogeneity in time (Fig. S6). ENSO indices vary through time but not space, raising the possibility that our results are confounded by time-varying global economic shocks. However, alternative specifications demonstrate that time-varying confounders are not driving our results: Adding country-specific trends to control for technological or demographic changes has little effect (Fig. S4) since ENSO is stochastic (*30*) and measured by detrended indices. Using a spatially varying country-level index of ENSO or discretizing the sample into teleconnected and non-teleconnected groups allow us to include both country and year fixed effects, and yield results as strong as our main estimates (Methods, Fig. S7), but we do not use these models in our main analysis since they do not preserve the independent and joint effects of ENSO amplitude and teleconnections (Methods). Bootstrap resampling by year or dropping each year or country, ensuring that single years or countries are not driving the results, yield similar effects (Fig. S3). Finally, dropping the 1983 and 1998 El Niño events, which coincided with financial crises, reduces the magnitude of ENSO effects by only ~12% (Fig. S4).

Our main observational analysis (Figs. 1, 2) uses 5 lags, which reflects a balance between tracing the long-run response to ENSO and a concern for statistical power given the short observational record. Additional lags fit the data better, but at the cost of model stability; using 5 lags balances these effects (Fig. S8). Yet models with more lags reveals that El Niño effects can persist to 12 years or beyond, though a rebound begins after ~10 years (Figs. S8, S9), implying that our 5-year results for the historical costs of El Niño are conservative. After >14 years, the effects of ENSO cannot confidently be distinguished from zero. However, data simulations using a perfect model framework, where we impute a permanent effect of El Niño to data, demonstrate that models with many lags can yield insignificant coefficients due to the reduced sample size and large number of parameters (Methods, Fig. S8). The perfect model framework implies that, even if the real-world effects of ENSO were permanent, we may not be able to detect them given the short observational record. Finally, even if economies do eventually rebound from ENSO, the fact that damages accumulate for more than a decade means that the costs of climate variability are much larger than typically assumed in climate-economy models (*31*).

Our empirical model includes both the E-index and C-index, allowing us to distinguish the effects of eastern Pacific (EP) El Niño and central Pacific (CP) La Niña (Methods). CP La Niña events have beneficial effects (Fig. S10), but they are several times weaker than the negative effects of EP El Niño and statistically insignificant under alternative standard error clustering (Table S2). These results reflect the skewness of ENSO itself, whereby EP El Niños tend to be stronger than both La Niñas and CP El Niños, and are consistent with studies showing that La Niña's economic effect is small (*19*, *20*).

The countries most affected by ENSO are generally lower-income, tropical countries (*19*). However, high-income countries also experience significant negative effects (Fig. S4), consistent with work showing that these countries are impacted by extreme rainfall (*32*) and heat (*33*), both of which ENSO affects. We also identify persistent losses across countries that experience wetting and drying in response to El Niño (Fig. S4), as both anomalously low and high rainfall can be damaging (*32*). We emphasize that some regions may experience benefits from El Niño or losses from La Niña. Our goal is to estimate a globally generalizable response to ENSO. That our findings are robust across multiple lines of country heterogeneity provides confidence that they are generalizable, even if individual regions may respond differently.

Losses from historical El Niño events

The persistent effect of ENSO implies that historical El Niño events have altered the income growth of teleconnected countries, potentially generating large economic losses. Here we quantify the costs of the two largest El Niño events in the last 60 years, in 1982-83 and 1997-98 (Fig. 2). Because an El Niño can trigger a subsequent La Niña (*34*), our analysis incorporates both the negative effects of each El Niño and the benefits of the following La Niña (Methods). Furthermore, because these events coincided with unrelated currency crises, we use a model excluding these events to more conservatively calculate their impacts (Fig. S4).

Consider strongly teleconnected Peru ($\tau^E = 1.18$): Its GDPpc declined in 1998 and stagnated for three more years (Fig. 2a). Given the 1997 financial crisis, Peru's slower growth in 1998 is not entirely attributable to ENSO, but Peru's economy would have grown more quickly if the 1997-98 El Niño had not occurred (Methods). Income for the average Peruvian would have been some $1,246 greater five years later in 2003 absent the event (CI: $853 – $1,793), a 19% increase (Fig. 2a). Other tropical countries such as Ecuador, Brazil, and Indonesia lost anywhere from 5% to 19% of GDPpc (Fig. S11).

We estimate global losses from the 1982-83 and 1997-98 events to be trillions of dollars each (Fig. 2b, S11). Our estimates exceed previous ones because we account for ENSO's growth effects: one study placed the total costs of the 1997-98 El Niño at $36 billion (*35*). Our accounting has losses from the 1997-98 event rising to three orders of magnitude more than that estimate, some $5.7T by 2003 (CI: $2.3T – $9.2T). The earlier 1982-83 event tallied $4.1T by 1988 (CI: $2.3T – $6T). The greater costs of the 1997-98 event result both because it was a stronger El Niño and because the global economy was larger. Absent the compensating benefits of the subsequent La Niñas, the 1983 (1998) event would have produced losses of $4.4T ($8T) (Fig. 2b).

We focus on 5 lags in this historical analysis to balance the imperatives of tracking the effects of ENSO and maximizing statistical power (Fig. S8). Because the effect of El Niño appears to persist for more than five years (Fig. S8), the ultimate toll of these events may be even higher than we show here. In fact, by incorporating growth reductions following the event and including all countries in a single framework, we show that estimates focusing on physical asset losses in low-income countries have strongly underestimated the global economic toll of El Niño.

Climate model projections of ENSO

ENSO's persistent effect raises the question of how it will shape the global economy with further warming. Using climate model simulations from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) that skillfully simulate eastern Pacific SSTs, we analyze projected changes to ENSO under four Shared Socioeconomic Pathways (SSPs) (Methods).

El Niño amplitude and teleconnections both increase with warming in CMIP6 (Fig. 3). This response is not scenario-dependent, likely due to the influence of internal climate variability on forced ENSO changes (*36*–*38*). Median amplitude increases by 5 – 21% across scenarios (Fig. 3a), a function of stronger wind-ocean coupling in the eastern Pacific (*9*, *12*). Global mean teleconnections increase by 4 – 15% (Fig. 3b), consistent with a more energetic atmospheric response to El Niño (*39*, *40*). Despite these forced responses, internal variability (proxied by multiple realizations from each model) can vary these responses by >60 p.p. (Fig. 3a, b, lower lines).

Beyond amplitude and teleconnection changes, climate projections differ in their E-index time series. Due to ENSO's sensitivity to initial conditions (*36*–*38*) and multidecadal variability (*41*, *42*), a wide range of E-index values across models and scenarios can occur in a given year, even controlling for amplitude (Fig. 3c, S12). For example, Figure 3c shows two SSP2-4.5 simulations with similar amplitude changes and E-index skewness but different sequences of EP El Niños and La Niñas. As quantified by the sum of the E-index over the 21st century, MIROC-ES2L r6i1p1f2 experiences strong El Niño events while CESM2-WACCM r3i1p1f1 is dominated by La Niña events. Such differences in the ENSO sequence shape projected damages, as an El Niño-dominated time series yields greater damages than a La Niña-dominated one due to their differential effects (Fig. S10). Crucially, because El Niños are stronger than La Niñas, the expectation from increased ENSO amplitude is net losses.

We combine these projections with our empirical estimates to quantify the economic effects of changes in ENSO. We use the SSPs as baselines against which we calculate country-level growth changes based on ENSO amplitude and teleconnection projections (Methods). Departing from our historical estimates (Figs. 1 and 2), we project future ENSO damages with a model that extends damages out to ~14 years because we can confidently detect damage accumulation that long, yet cannot identify truly permanent growth effects due to the short observational record (Fig. S8). As such, we make the conservative choice to allow economies to fully recover from future ENSO events after 14 years in our projections (Methods). This simplifying choice assumes that the time persistence of ENSO impacts is homogenous. However, it is possible that different countries recover over different time scales. For example, weakly teleconnected countries may rebound more quickly (Fig. 1d), and the sectoral makeup of an economy (e.g., agriculture- vs. manufacturing-dependent) may affect the speed with which it can reinvest in new growth after El Niño events. Further research into whether, how, and over what time scales economies recover from El Niño events would reduce uncertainty in our projections and help economies manage extreme climate events more broadly.

Economic impacts of future ENSO changes

Projected anthropogenic changes to El Niño amplitude and teleconnections will likely cause substantial economic losses over the 21st century (Fig. 4). Under a 2% discount rate (*43*) and a socioeconomic scenario consistent with current pledges to reduce greenhouse gas emissions (*44*) (SSP2-4.5), the median cumulative 2020-2099 global losses are \$84T (Fig. 4a), a ~1% reduction in global economic output over the 21st century. In all four scenarios, median losses exceed \$18T and damages are negatively skewed, consistent with the asymmetry in ENSO itself.

The range of these projections is large. Under SSP2-4.5, the 95% range spans losses of \$453T to benefits of \$80T (we write this CI as -\$453T – +\$80T) across 86,000 combinations of 86 simulations and 1,000 regression bootstraps (Fig. 4a). Reducing the discount rate to 1% amplifies median losses under SSP2-4.5 to \$130T (-\$687T – +\$130T), while increasing it to 5% diminishes losses to \$26T (-\$162T – +\$34T). The extreme end of these ranges implies a ~5% reduction in global economic output. In highly teleconnected countries, ENSO changes cause GDPpc reductions of >1% per year, though uncertainty is high even in these countries (Fig. S11).

Despite this range across realizations, models, and scenarios, increases in ENSO amplitude and teleconnections are systematically related to greater economic losses (Fig. 4b, c). Each 1% increase in ENSO amplitude is associated with \$4.1T in additional discounted losses over the 21st century ($p < 0.001$), and each 1% increase in teleconnections is associated with \$6.3T in losses ($p < 0.001$). These findings build upon previous projections of changes in ENSO amplitude (*9*, *11*) and teleconnections (*39*, *40*), demonstrating global socioeconomic effects of these physical changes.

These relationships, however, are heterogeneous, as the largely stochastic sequence of El Niños and La Niñas shapes the direction and magnitude of damages. Simulations with E-index sums greater than 0 (i.e., El Niño-dominated time series) exhibit a negative relationship between ENSO amplitude increases and damages (Fig. 4b, red dots), but the opposite is true for La Niña-dominated time series (blue dots). The same pattern holds for teleconnection changes (Fig. 4c). Critically, because El Niños are stronger than La Niñas, there are many more El Niño- than La Niña-dominated time series. On average, therefore, increases in ENSO amplitude and teleconnections produce large economic losses.

Alternative analytical choices, including incorporating C-index changes or holding teleconnections constant, alter the magnitude of losses but do not change the core result of negative damages with warming (Fig. S13). Using only one realization per model increases uncertainty across scenarios (Fig. S13b), highlighting the importance of large ensembles to capture ENSO variability (*37*). Assuming that damage persistence is permanent substantially increases the magnitude and uncertainty in projected damages (Fig. S13d). Finally, controlling for country-average temperature in our regression does not alter the effect of ENSO (Fig. S14), meaning our results are distinct from temperature-based damage projections (*13*). ENSO affects sub-national and sub-annual extreme heat or rainfall, and other hazards such as drought, all of which have independent impacts (*32*, *45*, *46*).

Our findings have implications for climate mitigation and adaptation. All else being equal, increased ENSO amplitude and teleconnections will generate major economic losses not currently included in assessments of climate damages or mitigation benefits. However, the facts that (1) ENSO-driven damages do not depend strongly on emissions scenario (Fig. 4a) and (2) a range of outcomes are possible due to uncertainty in the unique ENSO sequence going forward (Fig. 4b, c) together imply that emissions reductions alone are insufficient to protect economies from El Niño. While mitigation remains critical to blunt the catastrophic impacts of anthropogenic warming (*47*), our findings also raise the priority of climate adaptation and resilience efforts. Improved disaster risk management and ENSO early warning could reduce ENSO-driven damages (*48*), and scientific investments in decadal climate prediction could reduce the uncertainty in projections of these damages.

Conclusion

Our finding that El Niño has a persistent effect on economic growth has four key implications. Firstly, it demonstrates that growth is highly sensitive to climate variability independent of warming. Our findings demonstrate that the local extreme conditions associated with ENSO integrate into a globally persistent macroeconomic effect, implying large and underestimated costs of historical El Niño events. Secondly, our results demonstrate that future changes to ENSO may increase the macroeconomic costs of warming. Previous climate-economy studies have not incorporated changes in climate variability, and we show that this omission has hidden a potentially major cost of rising temperatures. Thirdly, stochastic variation in ENSO could result in either losses or benefits from warming, emphasizing the importance of investing in ENSO prediction, particularly on decadal time scales (*41*). Lastly, these findings together suggest that while climate mitigation is essential to reduce accumulating damages from warming, it is imperative to devote more resources to adapting to El Niño in the present day.

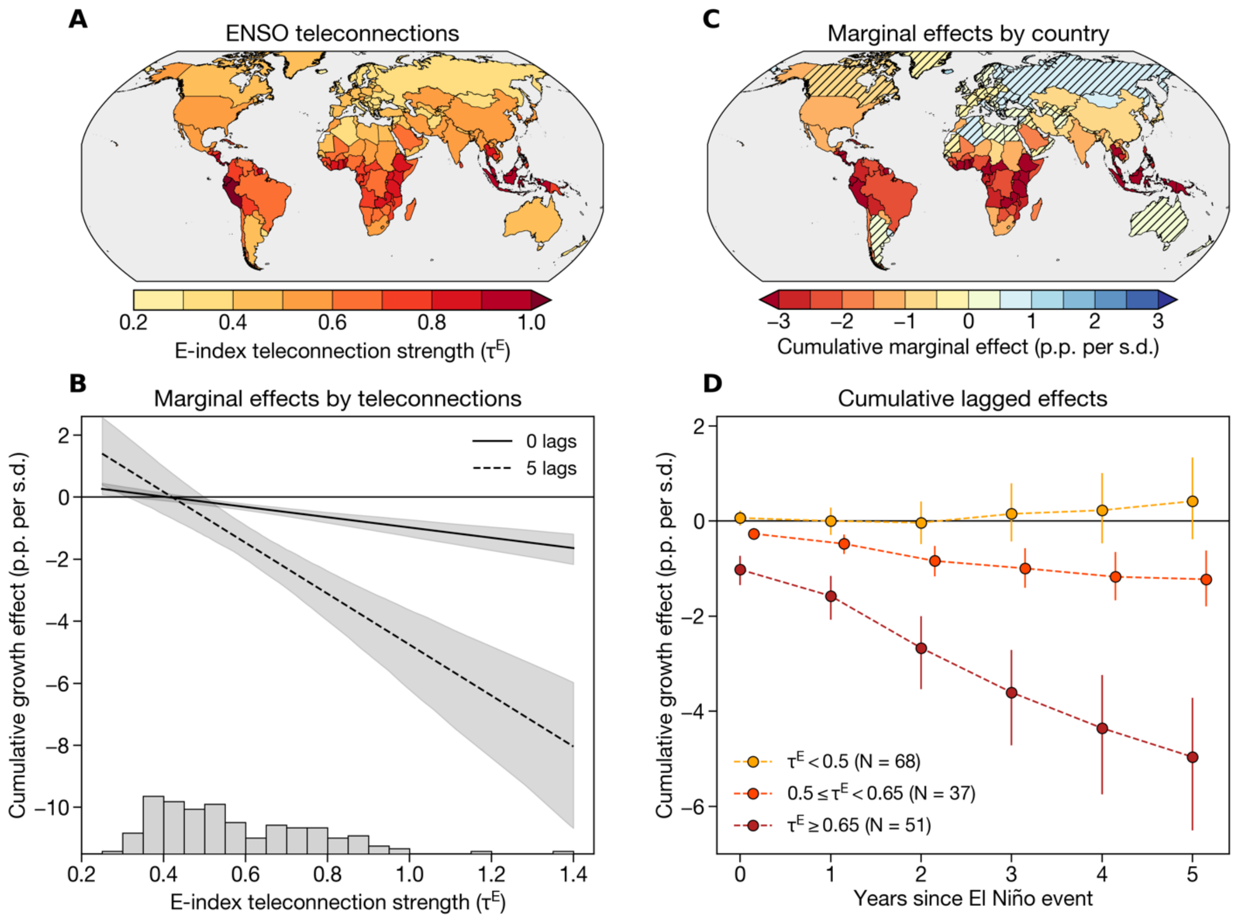

Fig. 1 | Teleconnections mediate the effect of El Niño on economic growth. A) Country-level ENSO teleconnections, calculated as the sum of the absolute value of the correlation coefficients between the E-index and monthly country-level temperature and precipitation (Methods). **B)** Marginal effects of El Niño on economic growth across teleconnection values in year of the event (0 lags, solid line) and the fifth year after the event (5 lags, dashed line). Black line shows the mean and shading shows 95% confidence intervals from bootstrap resampling (Methods). Lower histogram shows the density of teleconnection values in the sample. **C)** Cumulative 5-lag effect of El Niño on economic growth for each country. Hatching denotes countries whose effects are not distinguishable from zero (i.e., they fall on a location on the x-axis in (B) where the shading includes zero). **D)** Cumulative effects of El Niño over time, beginning with the year of the event (year 0) and accumulating to the fifth year after the event (year 5). Countries are grouped into three bins according to their teleconnection strength, with “N” denoting the number of countries in each bin. Dots show averages and bars show 95% confidence intervals.

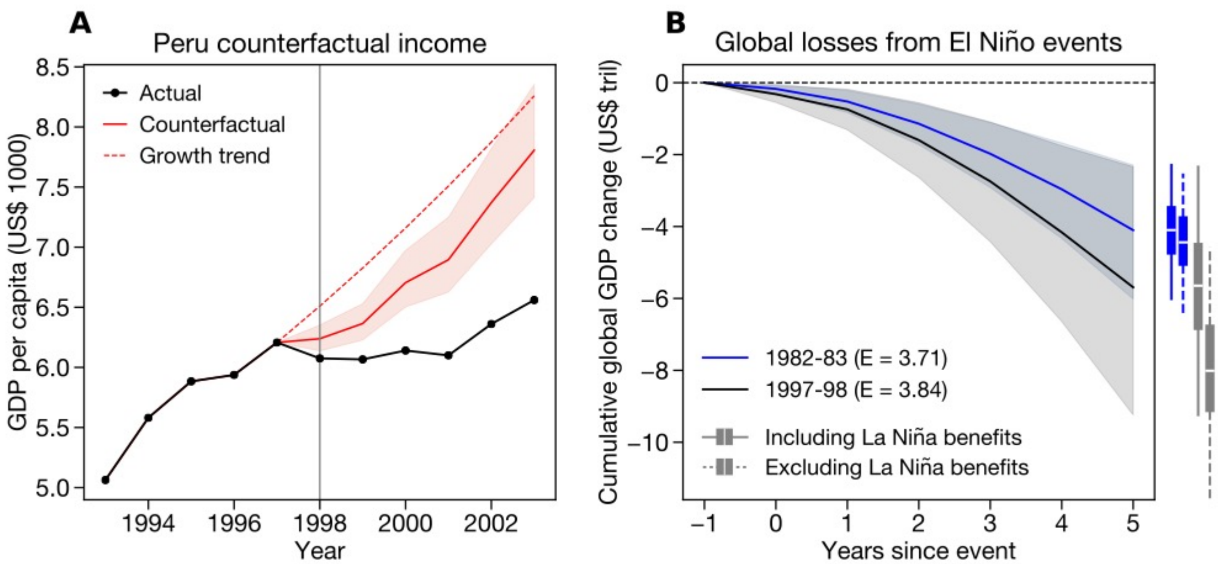

Fig. 2 | Damages from extreme El Niño events. A) GDP per capita (GDPpc) in Peru before and after the 1997-98 El Niño event. Black line shows actual GDPpc, red line shows the average counterfactual GDPpc across regression bootstrap samples (Methods), and red shading shows 95% confidence interval. Dashed line shows GDPpc if Peru had maintained its average growth rate from the 5 years preceding the event. **B)** Cumulative global GDP change for the 5 years after the 1982-83 (blue) and 1997-98 (black) El Niño events. Center line shows the mean and shading shows the 95% confidence intervals across regression bootstrap samples. Global GDP change is only calculated for countries with statistically significant marginal effects (Fig. 1c). Text in legends denotes the DJF-average E-index in the corresponding years. Boxplots at right show cumulative global GDP change when including the benefits of the following La Niña events (solid lines) and excluding those benefits (dashed lines). All dollar values are in constant 2017 prices.

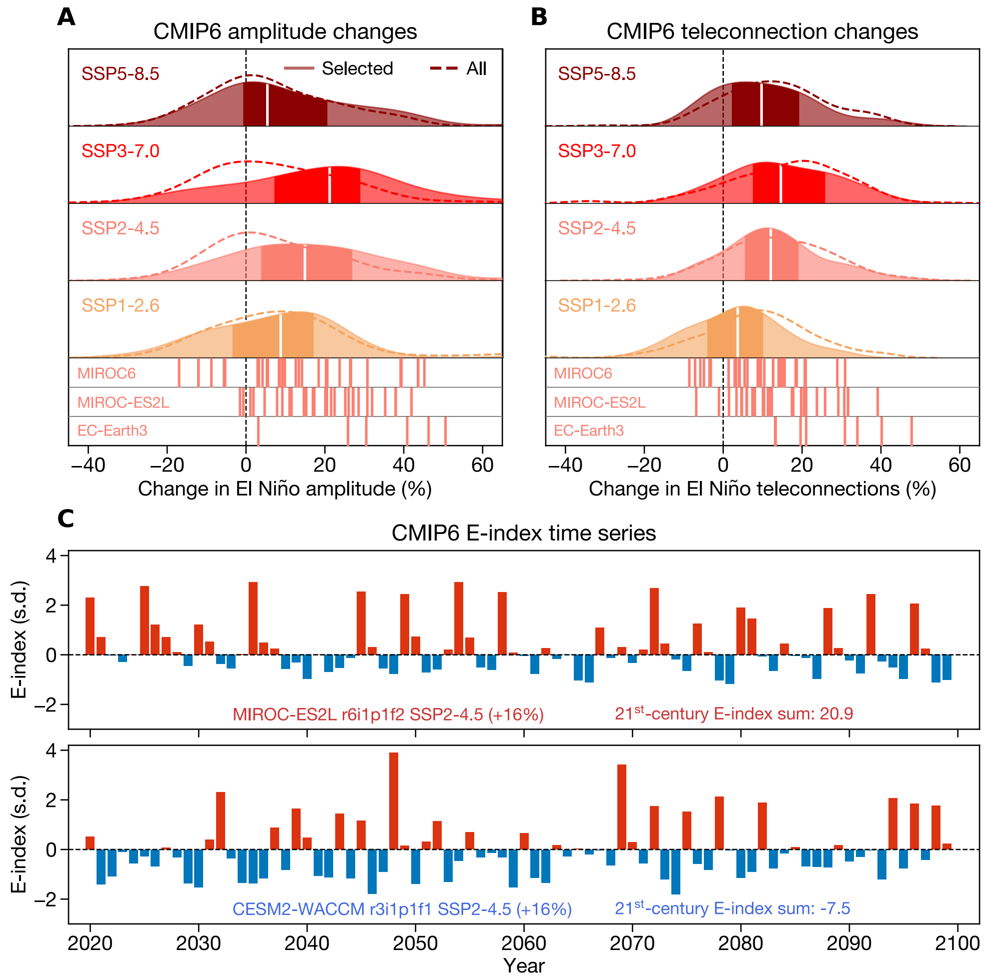

Fig. 3 | Climate model projections of ENSO. Change in ENSO amplitude (**A**) and global mean teleconnection strength (**B**) between 1940-2019 and 2020-2099 for an ensemble of CMIP6 simulations from four SSP experiments. In both panels, dashed density lines show changes from all simulations and solid density plots show amplitude changes from selected high-skill simulations used in the analysis (Methods). Vertical lines below density plots denote amplitude changes from the individual realizations of three models (MIROC6, MIROC-ES2L, and EC-Earth3), all drawn from the SSP2-4.5 experiment, illustrating the wide range of amplitude and teleconnection changes possible from internal variability alone. **C)** E-index time series from two example simulations with similar amplitude increases: MIROC-ES2L r6i1p1f2 (top) and CESM2-WACCM r3i1p1f1 (bottom), both from the SSP2-4.5 experiment. Red bars denote eastern Pacific El Niño (E > 0) and blue bars denote eastern Pacific La Niña (E < 0). Left inset text in each panel denotes the model information and amplitude change. Right inset text denotes the sum of each E-index time series over the 21st century (2020-99), with positive values indicating that the time series contains more El Niños than La Niñas and negative values indicating the opposite.

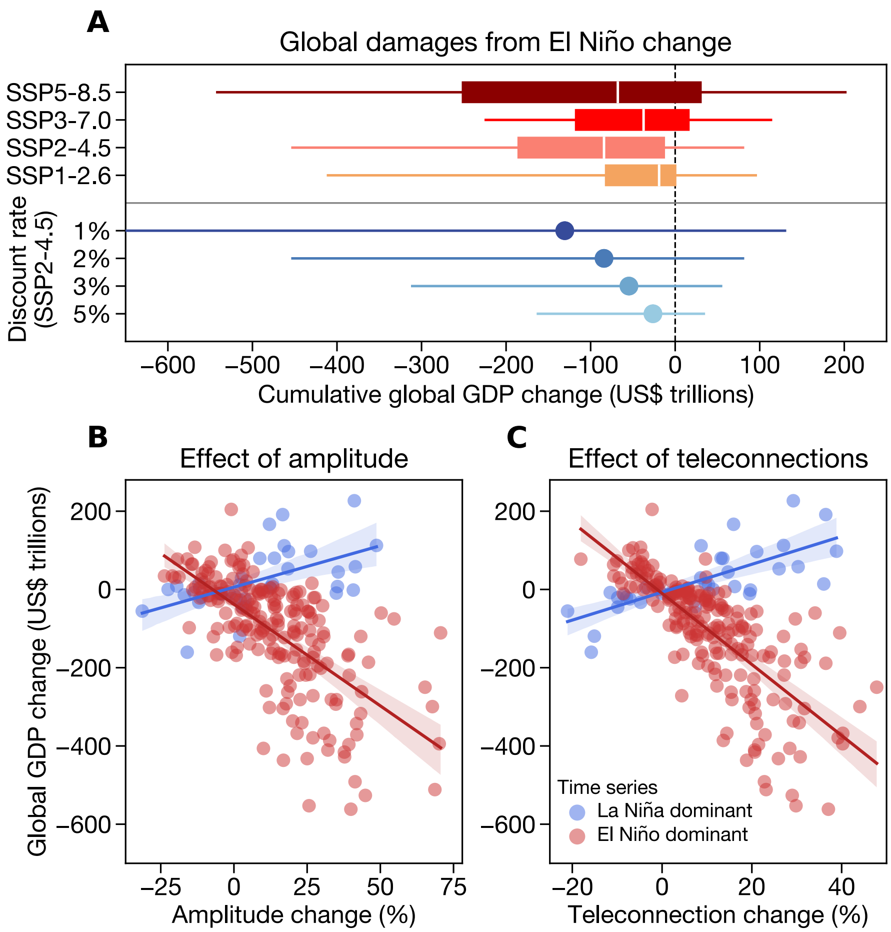

Fig. 4 | Global economic impacts of changes in El Niño amplitude and teleconnections. A) Boxplots show the cumulative global GDP change in each scenario under a 2% constant discount rate. Colors correspond to the scenario colors in Fig. 3. In each boxplot, white line denotes the median, box spans the first and third quartiles, and whiskers span the 95% range. Lower blue lines denote global economic losses under SSP2-4.5 and a range of discount rates. Dot denotes the median and lines span the 95% range. **B, C)** Cumulative global GDP change due to changes in ENSO amplitude (**B**) and teleconnections (**C**) with a 2% discount rate, with each dot corresponding to one climate model simulation. Simulations are pooled across all four scenarios. Red dots denote simulations in which the 21st-century E-index sum is greater than 0 (El Niño-dominated time series), while blue dots denote simulations in which the sum is less than 0 (La Niña-dominated time series). Red and blue regression lines and 95% CIs are drawn separately for each subset of simulations.

Supplementary Materials for

Persistent Effect of El Niño on Global Economic Growth

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This PDF file includes:

Materials and Methods
Supplementary Text
References (*49-84*)
Figs. S1 to S17
Tables S1 to S7

Materials and Methods

Data

We use observational climate data from multiple sources: Monthly mean sea surface temperatures (SST) from the HadISST dataset (*49*), monthly mean atmospheric temperatures from the Berkeley Earth dataset (*50*), and monthly total precipitation data from the Global Precipitation Climatology Center (*51*). Temperature and precipitation are aggregated to population-weighted country-level means using year-2000 population data from the Gridded Population of the World (*52*). We use population weighting to ensure that the spatial aggregation captures climate fluctuations that affect people and economic activity.

We use country-level economic data from the Penn World Tables version 10.0 (*53*), specifically Gross Domestic Product ("RGDPNA") (in 2017-equivalent dollars) and population ("POP") for all countries of the world. GDP per capita (GDPpc) is calculated as GDP divided by population. Growth for each year is calculated as the fractional GDPpc change relative to the previous year. Because macroeconomic data may contain measurement error (*54*), we also repeat the analysis using data from the World Bank World Development Indicators (*55*), finding similar results (Fig. S4).

The time period of analysis for both the teleconnection calculations and regression analysis is 1960-2019, so all observational economic and climate data is limited to that time period.

Climate model data come from the sixth phase of the Climate Model Intercomparison Project (*56*) (CMIP6). We use monthly SST, monthly atmospheric temperature, and daily precipitation data over 1850-2099 from the historical experiment and the four Tier 1 experiments from the Scenario Model Intercomparison Project (*57*). These four experiments—SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5—span a range of plausible policy futures, from aggressive mitigation (SSP1-2.6) to high emissions (SSP5-8.5) (*57*, *58*). Global mean temperatures rise by ~1.2 °C by 2081-2100 relative to 1995-2014 in the SSP1-2.6 scenario, 2.1 °C in SSP2-4.5, 3.2 °C in SSP3-7.0, and 4 °C in SSP5-8.5 (*58*). Not all models have data available for each experiment, so differences across the experiments are due both to differences in forcing and differences in the sampling of model structure (Tables S3-S6). All climate model data is regridded to a 2°-by-2° grid, using bilinear interpolation from Python's "xarray" package (*59*).

ENSO indices

We use the "E-index" and "C-index" to represent ENSO (*9*, *27*, *36*, *60*, *61*). The E-index represents eastern Pacific El Niño events and captures the nonlinear processes that generate skewness in eastern Pacific SSTs, whereby El Niño events are stronger than La Niña events (*9*, *27*). The E-index is a combination of the first two principal components (PCs) of an empirical orthogonal function (EOF) analysis applied to Pacific SSTs (*36*) over 20 °S – 20 °N and 140 °E – 80 °W, specifically as $E = (PC1 - PC2)/\sqrt{2}$. We calculate the E-index in observations using linearly detrended SST anomalies referenced to 1960-2019 long-term monthly means. We then average the E-index over winter (December-February, DJF), to focus on the season in which ENSO peaks (*62*); the E-index in year *t* is therefore defined as the average of the December E-index from year *t-1* and the January and February indices from year *t*.

The C-index (*27*) is a companion index to the E-index and is calculated as $C = (PC1 + PC2)/\sqrt{2}$. The C-index represents central Pacific La Niña and El Niño events, where La Niña events tend to be stronger than El Niño events. Positive E-index values represent an eastern Pacific El Niño event and negative C-index values represent a central Pacific La Niña event. The

E-index and C-index are orthogonal by construction (*27*), allowing us to include them both in a regression model without a concern for collinearity.

To assess the sensitivity of our results to these indices, we also calculate the Niño3 index, defined as linearly detrended SST anomalies averaged over 5 °S – 5 °N and 150 °W – 90 °W. The Niño3 index yields similar, though slightly weaker, results to the E-index (Fig. S4) since it corresponds to eastern Pacific conditions but does not distinguish the spatial structures of El Niño and La Niña.

We calculate the DJF E- and C-indices similarly in the CMIP6 models, using quadratically detrended (*9*) SST anomalies referenced to monthly means from 1850-2014.

<u>Country-level ENSO teleconnections</u>

Our analysis uses a country-specific teleconnection metric to quantify heterogeneity in growth responses according to a country's geophysical connection to ENSO. To calculate the teleconnection, we first standardize monthly country-level mean temperature and total precipitation by subtracting the long-term (1960-2019) monthly mean and dividing by the long-term monthly standard deviation. We then linearly detrend these standardized anomalies separately for each month to remove the effects of warming and low-frequency climate variability.

Next, we correlate these standardized temperature and precipitation time series with the DJF E-index separately for each month m and each country i. El Niño events begin and grow in year $t-1$, peak in the winter, and then decay in the spring and summer of year t, so we allow the DJF E-index to affect both the preceding (beginning just after the "spring predictability barrier" in June of $t-1$) and following years (ending in August of year t) (Fig. S1). We use partial correlations to control for precipitation when analyzing temperature and vice versa to control for the covariance between temperature and precipitation.

This calculation yields a distribution of 15 correlation coefficients (one per month from June of year $t-1$ through August of year t) for each country, separately for temperature and precipitation. We then take the three-month running mean of these coefficients across the 15 months to smooth out random variation and account for multiple months of exposure to ENSO. Finally, we take the maximum (absolute) correlation coefficients from these running means for both temperature and precipitation and add them together to calculate each country's E-index teleconnection τ^E. We use absolute values to allow the distinct effects of temperature and precipitation teleconnections to be additive, but our results are robust to considering both positive and negative precipitation teleconnections separately (Fig. S5).

This teleconnection metric estimates the degree to which each country's climate is influenced by ENSO, accounting for: (1) the effects of both temperature and precipitation; (2) multiple sustained months of exposure to ENSO; and (3) the varied timescales on which teleconnections may manifest. Additionally, this strategy allows teleconnections to be defined continuously rather than separating teleconnected and non-teleconnected countries based on arbitrary significance thresholds (*8*) or previously defined climate zones (*19*, *20*). Fig. S2 shows the steps in this teleconnection calculation, and we perform the same analysis with the C-index to calculate C-index teleconnections (τ^C).

<u>Econometric analysis</u>

The goal of our analysis is to quantify the multi-year effect of ENSO on economic growth. This task requires us to separate ENSO from the other constant and time-varying factors that affect economic growth. We use a distributed lag regression model, estimated with Ordinary Least Squares, to estimate the effects of eastern Pacific El Niño (the E-index) and central Pacific La Niña (the C-index) on growth:

$$g_{it} = \sum_{L=0}^{j} \left[\beta_L E_{t-L} + \Theta_L E_{t-L} * \tau_i^E + \Phi_L C_{t-L} + \Psi_L C_{t-L} * \tau_i^C \right] + \mu_i + \epsilon_{it} \quad (1)$$

Here, g refers to GDPpc growth in country *i* in time *t*, E refers to the E-index in year *t*, and C refers to the C-index in year *t*. μ is a country fixed effect, which controls for average differences between countries such as geography and ensures that our results are identified using within-country variation in growth. *L* is the lag at which the coefficient is estimated. The interactions of E with τ^E and C with τ^C allow the effect of ENSO to differ between countries based on how strongly coupled each country's climate is to ENSO.

The inclusion of lagged terms from years *L* to *j* allows us to distinguish between level and growth effects on the economy. If the effect of El Niño only falls on income levels, then a shock in year *t* will be recovered in year *t+1* as countries rebound to their original income trajectory, meaning that year *t+1* will see an abnormally high growth rate. If, instead, El Niño affects the underlying capacity of the economy to grow, then the years following an event should show either persistent declines in growth or no change. As such, our analysis focuses on the cumulative coefficients Ω, which represent the accumulated effect of ENSO in the years after an event. The interaction of E with country-specific teleconnections τ^E allows us to calculate unique cumulative effects for each country *i* and lag length *L*:

$$\Omega_{iL} = \sum_{L=0}^{j} \left[\beta_L + \Theta_L * \tau_i^E \right] \quad (2)$$

If Ω_{iL} is indistinguishable from zero, then we cannot reject the hypothesis that El Niño has only level effects; growth effects are identified if Ω_{iL} is significantly different from zero ($p < 0.05$). Note that the E-index is not highly correlated with itself across lag lengths (Table S7), meaning that including multiple lags in a single model should not generate multicollinearity.

The identifying variation in our model comes from stochastic and unpredictable (*30*, *63*) shifts in SSTs from year to year, along with the differential effects of those SSTs depending on teleconnection strength. The E- and C-indices are constant throughout space within a given year, raising the concern that other time-varying confounders could be correlated with ENSO and generating spurious results. A typical strategy in empirical climate-economy studies is to include both unit and time fixed effects in regression models (*64*), which separate local weather variation from both time-invariant average conditions and global time-varying shocks. However, because the E- and C-index terms in Eqn. 1 would be collinear with the year fixed effect, we cannot estimate our main specification with year effects.

We do, however, show results from several alternative models that separate the influence of ENSO from time-varying confounders. First, adding linear or linear and quadratic country-level time trends to control for secular trends in technology or demographics does not alter our results (Fig. S4). Second, bootstrap resampling by year permutes the years in the regression model and ensures that no single year has a disproportionate influence on the results (Fig. S3). Third, dropping 1983 and 1998 from our data, which were major El Niño events that coincided with financial crises in tropical countries, reduces the magnitude of the effects we find by ~12% but does not alter their statistical or economic significance (Fig. S4). Fourth, we define a unique spatiotemporally varying ENSO index for each country and year by multiplying E_t by τ_i^E. Because this index differs across countries within years, we can estimate the model with country and year fixed effects, and we find negative effects that exceed the results of our main model (Fig. S7). For example, this model predicts that Peru experiences an 8.7-p.p. decline in growth five years after an El Niño, compared to 6.2 p.p. from our original model. Finally, we estimate a discretized version of our main model, where we defined "untreated" countries as countries with $\tau_i^E < 0.5$ and "treated" countries as countries with $\tau_i^E > 0.5$. This allows us to estimate the model with country and year fixed effects, interpreting the discretized interaction term as the effect of ENSO on treated countries. In this case, we find that treated countries experience >3-p.p. declines in growth five years after El Niños, which exceeds the 2.3-p.p. average loss for countries with $\tau_i^E > 0.5$ from our main model (Fig. S7). The inclusion of year fixed effects in these latter two models, along with the other checks we show, supports our conclusion that our results are not driven by time-varying confounders.

We estimate confidence intervals by bootstrapping (N = 1,000), with countries resampled from a uniform distribution with replacement. Countries are sampled as a block to account for within-country autocorrelation (*65*). However, alternative bootstrapping schemes yield similar results, such as sampling by year globally or within continents to account for spatial correlation in growth, sampling by continent to account for simultaneous spatial and temporal correlation, and sampling by five-year blocks to account for spatial and short-term temporal correlation (*65*) (Fig. S3). Multiple forms of clustered parametric standard errors, which are robust to both spatiotemporal autocorrelation in errors and heteroskedasticity across clusters, do not reduce the statistical significance of our results (Table S1, S2).

We remove growth values from our sample that are above 18% or below -18%, approximately the 3σ range. We drop 146 values because of this choice, less than 2% of the sample. Including these values does not reduce the average effect, but it does increase the uncertainty (Fig. S4), so we drop these outliers while noting that our results would be similar if we included them.

When we estimate separate responses for high-income and low-income countries (Fig. S4), we use the World Bank's income classifications, grouping low and lower-middle income countries together as well as high and higher-middle income countries. Again, the results accord with our main model.

Other time series analysis tools have been used to assess the effect of ENSO such as vector autoregression (VAR) models (*18*, *21–23*) or local projections (*18*). We use a distributed lag (DL) model for two reasons. Firstly, DL models have been widely used in the empirical climate-economy literature (*13*, *15*, *66*, *67*), so our approach is consistent with this work. Secondly, VAR models are primarily used in macroeconomic settings where endogeneity is at issue (*68*). Because ENSO is plausibly exogeneous to country-level growth rates, we adopt the more parsimonious DL model.

Synthetic data simulations

Estimating the effect of El Niño with models that include 14 or more lags results in unstable coefficients and confidence intervals that include zero (Fig. S8). Two plausible interpretations of this result are: (1) that there is no statistically significant growth effect of El Niño after 14 years;

or (2) that there is a permanent growth effect, but models with many lags cannot confidently identify this effect due to the reduced sample size and increased number of parameters being estimated simultaneously.

To examine this issue, we use a perfect model framework where we impute a known El Niño effect to synthetic growth data and then estimate the regression on that data to assess whether we can recover the effect. We construct growth as the combination of a first-order autocorrelated process (AR(1)) with Gaussian noise of mean 0 and s.d. 0.05, a linear trend randomly chosen from a Gaussian distribution of mean 0 and s.d. 0.2 (in p.p. per year), and an El Niño effect. The AR(1) coefficient is set to 0.1, within the range of AR(1) coefficients from the data, and the distribution of trends we choose from is also similar to the distribution of country-level growth trends from the data (Fig. S15).

We then create a "true" effect of ENSO on growth and attempt to recover it with the DL model. This predetermined ENSO effect is ultimately arbitrary, but we choose country-level effects that are similar in magnitude to the effects we find in our main regression. We set these effects to accumulate over the first 5 years and plateau at that 5-year value permanently. The non-interacted effect of E is set to sum to 3 p.p. per s.d. and the interaction coefficient with τ is set to sum to -6 p.p. per s.d., meaning that a country with $\tau^E = 1.0$ experiences a cumulative effect of -3.0 p.p. per s.d. (3 + 1.0*-6).

We then fit Eqn. 1 using this synthetic growth data and the actual E-index and τ^E values, using between 5 and 18 lags in the regression (beyond 18 lags, the coefficients become undefined as the degrees of freedom decrease). We repeat this entire process 1,000 times for each number of lags, keeping the set El Niño effect constant. Fig. S8 shows the results from these estimations for one example teleconnection value ($\tau^E = 1.0$). These models are generally unbiased, with the central estimate matching the imputed effect. However, confidence intervals steadily grow as lags are added. With 14 or more lags, the coefficients become statistically insignificant. These results demonstrate that even with a known permanent effect of El Niño, estimating additional lag terms induces sufficient uncertainty to yield insignificant coefficients. To assume that El Niño has no effect in the 14-lag model therefore risks a Type II error. That being said, as a conservative choice in our historical attribution and in our damage projections, we only allow the effects to be partially persistent rather than permanently persistent (see *Economic damages from changes to ENSO*). In our attribution of the costs of the 1982-83 and 1997-98 events, we estimate costs accumulating to 5 years after the event. In our projections, we allow effects to accumulate to 14 years, the maximum length we can confidently identify effects from the observational data (Fig. S8). In a sensitivity test, we allow the effects to be permanent (Fig. S13).

<u>Economic damages from historical extreme El Niño events</u>

The regression coefficients derived from Eqn. 1, β and θ, provide estimates of the change in economic growth for a 1-s.d. change in the E-index. These coefficients can then be applied to actual and hypothetical E-index time series to calculate the growth effects of specific historical El Niño events. Here we focus on the two major El Niño events of 1982-83 and 1997-98. We develop "counterfactual" E-index time series wherein these events did not occur by setting the corresponding E-index values (1983 and 1998) to zero. We then apply the regression coefficients to the actual and counterfactual time series to calculate the growth difference between them over the five years after the event. Formally, if E^O represents the observed E-index in the year of the event (t), and E^{CF} represents the counterfactual E-index in that year, we calculate the growth change in country i from year t through year $t+L$ as:

$$\Delta g_{i(t+L)} = [\beta_L E_t^{CF} + \Theta_L E_t^{CF} * \tau_i^E] - [\beta_L E_t^{O} + \Theta_L E_t^{O} * \tau_i^E] \tag{3}$$

We add these growth change values to the observed growth data, yielding a counterfactual growth time series, and we integrate counterfactual growth to calculate counterfactual income from the year of the event to 5 years after the event. Losses due to each event are calculated as the difference between observed and counterfactual income. Details of this procedure can be found in Diffenbaugh and Burke (*69*).

Note that E^{CF} is zero in our analysis, so the first bracketed term on the right-hand-side of Eqn. 3 is zero, but we provide the full equation because it generalizes to other counterfactual E-index values.

The above analysis only incorporates reductions in growth due to the El Niño events. However, because El Niño events can dynamically trigger La Niña events (*34*), which have beneficial effects (Fig. S10), a full accounting of the effects of El Niño should incorporate these offsetting beneficial events. The 1982-83 El Niño may have triggered the La Niña of 1984-85 (while the C-index was only -0.07 in 1984, it was -1.1 in 1985), and the 1997-98 El Niño may have triggered the major La Niña of 1999-2000 (the C-index was -2.1 in 1999 and -2.0 in 2000). We incorporate these beneficial effects for both El Niño events by setting the C-index values for the following two years (i.e., 1999 and 2000 in the case of the 1998 El Niño) to zero and calculating the growth difference between the actual and counterfactual C-index time series. The total growth change over the five years following the El Niño event is therefore the reduction due to the El Niño event plus the increase due to the following La Niña events.

For both events, we limit our analysis to countries with continuous GDPpc data since 1982 to ensure that the same countries are included in both calculations. This restriction means that nations with short GDPpc records (e.g., post-Soviet nations like Ukraine) are not included in these calculations.

Climate model selection

Many climate models do not realistically represent the physical processes that drive ENSO (*70–72*). To ensure that our projections are physically realistic, we filter the simulations we use based on criteria set out in previous studies (*9*, *36*, *72*). We calculate a parameter known as α from each model, which is the quadratic coefficient on the relationship between the first and second principal components from the EOF analysis used to calculate the E-index and C-index (*72*) (see *ENSO indices*).

The observed value of α is -0.34, indicating a strong nonlinearity in the principal component space and a strong differentiation between eastern Pacific and central Pacific El Niño events. Models which simulate an α value closer to the observed value also more effectively represent the variance and skewness in SST anomalies, as well as the distinct eastern and central Pacific El Niño phases (*9*, *72*). We follow Cai et al. (*9*) in selecting all models with α at least 50% of the observed value, meaning -0.17 or less. Tables S3-S6 show the total and selected realizations for each experiment. We also test the sensitivity of our results to using only one realization from each model (Fig. S13).

ENSO amplitude and teleconnections in climate models

We define ENSO amplitude as the standard deviation of the quadratically detrended E-index (*9*, *42*). We calculate each climate model simulation's amplitude in the historical period, which we define as 1940-2019 to parallel the observational data, and in the future, which we define as 2020-2099. The 1940-2019 historical period is chosen so that the historical period is the same length as the future period.

We calculate model-based ENSO teleconnections using the same method as the observations. We perform this calculation separately for the historical and future periods, standardizing and linearly detrending each country's temperature and precipitation time series independently for each period. This method removes mean shifts due to global warming or low-frequency variability and allows us to isolate the interannual signal of ENSO.

<u>Economic damages from changes to ENSO</u>

Calculating economic damages from warming-driven ENSO changes requires a counterfactual world where ENSO evolves without rising temperatures. We calculate the counterfactual ENSO time series for each simulation by re-scaling its future time series to have the amplitude that simulation had in the historical period. For example, if E-index amplitude increases by 20% for a given model realization, we calculate its counterfactual E-index time series by multiplying its future time series by 0.8 (i.e., 0.8 = 1 – 0.2). This method preserves the particular sequence of El Niño and La Niña events in the future, since this sequence is assumed to be unforced (Fig. S12), but eliminates the forced change in ENSO amplitude.

We calculate counterfactual ENSO teleconnections with a similar "delta method." For each country in each model, we calculate the change in teleconnection value between the historical and future simulations. We then add this change to each country's observed teleconnection value to implicitly bias-correct the model output. The "counterfactual" teleconnections are thus equal to the observed values and the "future" teleconnections are the observed-plus-change values.

We then calculate the economic effects of changes to ENSO by comparing the future and counterfactual time series and teleconnections from each model. For each year *t* between 2020 and 2099, we calculate the growth change from year *t* to year *t+5* as the difference between the future and counterfactual time series and teleconnections:

$$\Delta g_{i(t+L)} = \left[\beta_L E_t^{CF} + \Theta_L E_t^{CF} * \tau_i^{CF}\right] - \left[\beta_L E_t^{F} + \Theta_L E_t^{F} * \tau_i^{F}\right] \tag{4}$$

Here, E^F refers to the future E-index time series and E^{CF} refers to the counterfactual E-index time series. Similarly, τ^F refers to future teleconnections and τ^{CF} refers to counterfactual teleconnections. This calculation yields a growth change time series where each value is the combined effect of the contemporaneous and lagged effects. We then calculate economic growth caused by changes in ENSO by subtracting these growth change values from the SSP income growth projections and integrating growth to calculate income; the new time series represent the deviations from the SSP baselines caused by changes in ENSO amplitude. Damages are calculated as the difference between this new time series and the SSP baseline. Details of this procedure can be found in Burke et al. (*13*). We perform an analogous calculation using the C-index time series and teleconnections to calculate C-index damages.

We note that this procedure calculates counterfactual income as accumulated over the entire 21st century, rather than preceding specific events such as in Fig. 2. This distinction is because these two methods are aimed at answering different questions. In Fig. 2, we are interested in the effects of specific El Niño events, whereas in Fig. 4, we are interested in the accumulated effect of human-caused changes in ENSO over the 21st century.

Finally, given the rebound effects observed after ~10 lags, as well as the large uncertainties in models including longer lags (Fig. S8), we adopt a conservative approach to damage persistence in these calculations. Because we cannot confidently identify permanent effects after 14 years, we allow the growth effect of ENSO to rebound to zero 14 years after the event, meaning that each El Niño affects the global economy for 15 years total (14 lags plus a contemporaneous effect). We do this by applying Eqn. 4 for the first six years (year 0 through year 5) using the coefficients from the main 5-lag model, then allowing the effect to plateau for years 6 through 8, then reversing those coefficients and allowing economies to rebound from years 9 through 14. Thus, while we prevent El Niño events from having more than 15 years of an effect, this does not mean that their effect is zero; an affected country has lost substantial economic output during those 15 years that is never recovered. Fig. S16 illustrates this schematically. In a sensitivity analysis, we show results if we assume that damages are permanent and never recovered, a choice which yields substantially greater losses as well as greater uncertainty in those losses (Fig. S13d).

Supplementary Text

Regression-based teleconnections

Our main analysis uses a correlation coefficient to calculate teleconnections, but we also assess the sensitivity of this choice by using partial regression coefficients instead. Using a regression coefficient leads Peru and Ecuador to be strong outliers from the rest of the distribution (fig. S4e), with values at or above 2. Estimating the growth regression with these values leads to large uncertainties as Peru and Ecuador have an outsized influence on the regression (fig. S4e), so the correlation coefficient is a more stable metric for use in the growth regression. However, we emphasize that the effect of El Niño is still strong and statistically significant when using regression coefficients (Fig. S4e), so our results are not an artifact of the choice to use the correlation coefficient.

Temperature- or precipitation-based teleconnections

Our main analysis defines teleconnections using the combination of temperature and precipitation correlations. We can also define teleconnections solely based on the temperature or precipitation portions of the calculation, similar to previous studies that have focused on temperature to define teleconnections (*6*, *8*). Results for this sensitivity analysis are shown in Fig. S5. The temperature-based estimate is similar to that from both temperature and precipitation, but the effect is weaker with precipitation alone. Our interpretation is that aggregating the data to the monthly time scale and country spatial scale dampens the signal of precipitation more than it does temperature. Consistent with this interpretation, empirical climate-economy studies tend to find little effect of precipitation on country-level growth (*13*, *16*).

Cumulative teleconnections

By using the maximum of three-month running means, our main teleconnection analysis focuses on countries' short-term extreme exposure to ENSO rather than capturing cumulative exposure over the entire ENSO life cycle. An alternative teleconnection metric which uses the sum of statistically significant ($p < 0.05$) correlation coefficients across the 15 months for each country yields very similar results, with high correlations between this and our original metric and nearly identical marginal growth effects (fig. S5). This analysis implies that focusing on the few months of maximum exposure is sufficient to capture the effects of ENSO on economies broadly.

Heterogeneity in historical teleconnections

Our main analysis treats teleconnections as constant in time in the observational period. However, sampling variability and changes in ENSO behavior (among other things) may result in temporal heterogeneity in teleconnections. Fig. S17 shows teleconnections calculated in rolling 30-windows over the historical period. Temporal variation is apparent, at least partly due to the shorter time period used to calculate these teleconnections. However, the distribution of teleconnection values is relatively stable, and the average country experiences temporal variation of only about 13% of its mean value. As such, we use the teleconnection values calculated across the entire time period in our main analysis, though we do allow teleconnections to change with forcing in our climate model analysis.

Finally, a key consideration in empirical climate-economy studies is the need to aggregate physical variables to the country scale, which is not a geophysically meaningful scale. To understand the implications of this aggregation, we re-calculate E-index teleconnections at the gridded scale (fig. S17). Teleconnections can vary across grid cells, but the average country only experiences within-country spatial variation of about 11% of its mean teleconnection value (fig. S17). Furthermore, population-weighted country-average grid-cell teleconnection values are similar to the original teleconnection values calculated from country-average temperature and precipitation (fig. S17), implying that subnational spatial variation in ENSO teleconnections does not substantially affect our results.

Relationship between our work and recent differences-in-differences literature

Our empirical framework is very similar to typical "differences-in-differences" (DID) approaches in economics, involving a treatment variable that varies over time (E and C) and a cross-sectional variable that denotes treatment status (τ). A series of recent papers have illustrated problems with traditional DID approaches, especially when treatment effects are heterogeneous in time and space and treatment timing is staggered (*73–75*). This type of research design can produce inappropriate comparisons between already treated and newly treated units, resulting in average treatment effect estimates that differ in magnitude and sign from the true effects. While novel estimators have been proposed to avoid these problems (*76–78*), this literature is still emerging and it is not clear that such estimators are designed for settings with continuous treatments that vary year-to-year and have dynamic effects (*79*). In lieu of using an alternative estimator, we run several robustness tests to examine the heterogeneity of the effects of ENSO over time and space, which can indicate whether our results are biased by this heterogeneity (*80*). We estimate the effect in rolling thirty-year windows over the 1960-2019 sample period, after dropping individual countries, and after dropping individual years (Fig. S6). In all cases, these estimates are quite similar to our main effect, indicating that unmodeled treatment effect heterogeneity should not pose a threat to our main analysis.

Value of climate model selection

Our climate model selection criterion preserves the benefit of a multi-model ensemble, allowing us to sample structural uncertainty in model representation of ENSO as well as initial-condition uncertainty, while incorporating information about model skill (*81*). Treating all simulations in a multi-model ensemble equally has been criticized for assuming that all simulations are independent samples that represent the climate system with equal skill (*82*), especially since CMIP is an ensemble of opportunity rather than a systematic sampling of uncertainty space. Our consideration of model skill provides an ensemble estimate that is likely more accurate than could be achieved without such consideration. Other methods such as bias correction (*83*, *84*) could also improve ensemble skill, but we use the simpler selection criterion based on α given its consistency with the E- and C-indices and its use in the ENSO modeling community.

Sensitivity of damages calculation to alternative choices

We incorporate both amplitude and teleconnection changes in our damage projections. Holding teleconnections constant reduces both the magnitude and uncertainty of the damage projections, though they remain negative on average and negatively skewed (fig. S13). Further, a key assumption in these calculations is that the β and θ coefficients (Eqn. 1) remain consistent at a given teleconnection level between the past and future, though individual countries' actual teleconnections may change. This assumption would be violated if societies undertook adaptation measures in response to changes in ENSO amplitude or teleconnections to reduce their sensitivity to ENSO, which is why the need for increased adaptation is a key theme in our results.

Finally, our damages calculations use as many simulations from each model as possible (Tables S3-S6) to sample both model structural differences and differences in outcomes due to internal climate variability. Using only the first simulation from each model can generate different results; for example, the SSP5-8.5 simulation yields benefits and SSP1-2.6 yields stronger losses. However, we emphasize that—conditional on our model selection criterion—all selected simulations from a given model are physically plausible given the forcing and boundary conditions. Therefore, the results we present in Fig. 4 are a more complete accounting of the possible effects of ENSO changes.

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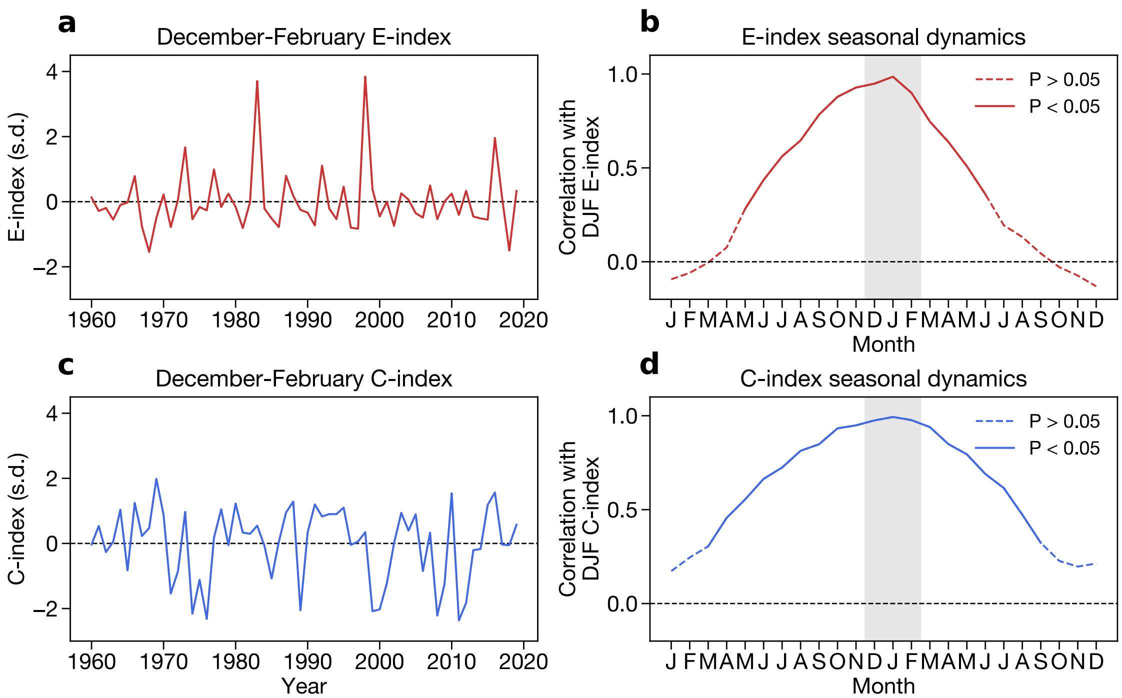

Fig. S1.

Interannual and seasonal dynamics of the E- and C-index. A) Timeseries of the average E-index over December, January, and February (DJF) of each year, where the values are referenced to the year of January and February. B) Pearson correlation coefficient between the E-index in each month and the DJF-mean E-index. Solid lines denote correlation coefficients that are statistically significant ($p < 0.05$) and dashed lines denote correlation coefficients that are statistically insignificant ($p > 0.05$). C) As in (A), but for the DJF C-index. D) As in (B), but for the DJF C-index.

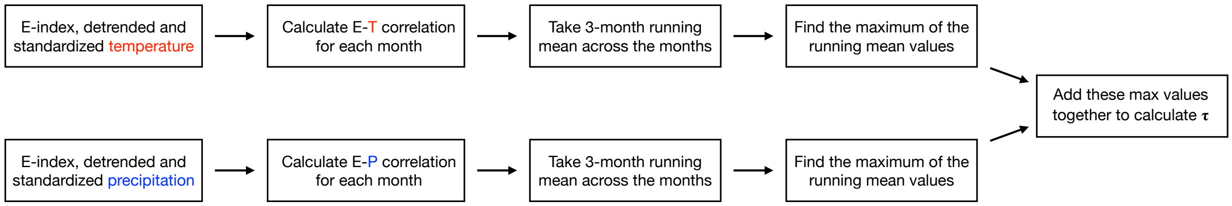

Fig. S2

Flow chart for calculation of country-level E-index teleconnections. An analogous calculation is made for C-index teleconnections.

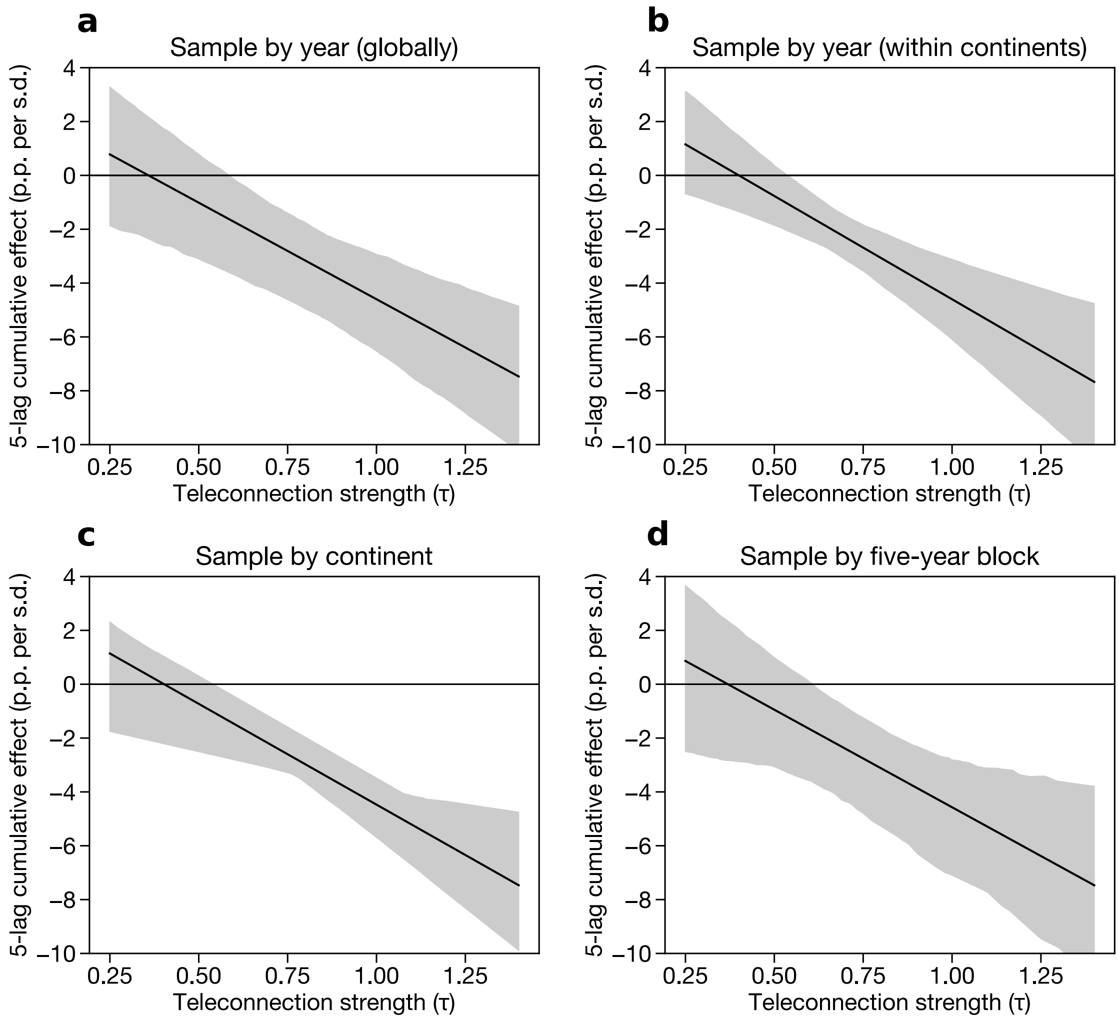

Fig. S3

Regression results using alternative bootstrap sampling schemes. A) Cumulative 5-lag effect of ENSO on economic growth when sampling by year, keeping all countries from a given year together, to account for global spatial correlation in growth within a given year. B) Effect when sampling by continent-year combinations to account for spatial correlation in growth within specific continents in a given year. C) Effect when sampling by continents to account for simultaneous within-continent temporal and spatial correlation in growth. D) Effect when sampling by five-year blocks to account for global spatial correlation in growth and short-term (i.e., five-year) temporal correlation in growth. In all cases, solid line shows the mean and shading shows the 95% confidence intervals. All samples are taken from uniform distributions with replacement. All axes are the same ranges across panels.

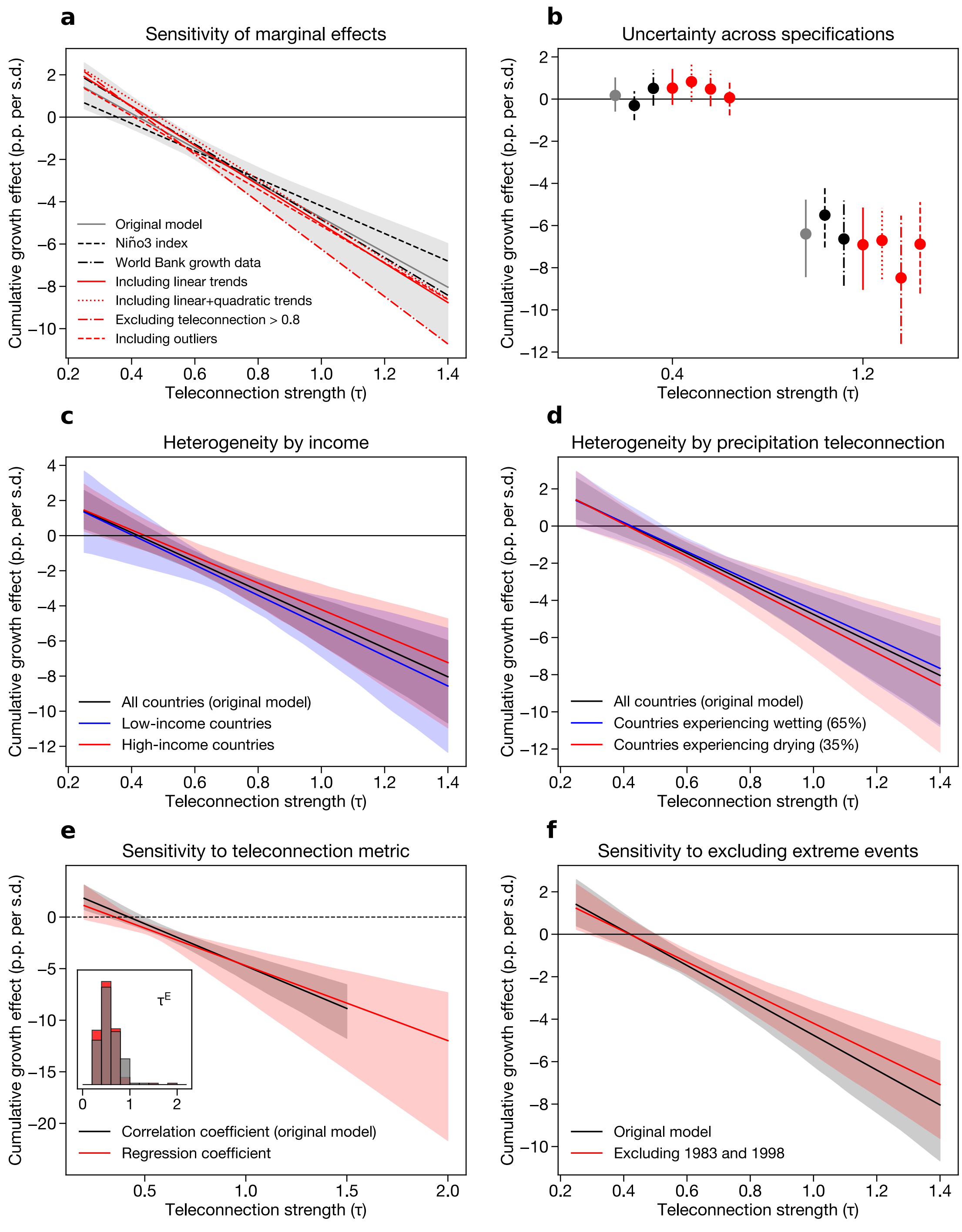

Fig. S4

Sensitivity and heterogeneity of the effect of El Niño. A) Cumulative 5-lag effect of El Niño on growth across a range of specifications: the main model (gray line shows mean and shading shows 95% confidence intervals), a model using the Niño3 index instead of the E- and C-index (black dashed line), a model using World Bank growth data instead of the Penn World Tables (black dash-dot line), a model that includes a country-specific linear trend in growth (red solid line), a model that includes both linear and quadratic country-specific trends (red dotted line), a model that excludes countries with teleconnection values greater than 0.8 (red dash-dot line), and a model that includes outliers with absolute values of growth greater than 18% (red dashed line). B) Uncertainty in the 5-year cumulative marginal effects of El Niño across each model specification at two representative teleconnection values (0.4 and 1.2). Line styles denote alternative models presented in (A). C) Cumulative marginal effects of El Niño for low-income countries (blue) and high-income countries (red), as defined by World Bank income classifications (Methods). D) Cumulative marginal effects of El Niño for countries experiencing wetting in response to El Niño (positive correlation between the E-index and precipitation, blue) and countries experiencing drying (negative correlation between the E-index and precipitation, red). For each of these samples, we use the original teleconnection value calculated with absolute values in the distributed lag model, but split the sample by the sign of the precipitation teleconnection. In (C) and (D), the original model estimated for all countries is shown in black. E) Cumulative marginal effects of El Niño when using the partial correlation coefficient to measure teleconnections (the main analysis) and when using the regression coefficient instead (red). Inset histograms show the distribution of the two teleconnection metrics. F) Cumulative marginal effects of El Niño when using the full sample (the main analysis, black) and when dropping 1983 and 1998 from the sample (red). In panels (C), (D), (E), and (F), solid line denotes the average and shading denotes 95% confidence intervals from bootstrap resampling by country (Methods).

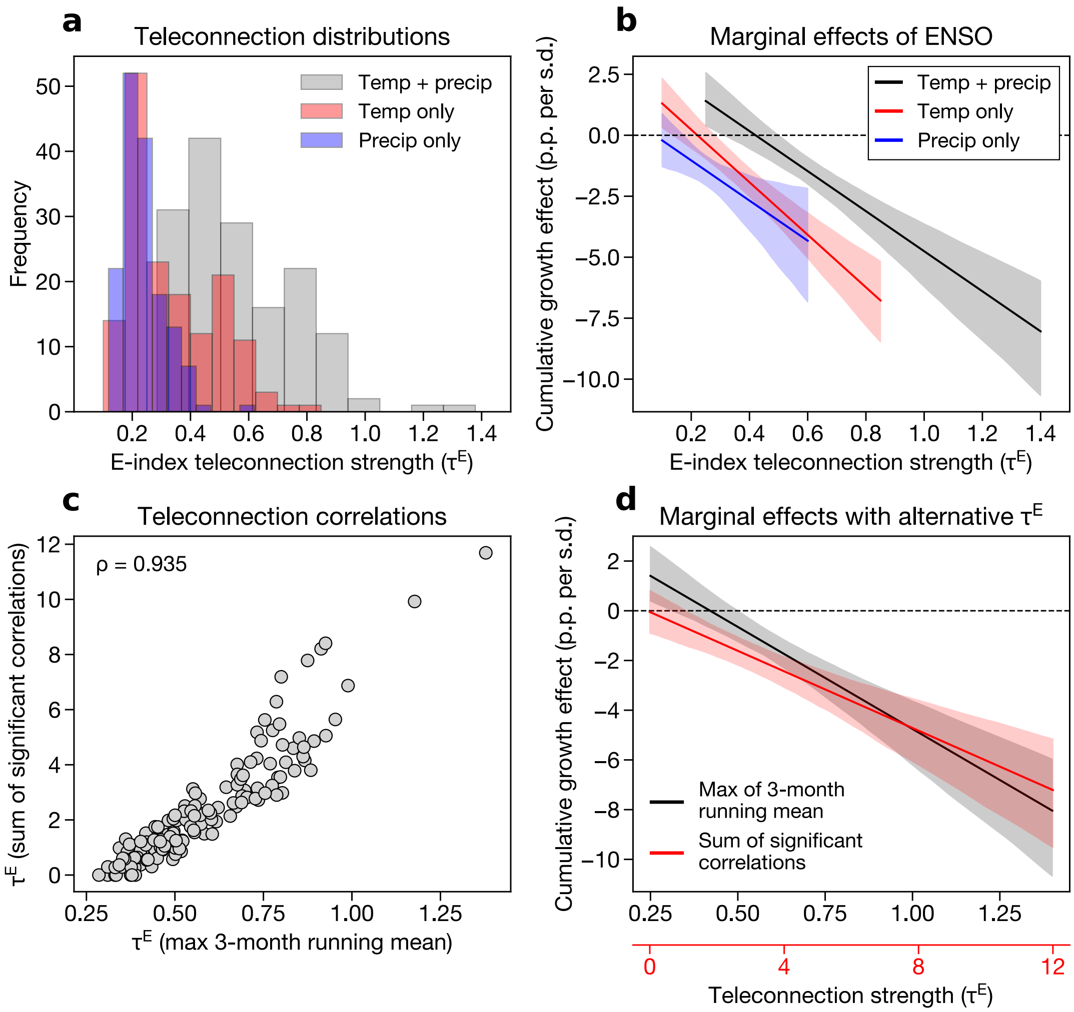

Fig. S5

Comparison of results using alternative teleconnection metrics. A) Distributions of country-level teleconnections using monthly temperature correlation coefficients (red), monthly precipitation correlation coefficients (blue), and their sum (gray). All values are positive since we transform the correlations to absolute values. B) Cumulative 5-lag effect of ENSO on economic growth using temperature-only teleconnections (red), precipitation-only teleconnections (blue), and temperature-plus-precipitation teleconnections (black). C) Relationship between teleconnections from our main analysis (maximum of three-month running mean) and alternative teleconnections using the sum of all statistically significant correlation coefficients across the months for each country. Rho denotes the Spearman's rank correlation coefficient between the two teleconnection metrics. D) Cumulative 5-lag effect of ENSO on economic growth using the original metric (black) and the summed correlation coefficient teleconnection metric (red). In (B) and (D), solid line shows mean and shading shows 95% confidence intervals across 1000 bootstrap iterations, as in the main analysis.

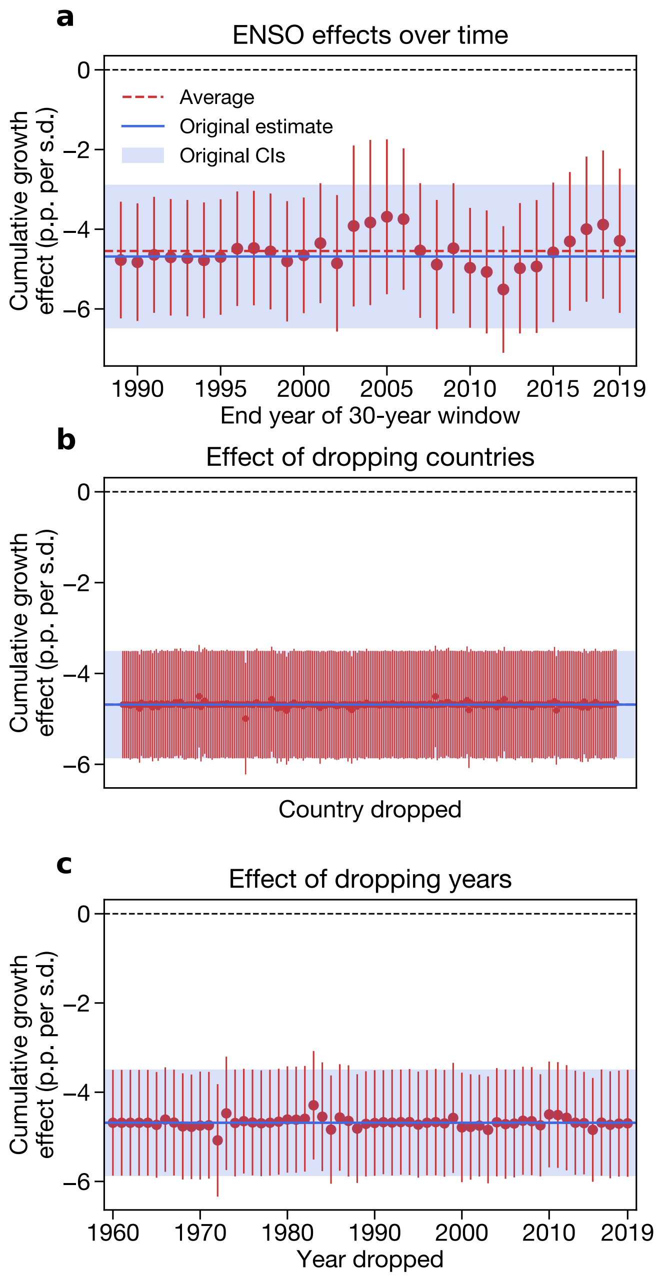

Fig. S6

Treatment effect heterogeneity. Panel (A) shows the effect of ENSO on countries with $\tau = 1.0$ calculated in thirty-year rolling windows. X-axis tick refers to the last year of the window. Panel (B) shows the effect of ENSO on countries with $\tau = 1.0$ when individual countries are dropped from the sample. We omit country labels for simplicity. Panel (C) shows the effect of ENSO on countries with $\tau = 1.0$ when individual years are dropped from the sample. In all panels, dashed red line shows the average effect from all the subsamples, solid blue line shows the central estimate from our original model, and blue shading shows the 95% confidence interval from our original model.

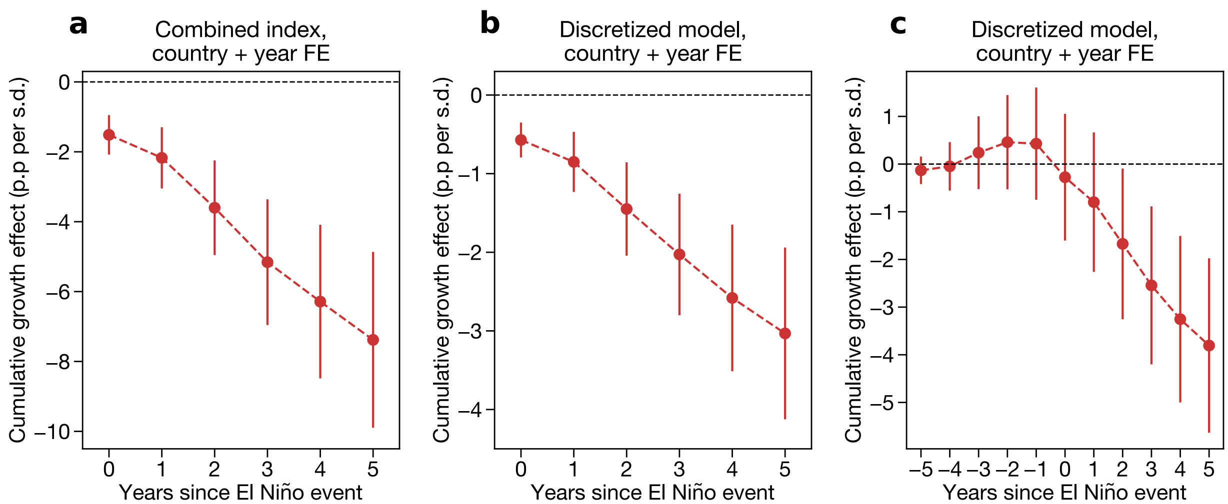

Fig. S7

Regression results using several alternative models with both country and year fixed effects. Panel (A) shows the cumulative effect of a 1-unit increase in the combined index resulting from multiplying E and τ^E. This index varies in both space and time simultaneously, meaning that both country and year fixed effects can be included. Panel (B) shows the average cumulative effect of a 1-s.d. increase in E across all "treated" countries, where treated countries are defined as those with $\tau^E > 0.5$. Panel (C) shows the same result as (B), with five leads of the E-index added along with lags. In all cases, the central dashed line shows the mean marginal effect and vertical bars show the 95% confidence intervals from bootstrap resampling by country.

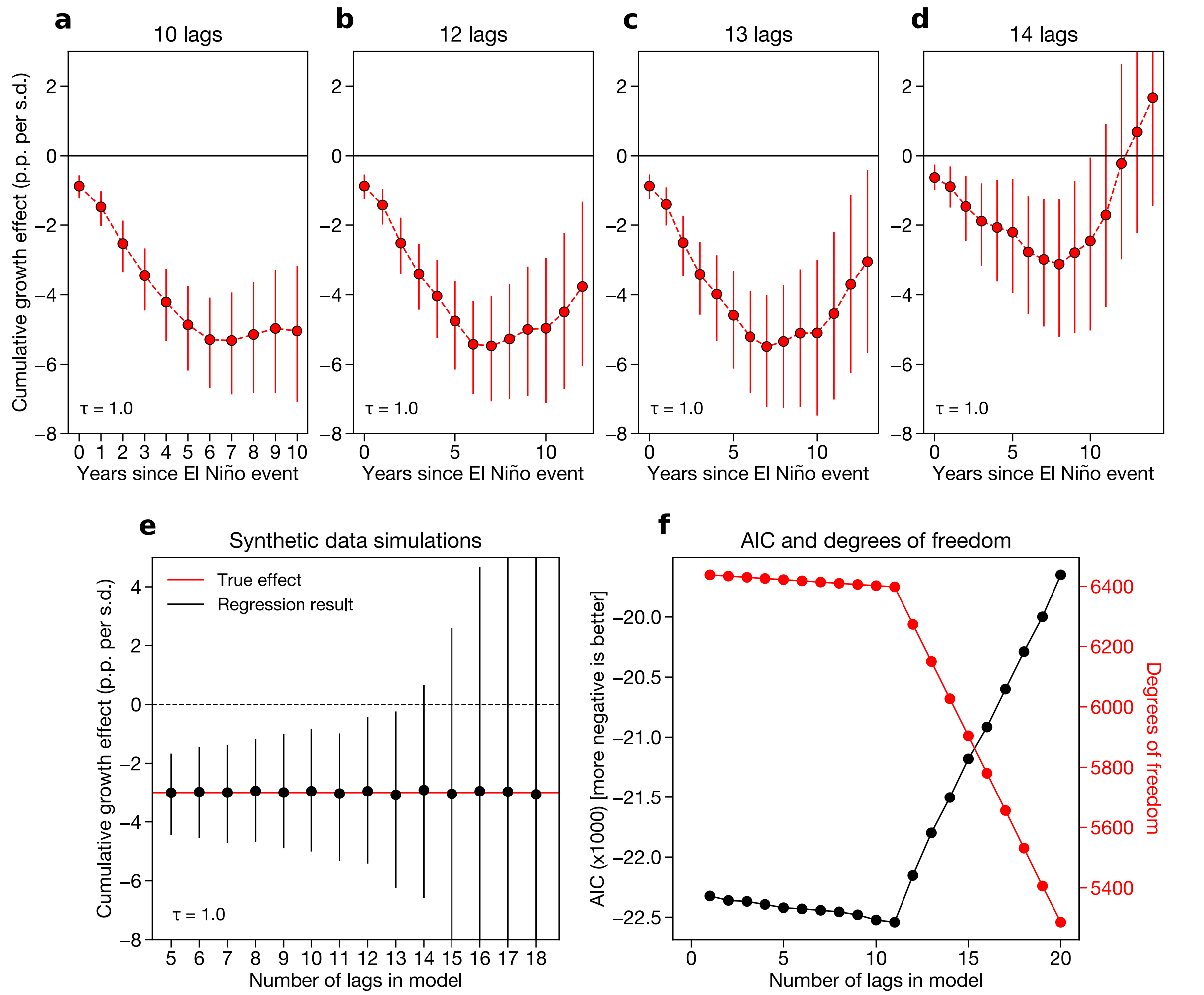

Fig. S8

Sensitivity of main regression results to additional lags. A-D) Regression results for countries with teleconnections greater than or equal to 1.0, estimated with 10 (A), 12 (B), 13 (C), or 14 (D) lags in the regression model. Confidence intervals are estimated by bootstrap resampling as in the main analysis. E) Results from synthetic data simulations where a “true” negative ENSO growth effect is imputed to the data and then estimated using models with lags between 5 and 18 (Methods). Coefficients estimated using this perfect model framework are shown for a hypothetical country with τ = 1.0. F) Black line shows Akaike Information Criterion (AIC) values for a series of regression models with an increasing number of lags from 1 to 20. More negative AIC values are more desirable. AIC values are divided by 1000 for readability. Red line shows the number of degrees of freedom for the same set of models.

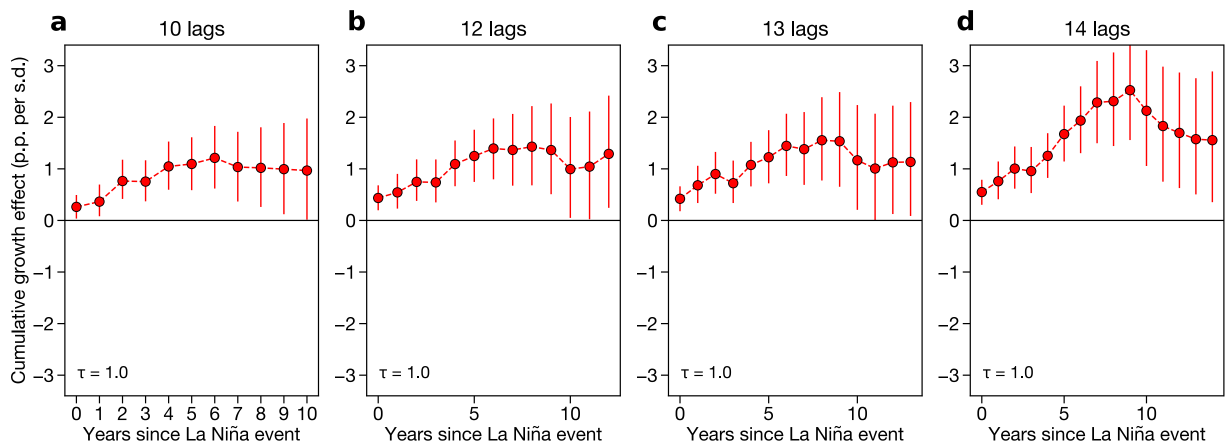

Fig. S9

Sensitivity of C-index regression results to additional lags. As in Fig. S7a-d, but for the C-index coefficients. The sign on the coefficients is flipped to measure the effect of moving from 0 to -1 (i.e., moving a neutral state to a La Niña state).

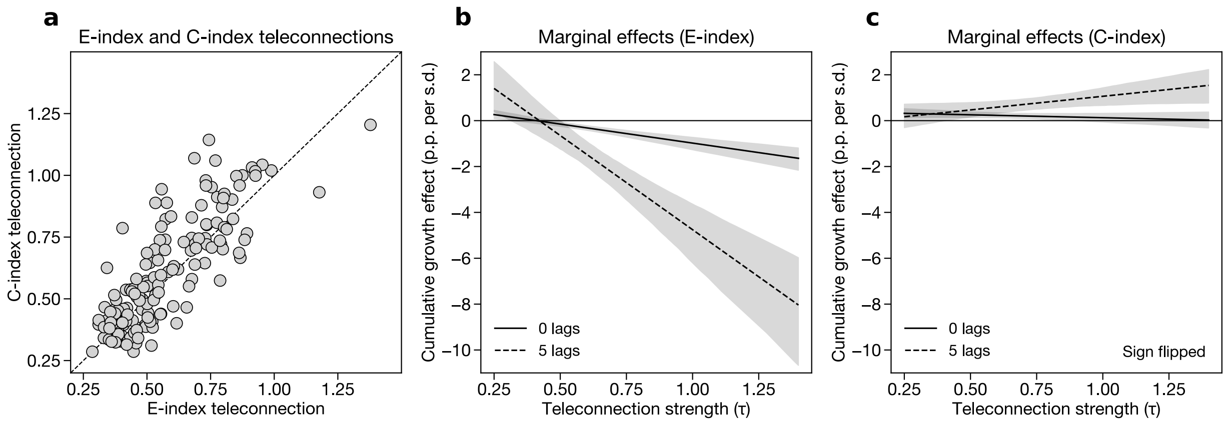

Fig. S10

Teleconnections and marginal effects for both the E-index and C-index. A) Comparison of country-specific teleconnection metrics calculated using the E-index (x-axis) and C-index (y-axis). Dashed line denotes the one-to-one line. B) Marginal effects of El Niño (measured by the E-index) at 0 and 5 lags across a range of teleconnection values. C) Marginal effects of La Niña (measured by the C-index) at 0 and 5 lags across a range of teleconnection values. The sign on the coefficients in (C) is flipped to measure the effect of moving from 0 to -1 (i.e., moving from a neutral state to a La Niña state). In (B) and (C), effects are calculated from a regression that includes both the E-index and C-index and their corresponding teleconnection metrics (Methods). Lines denote averages and shading denotes 95% confidence intervals using bootstrap resampling by country (Methods).

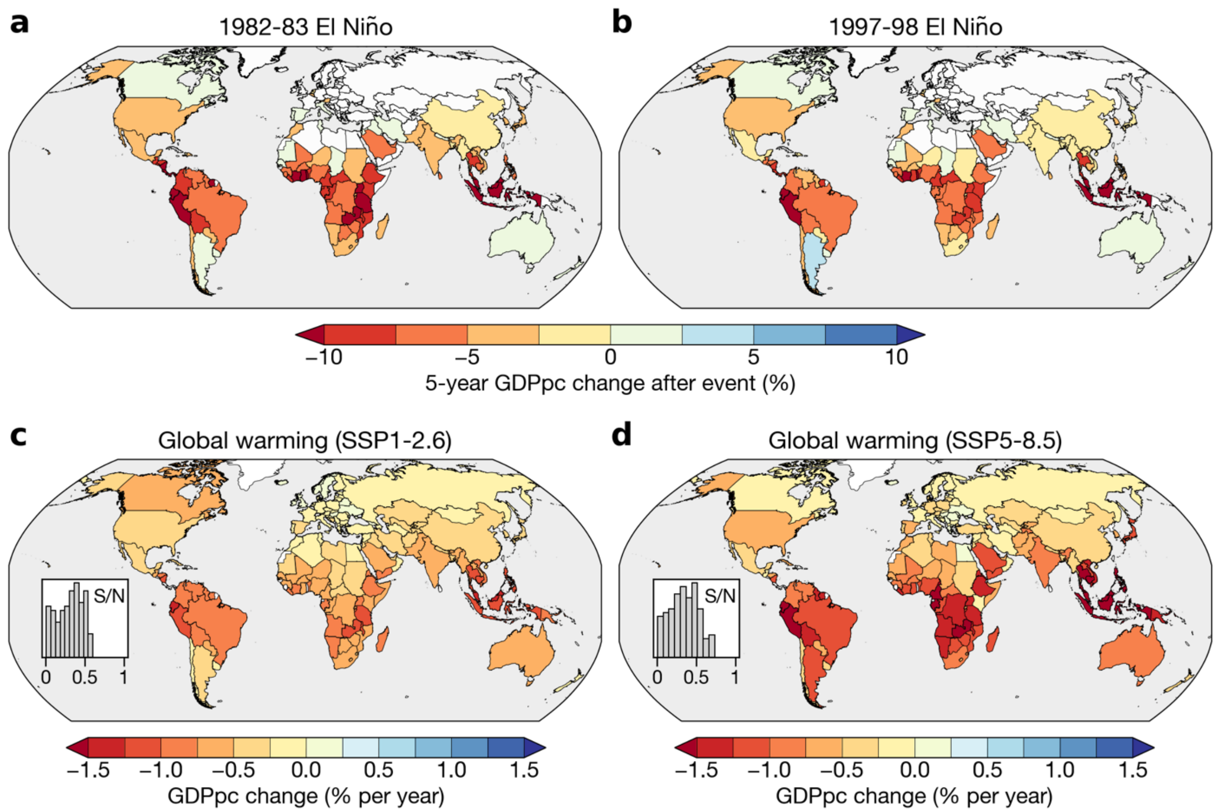

Fig. S11

Country-level losses from extreme El Niño events and global warming. A, B) Change in country-level GDPpc five years after two specific extreme El Niño events: 1982-83 (A) and 1997-98 (B). Changes are calculated relative to counterfactual trajectories in which the event did not occur (see Fig. 2a for example of Peru). That is, the color for Brazil in panel B indicates that Brazil's GDP per capita would have been 5% larger in 2003 if the 1997-98 El Niño event did not occur. Countries are masked in white if they either have no significant marginal effect of ENSO or do not have continuous GDPpc data since 1982 (Methods). C, D) 2020-2099 average change in country-level GDPpc under the SSP1-2.6 (C) and SSP5-8.5 (D) scenarios for the average case across climate models and regression bootstraps. Insets in C and D show the signal-to-noise ratios (S/N), meaning the absolute value of the ratio of the ensemble mean GDPpc change to the ensemble standard deviation GDPpc change. "Ensemble" is defined as all possible combinations of climate model projections and regression bootstraps.

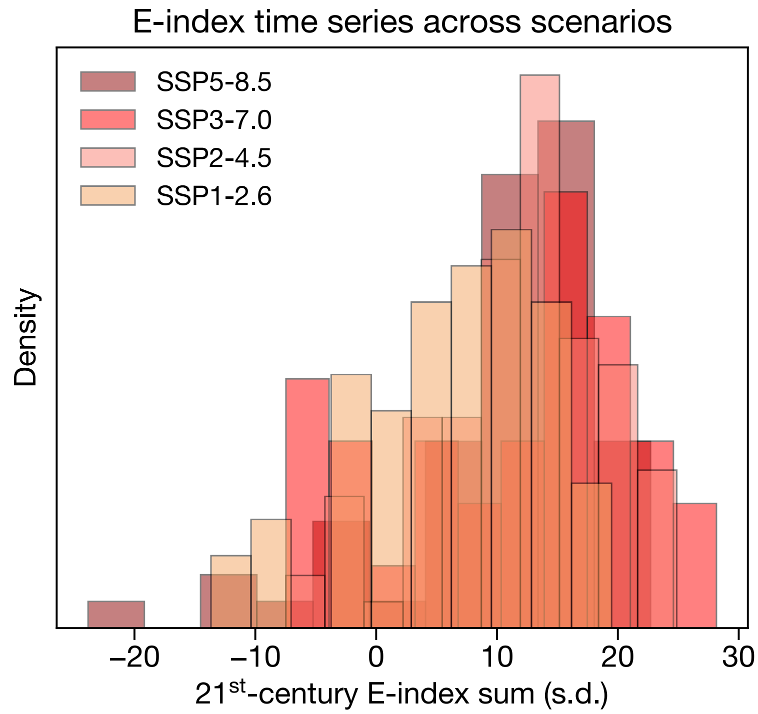

Fig. S12

E-index sum across scenarios. Histograms show the distribution of 2020-99 E-index sum values across simulations within each SSP scenario. Positive values mean that the simulation's E-index time series has more El Niños than La Niñas.

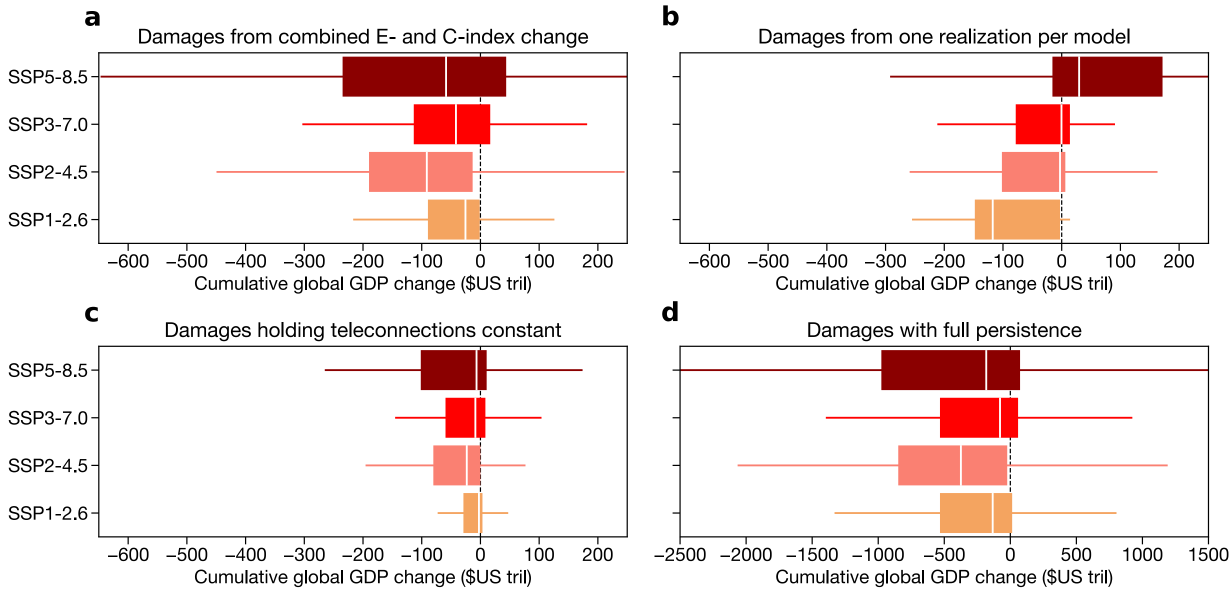

Fig. S13

Sensitivity of damage calculations to alternative choices. As in main text Fig. 4a, but for damages due to the combination of changes in E- and C-index amplitude and teleconnections (A), E-index damages using only the first realization from each model (B), E-index damages using amplitude change but holding teleconnections constant (C), and E-index damages when allowing damages to be permanently persistent (i.e., using the 5-lag model and assuming that the cumulative effects are never recovered) (D). All panels use a constant 2% discount rate.

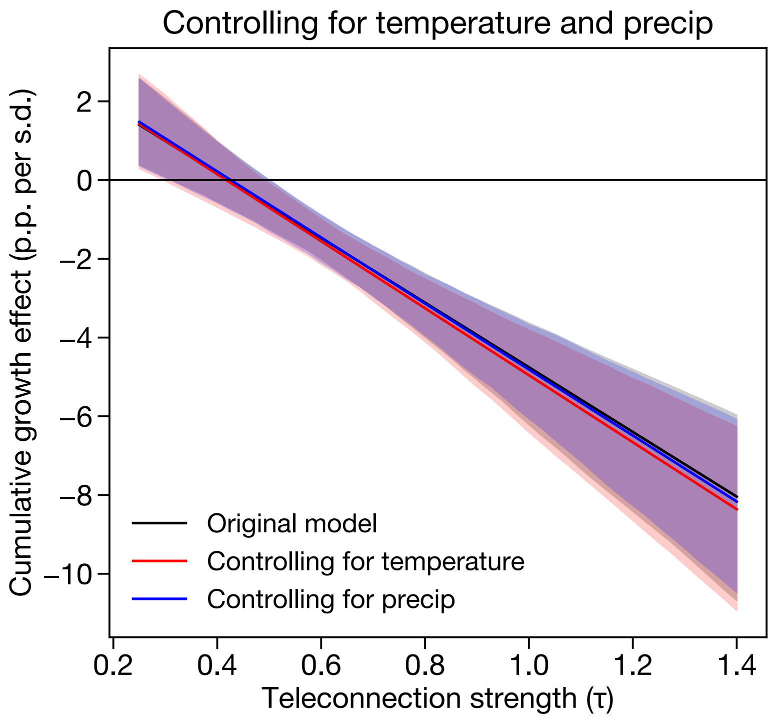

Fig. S14

Effects of controlling for temperature and precipitation in our regression model. Black line shows results from the original model, red line shows results with the addition of linear and quadratic terms for country-level annual mean temperature, and blue line shows results with the addition of linear and quadratic terms for the country-level annual average of monthly total precipitation. Shading shows the 95% confidence intervals from bootstrap resampling by country, as in the main analysis.

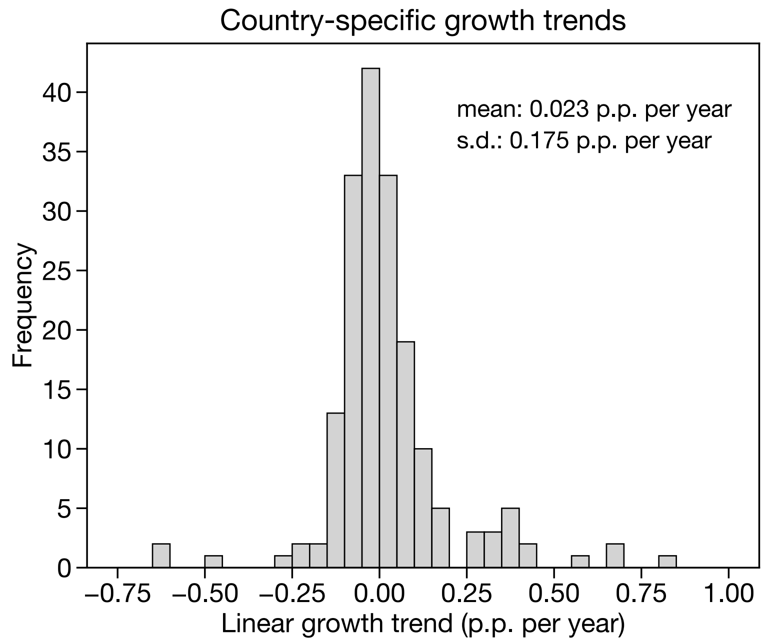

Fig. S15

Linear trends in growth. Growth trends are calculated as the linear coefficient on the univariate regression of each country's growth time series onto time. Only countries with 10 or more years of growth data are included in this histogram. Text in the top right denotes the mean and standard deviation of the distribution of trends across countries.

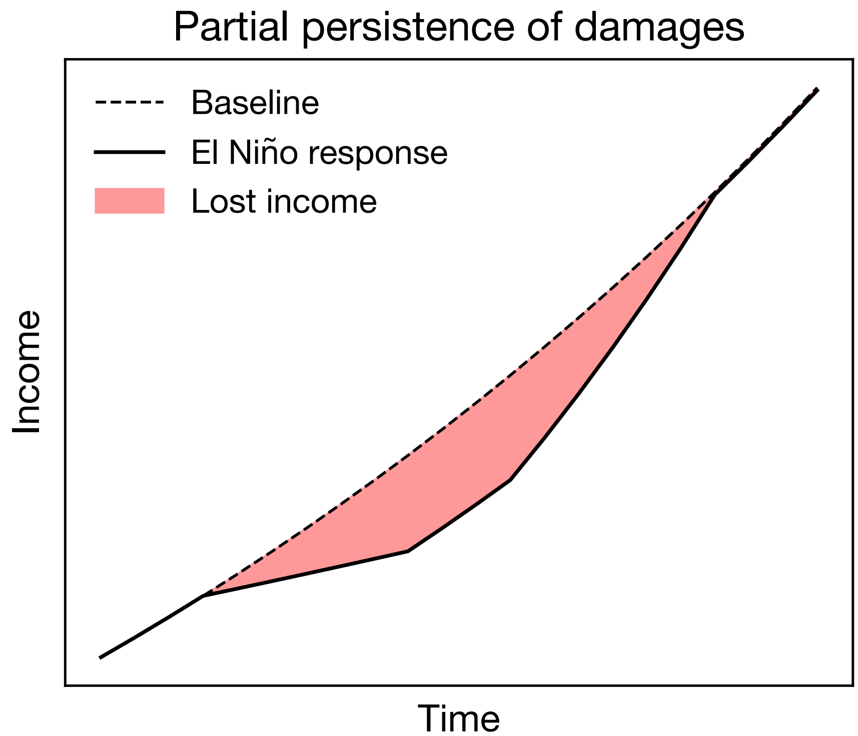

Fig. S16

Partial persistence of economic damages. This figure shows a schematic of how we implement the recovery period in our damage projections. El Niño events negatively affect growth in the year of the event and in the five years following the event, as in our main model. However, from years 9 to 14, we allow economies to recover back to their baseline economic trajectory. In the meantime, there is substantial lost income relative to that baseline trajectory, shown as the red shaded area.

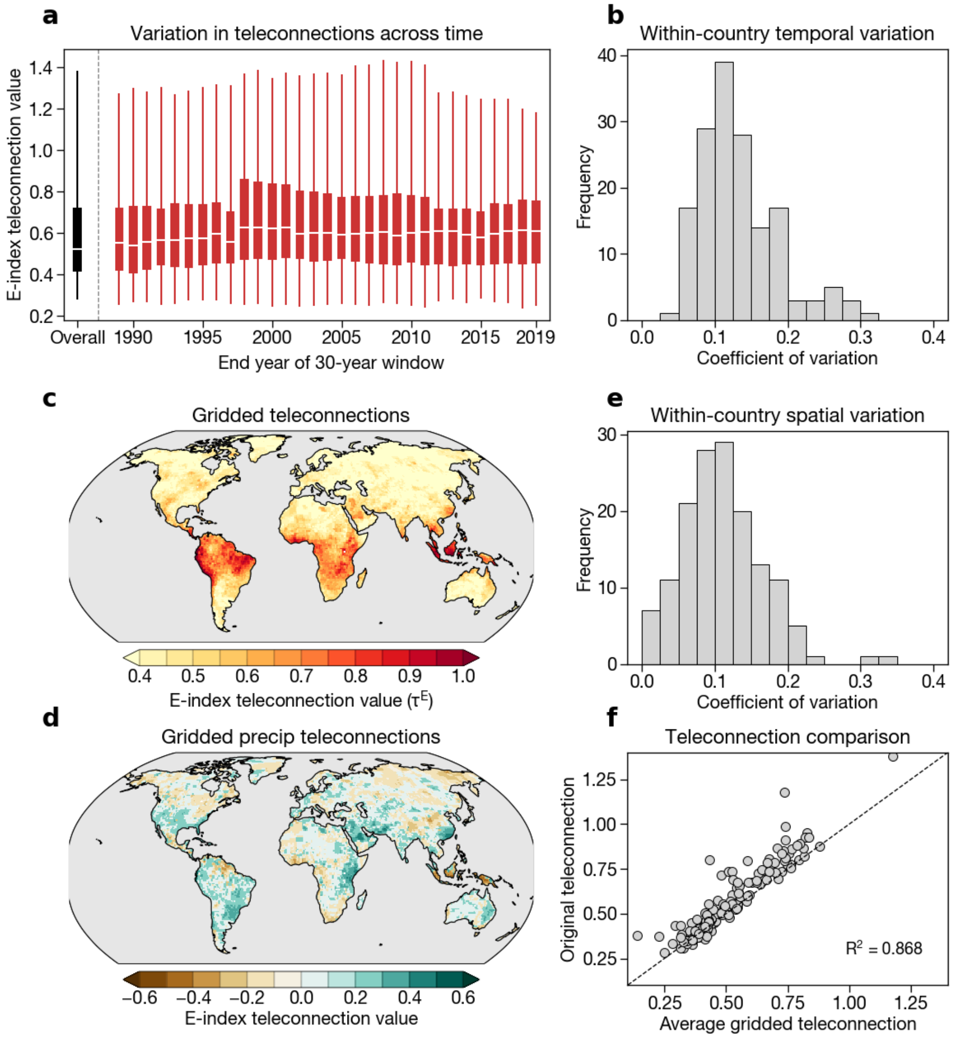

Fig. S17

Spatiotemporal heterogeneity of observed teleconnections. A) Distribution of E-index teleconnections in 30-year windows, with x-axis marking the final year of the 30-year window. An end year of 2015, for example, implies a start year of 1986. The black boxplot shows the original distribution of teleconnections calculated over the whole 1960-2019 period. White lines show medians, boxes extend to the 25th and 75th percentiles, and whiskers span the range of the data. B) Within-country temporal variation, calculated as the coefficient of variation over the 30-year windows shown in (A). This calculation is performed by dividing the standard deviation of each country's teleconnection values over all 30-year windows by its mean teleconnection over those windows. C) Grid-cell E-index teleconnections, calculated using the same method as the country-level teleconnections, but with standardized grid-cell temperature and precipitation data. D) Grid-cell precipitation teleconnections, meaning the precipitation component of (C). Note that the sign is preserved in (D), whereas the teleconnections in (C) and in the main analysis use absolute values. E) Within-country spatial variation in teleconnections, calculated as the coefficient of variation of the grid-cell teleconnections when aggregated to the country scale. F) Relationship between gridded teleconnections averaged at the country scale (with population weighting) and the original teleconnections using country-average temperature and precipitation.

Table S1.

E-index coefficients with alternative clustering techniques. E-index regression coefficients from the main regression model (Eqn. 1) using various parametric standard error clustering schemes. The marginal effect of the E-index for a country *i* is calculated as the main effect of the E-index plus the interaction term times τ^{E}_{i} ($\beta + \theta * \tau^{E}_{i}$, Eqn. 2). Clustering accounts for both spatiotemporal autocorrelation in errors as well as heteroskedasticity across clusters. In all models, the C-index terms and the country fixed effect are included but not shown in the table for simplicity.

	Dependent variable: growth				
	(1)	(2)	(3)	(4)	(5)
E_t (β_0)	0.0066***	0.0066*	0.0066	0.0066*	0.0066
	(0.0016)	(0.0033)	(0.0035)	(0.0025)	(0.0041)
E_{t-1} (β_1)	0.0019	0.0019	0.0019	0.0019	0.0019
	(0.0018)	(0.0028)	(0.0034)	(0.0025)	(0.0033)
E_{t-2} (β_2)	0.0054*	0.0054	0.0054	0.0054	0.0054
	(0.0022)	(0.0044)	(0.0043)	(0.0041)	(0.0039)
E_{t-3} (β_3)	0.0081***	0.0081*	0.0081*	0.0081*	0.0081*
	(0.0021)	(0.0036)	(0.0035)	(0.0029)	(0.0032)
E_{t-4} (β_4)	0.0053**	0.0053	0.0053*	0.0053*	0.0053*
	(0.0019)	(0.0033)	(0.0026)	(0.0020)	(0.0023)
E_{t-5} (β_5)	0.0064**	0.0064*	0.0064*	0.0064**	0.0064*
	(0.0021)	(0.0031)	(0.0030)	(0.0014)	(0.0031)
$E_t \times \tau_i^E$ (Θ_0)	−0.0163***	−0.0163**	−0.0163***	−0.0163**	−0.0163**
	(0.0028)	(0.0055)	(0.0042)	(0.0036)	(0.0051)
$E_{t-1} \times \tau_i^E$ (Θ_1)	−0.0072*	−0.0072	−0.0072	−0.0072	−0.0072
	(0.0028)	(0.0039)	(0.0043)	(0.0030)	(0.0047)
$E_{t-2} \times \tau_i^E$ (Θ_2)	−0.0158***	−0.0158**	−0.0158***	−0.0158*	−0.0158***
	(0.0036)	(0.0059)	(0.0048)	(0.0061)	(0.0046)
$E_{t-3} \times \tau_i^E$ (Θ_3)	−0.0169***	−0.0169***	−0.0169***	−0.0169**	−0.0169***
	(0.0032)	(0.0050)	(0.0042)	(0.0036)	(0.0038)
$E_{t-4} \times \tau_i^E$ (Θ_4)	−0.0123***	−0.0123**	−0.0123***	−0.0123**	−0.0123***
	(0.0032)	(0.0045)	(0.0029)	(0.0024)	(0.0025)
$E_{t-5} \times \tau_i^E$ (Θ_5)	−0.0121***	−0.0121*	−0.0121***	−0.0121***	−0.0121***
	(0.0034)	(0.0048)	(0.0035)	(0.0010)	(0.0035)
Observations	7183	7183	7183	7183	7183
Clustering	Country	Year-continent	Year	Continent	Five-year block

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S2.

C-index coefficients with alternative clustering techniques. C-index regression coefficients from the main regression model (Eqn. 1) using various parametric standard error clustering schemes. The marginal effect of the C-index for a country *i* is calculated as the main effect of the C-index plus the interaction term times τ^C_i ($\phi + \Psi * \tau^C_i$, Eqn. 2). Clustering accounts for both spatiotemporal autocorrelation in errors as well as heteroskedasticity across clusters. In all models, the E-index terms and the country fixed effect are included but not shown in the table for simplicity.

	Dependent variable: growth				
	(1)	(2)	(3)	(4)	(5)
C_t (Φ_0)	−0.0038*	−0.0038	−0.0038	−0.0038	−0.0038
	(0.0016)	(0.0028)	(0.0032)	(0.0015)	(0.0052)
C_{t-1} (Φ_1)	0.0048***	0.0048	0.0048	0.0048	0.0048
	(0.0013)	(0.0043)	(0.0044)	(0.0020)	(0.0041)
C_{t-2} (Φ_2)	0.0021	0.0021	0.0021	0.0021	0.0021
	(0.0012)	(0.0036)	(0.0042)	(0.0009)	(0.0021)
C_{t-3} (Φ_3)	0.0028**	0.0028	0.0028	0.0028	0.0028
	(0.0010)	(0.0033)	(0.0039)	(0.0014)	(0.0027)
C_{t-4} (Φ_4)	−0.0015	−0.0015	−0.0015	−0.0015	−0.0015
	(0.0013)	(0.0035)	(0.0040)	(0.0011)	(0.0021)
C_{t-5} (Φ_5)	−0.0031*	−0.0031	−0.0031	−0.0031***	−0.0031
	(0.0015)	(0.0026)	(0.0032)	(0.0004)	(0.0042)
$C_t \times \tau_i^C$ (Ψ_0)	0.0026	0.0026	0.0026	0.0026	0.0026
	(0.0023)	(0.0039)	(0.0042)	(0.0017)	(0.0067)
$C_{t-1} \times \tau_i^C$ (Ψ_1)	−0.0074***	−0.0074	−0.0074	−0.0074	−0.0074
	(0.0018)	(0.0056)	(0.0051)	(0.0031)	(0.0047)
$C_{t-2} \times \tau_i^C$ (Ψ_2)	−0.0059**	−0.0059	−0.0059	−0.0059**	−0.0059*
	(0.0018)	(0.0047)	(0.0048)	(0.0011)	(0.0026)
$C_{t-3} \times \tau_i^C$ (Ψ_3)	−0.0041**	−0.0041	−0.0041	−0.0041*	−0.0041
	(0.0015)	(0.0044)	(0.0046)	(0.0013)	(0.0034)
$C_{t-4} \times \tau_i^C$ (Ψ_4)	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0019)	(0.0047)	(0.0046)	(0.0012)	(0.0028)
$C_{t-5} \times \tau_i^C$ (Ψ_5)	0.0025	0.0025	0.0025	0.0025*	0.0025
	(0.0020)	(0.0035)	(0.0034)	(0.0007)	(0.0045)
Observations	7183	7183	7183	7183	7183
Clustering	Country	Year-continent	Year	Continent	Five-year block

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S3.

CMIP6 models and realizations used from the SSP1-2.6 scenario. Monthly sea surface temperature (“tos”), monthly atmospheric temperature (“tas”), and daily precipitation (“pr”) are used from each model. Bolded models are those that have at least 1 realization selected for the final analysis (Methods).

Model	Total realizations	Selected realizations
CanESM5	50	0
KACE-1-0-G	3	0
MIROC-ES2L	7	7
MIROC6	50	50
MRI-ESM2-0	5	4

Table S4.

CMIP6 models and realizations used from the SSP2-4.5 scenario. Monthly sea surface temperature (“tos”), monthly atmospheric temperature (“tas”), and daily precipitation (“pr”) are used from each model. Bolded models are those that have at least 1 realization selected for the final analysis (Methods).

Model	**Total realizations**	**Selected realizations**
ACCESS-CM2	3	0
ACCESS-ESM1-5	11	0
CAMS-CSM1-0	1	0
CESM2	2	0
CESM2-WACCM	3	2
CMCC-CM2-SR5	1	1
CMCC-ESM2	1	1
CNRM-CM6-1	1	0
CanESM5	50	0
EC-Earth3	8	8
FGOALS-g3	3	0
GFDL-ESM4	1	0
HadGEM3-GC31-LL	1	0
INM-CM4-8	1	0
INM-CM5-0	1	0
IPSL-CM6A-LR	5	0
KACE-1-0-G	3	0
MIROC-ES2L	30	30
MIROC6	33	33
MPI-ESM1-2-HR	2	1
MPI-ESM1-2-LR	10	9
NorESM2-LM	2	0
NorESM2-MM	2	1
UKESM1-0-LL	5	0

Table S5.

CMIP6 models and realizations used from the SSP3-7.0 scenario. Monthly sea surface temperature (“tos”), monthly atmospheric temperature (“tas”), and daily precipitation (“pr”) are used from each model. Bolded models are those that have at least 1 realization selected for the final analysis (Methods).

Model	**Total realizations**	**Selected realizations**
ACCESS-CM2	3	0
ACCESS-ESM1-5	10	0
CAMS-CSM1-0	1	0
CESM2	2	0
CESM2-WACCM	1	1
CMCC-CM2-SR5	1	1
CMCC-ESM2	1	1
CNRM-CM6-1	1	0
CanESM5	50	0
FGOALS-g3	4	0
GFDL-ESM4	1	0
INM-CM4-8	1	0
INM-CM5-0	5	0
IPSL-CM6A-LR	5	0
KACE-1-0-G	3	0
MIROC-ES2L	10	10
MIROC6	3	3
MPI-ESM1-2-HR	10	4
MPI-ESM1-2-LR	7	6
MRI-ESM2-0	5	5
NorESM2-LM	1	1
NorESM2-MM	1	1
UKESM1-0-LL	13	0

Table S6.

CMIP6 models and realizations used from the SSP5-8.5 scenario. Monthly sea surface temperature (“tos”), monthly atmospheric temperature (“tas”), and daily precipitation (“pr”) are used from each model. Bolded models are those that have at least 1 realization selected for the final analysis (Methods).

Model	Total realizations	Selected realizations
ACCESS-CM2	2	0
ACCESS-ESM1-5	6	0
CAMS-CSM1-0	1	0
CESM2	0	0
CESM2-WACCM	3	1
CMCC-CM2-SR5	1	1
CMCC-ESM2	1	1
CNRM-CM6-1	1	0
CanESM5	50	0
FGOALS-g3	3	0
GFDL-ESM4	1	0
HadGEM3-GC31-LL	4	0
HadGEM3-GC31-MM	4	0
INM-CM4-8	1	0
INM-CM5-0	1	0
IPSL-CM6A-LR	4	0
KACE-1-0-G	3	0
MIROC-ES2L	1	1
MIROC6	50	50
MPI-ESM1-2-HR	2	1
NorESM2-LM	1	1
NorESM2-MM	1	1
UKESM1-0-LL	5	0

Table S7.

Correlation matrix for the E-index and its lags. Each table entry shows the Pearson correlation coefficient between the E-index at various time lags and the E-index at each other time lag.

	E_t	E_{t-1}	E_{t-2}	E_{t-3}	E_{t-4}	E_{t-5}
E_t		-0.101	-0.335	0.002	0.034	0.002
E_{t-1}			-0.092	-0.336	-0.01	0.037
E_{t-2}				-0.089	-0.291	-0.029
E_{t-3}					-0.094	-0.291
E_{t-4}						-0.076

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Supplementary Materials

Materials and Methods

Supplementary Text

References (*49-84*)

Figs. S1 to S17

Tables S1 to S7

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