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Supplementary Materials for

Escaping the perfect storm of simultaneous climate change impacts on agriculture and marine fisheries

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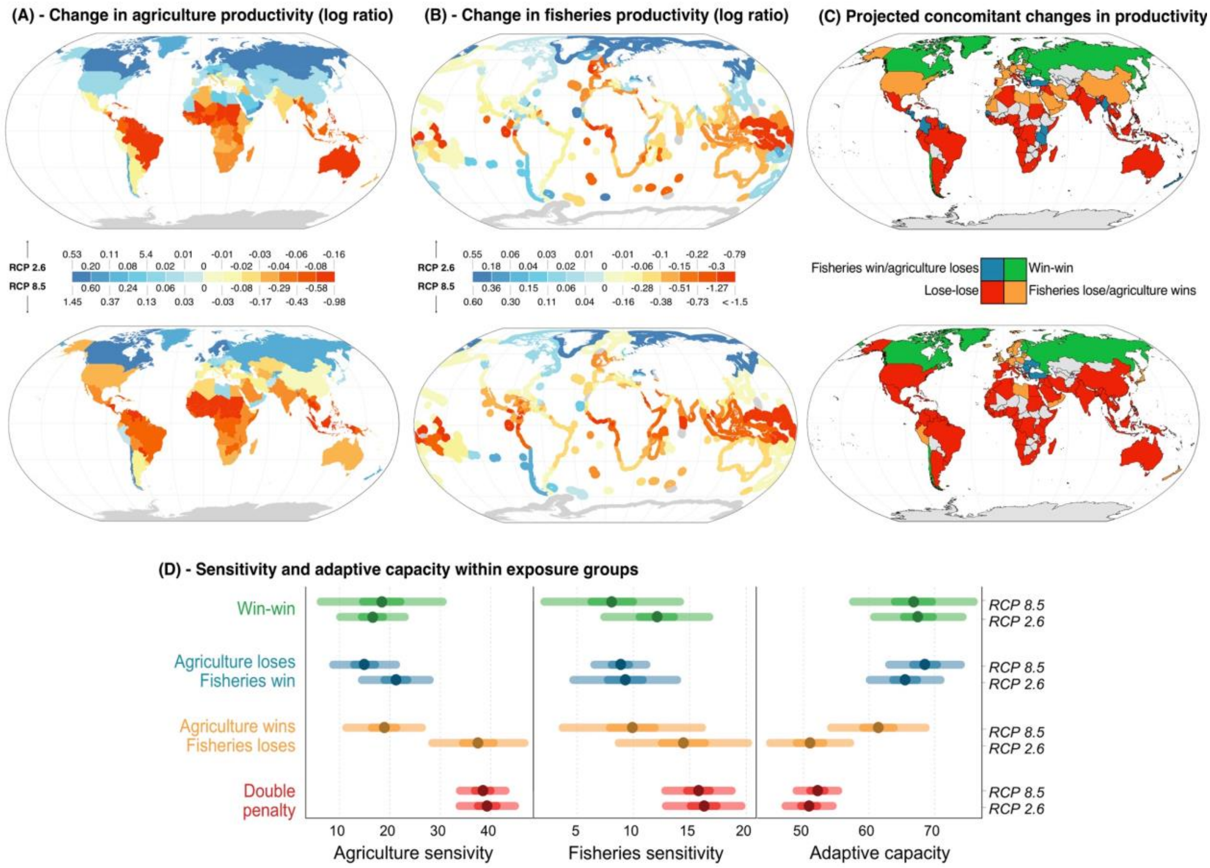

Fig. S1. Spatial variation in agriculture and marine fisheries exposure, and associated levels of sensitivity and adaptive capacity according to emission scenarios RCP2.6 and RCP8.5. Concomitant changes in agriculture (**A**) and marine fisheries (**B**) productivity describe (**C**) lose-lose (red), win-lose (yellow and blue), and win-win (green) situations for multi-sector countries (i.e., excluding landlocked countries that have no or negligible marine fisheries sector). (**D**) Levels of sensitivity and adaptive capacity (average weighted by population size +/-50% and 95% confidence intervals) for each exposure category under RCP8.5 and RCP2.6. Note that changes in sensitivity and adaptive capacity are only due to changes in countries within each exposure category and do not reflect climate-induced changes in these vulnerability dimensions. See fig. S5 for model uncertainty surrounding these estimates.

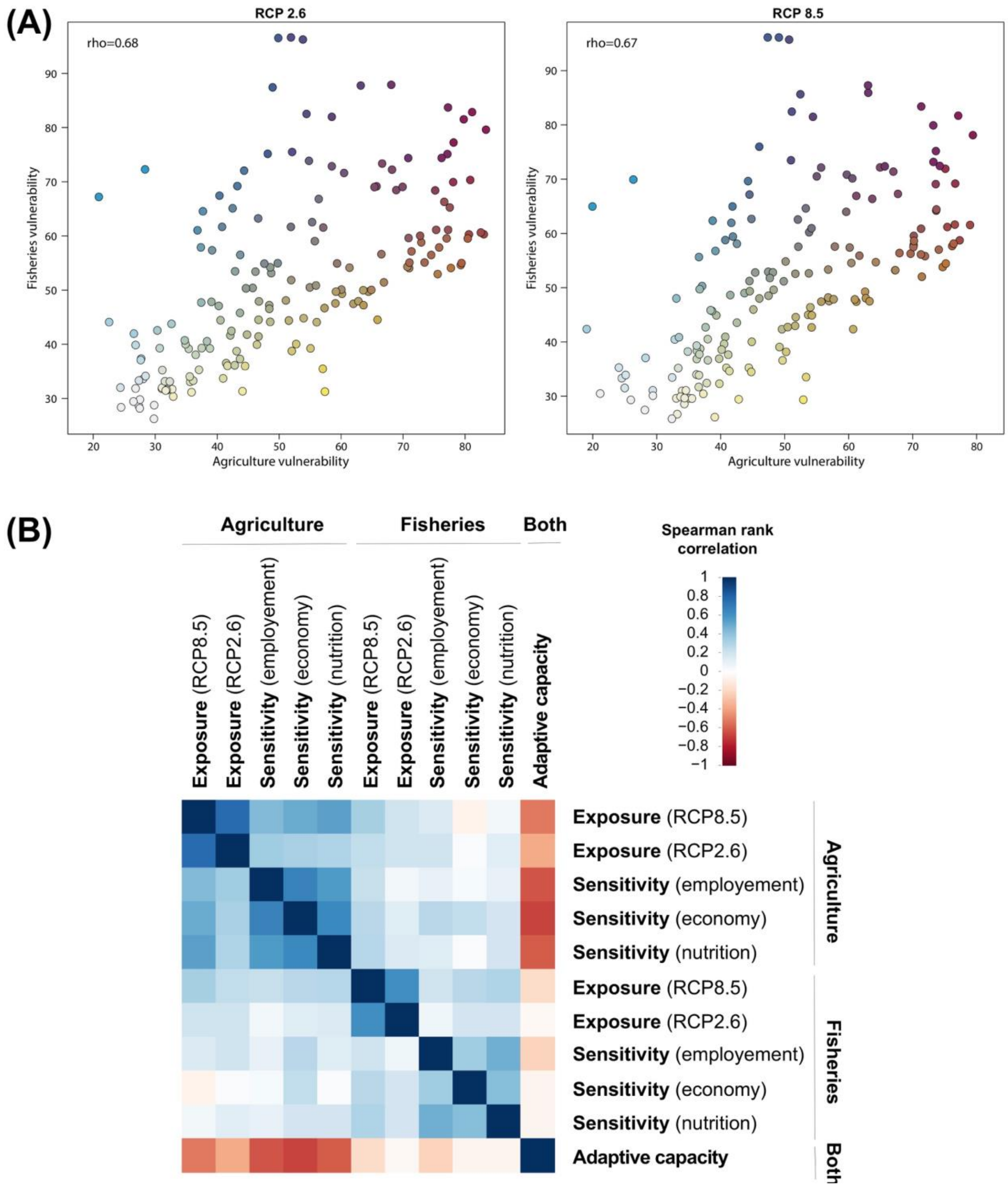

Fig. S2. Relationships between agriculture and marine fisheries vulnerability to climate change under RCP8.5 and RCP2.6. Rho indicate Spearman's rank coefficient. (**A**) Vulnerability scores. (**B**) Spearman's rank correlations among pairs of indicators used to evaluate agriculture and marine fisheries vulnerability.

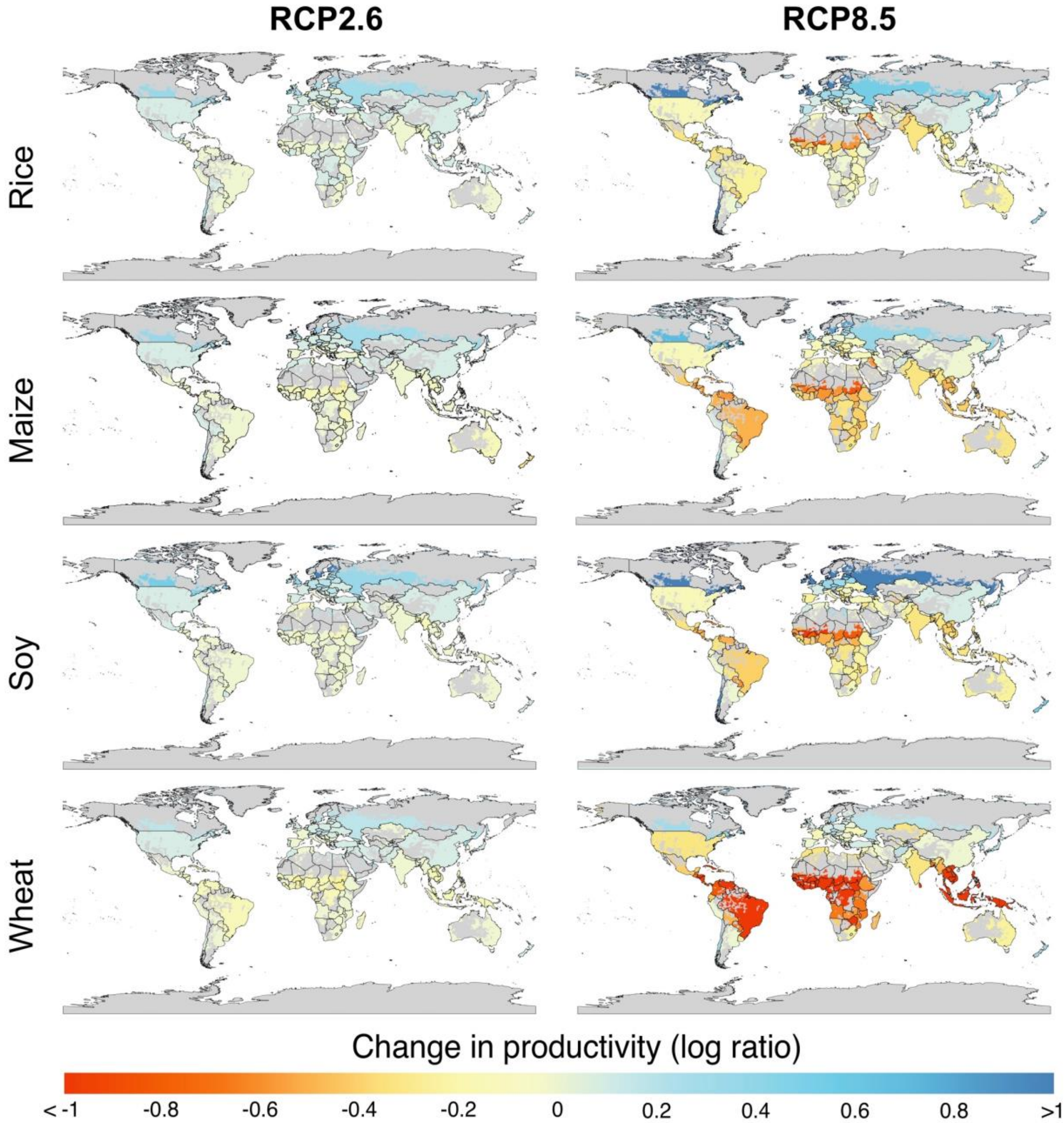

Fig. S3. Changes in productivity for maize, rice, soy, and wheat crops under RCP2.6 and RCP8.5. Values indicate average productivity changes (log-ratio) for RCP2.6 and RCP8.5 (2090-99 in comparison to 2001-10 baseline) over all models and assumptions. Gray areas indicate historical areas with little to no yield capacity.

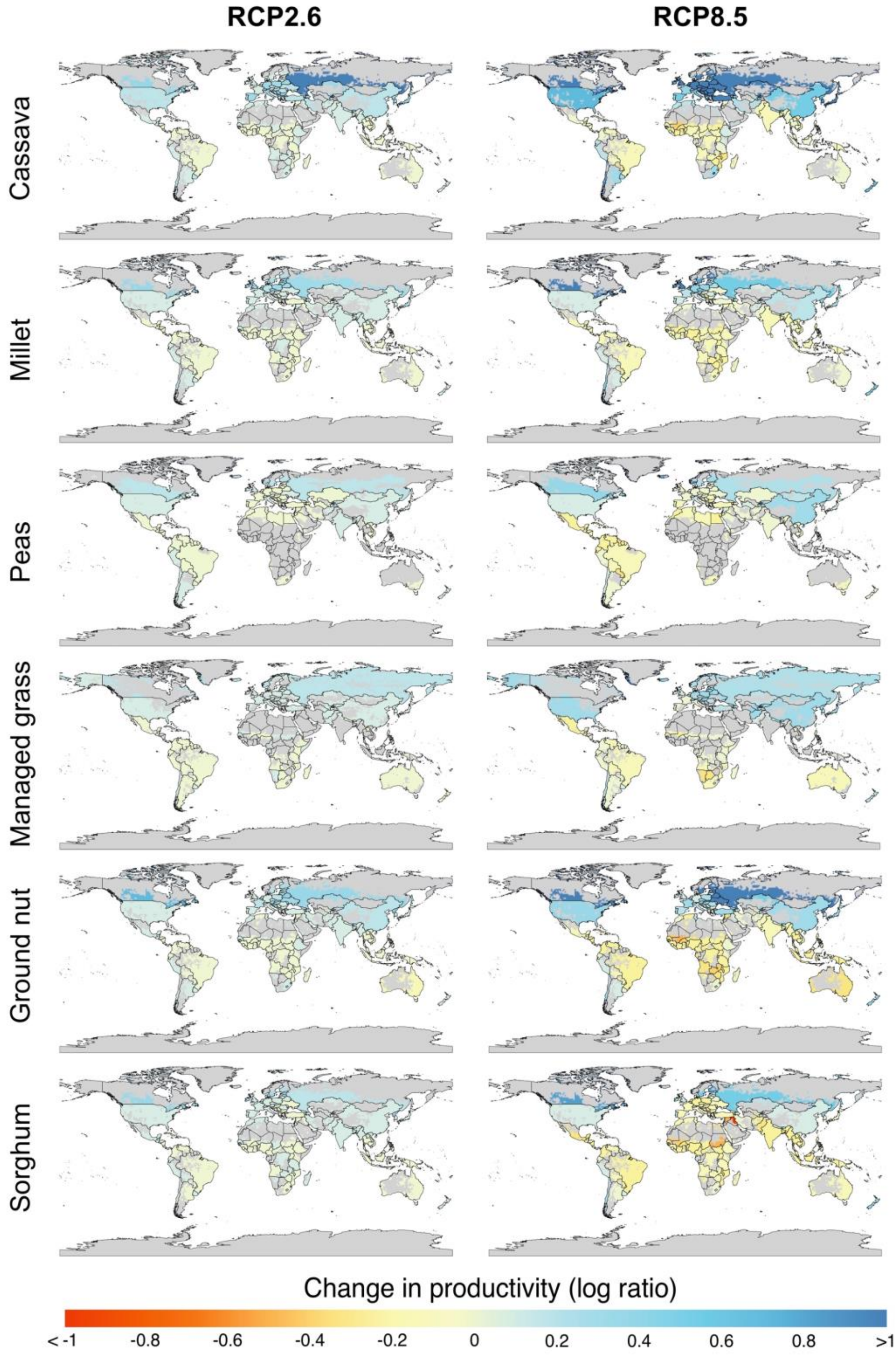

Fig. S4. Changes in productivity for six other crops under RCP2.6 and RCP8.5. Values indicate average productivity changes (log ratio) for RCP2.6 and RCP8.5 (2090-99 in comparison to 2001-10 baseline) over all models and assumptions. We used the same set of experiments and GCMs as for maize, rice, soy and wheat projections, but only used global gridded crop models for which data was available (EPIC, IMAGE and LPjmL). Gray areas indicate historical areas with little to no yield capacity.

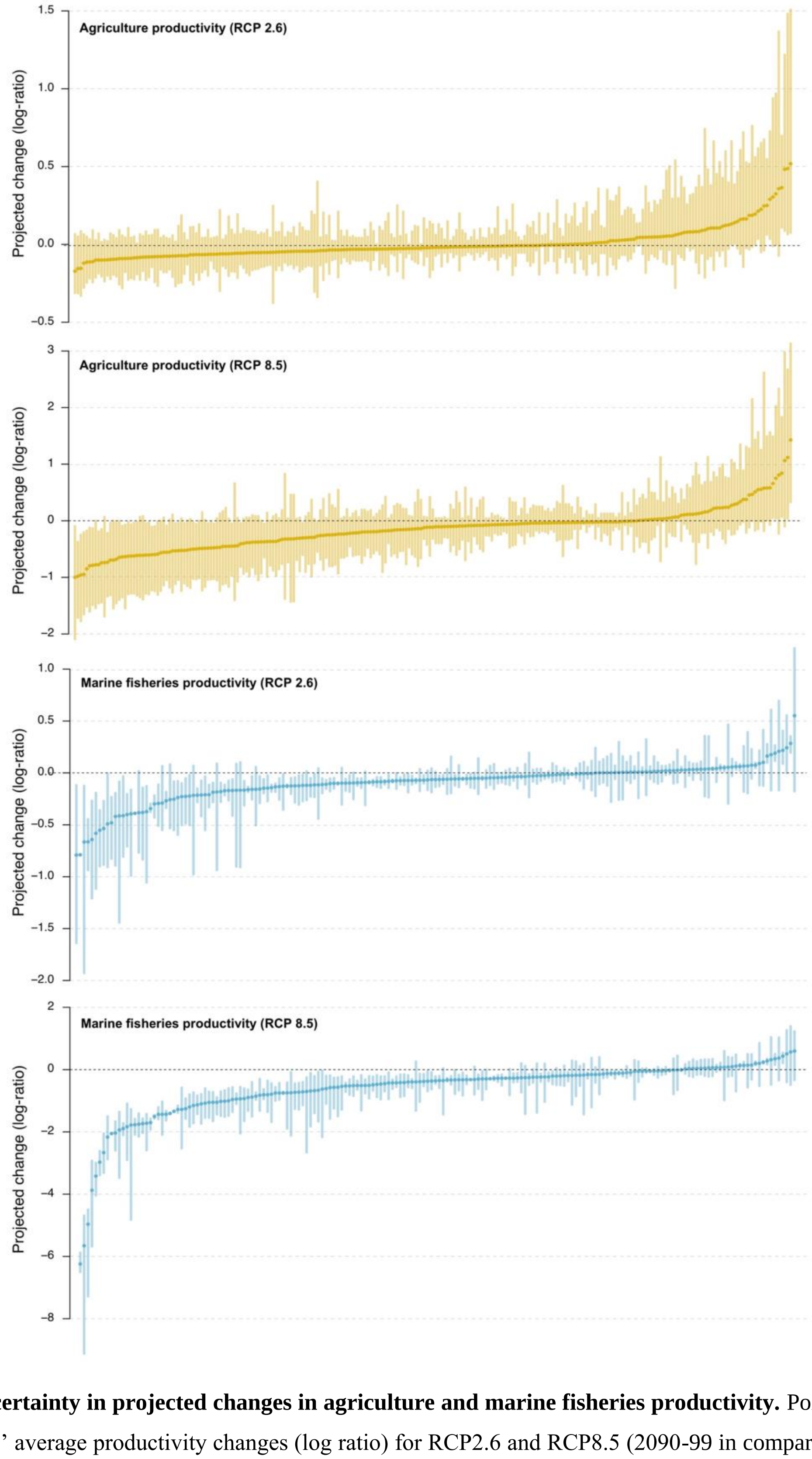

Fig. S5. Uncertainty in projected changes in agriculture and marine fisheries productivity. Points represent the countries' average productivity changes (log ratio) for RCP2.6 and RCP8.5 (2090-99 in comparison to 2001-10 baseline) over all models and assumptions (see Methods) used to evaluate exposure in the main text. Error bars indicate minimum and maximum values obtained from the ensemble members.

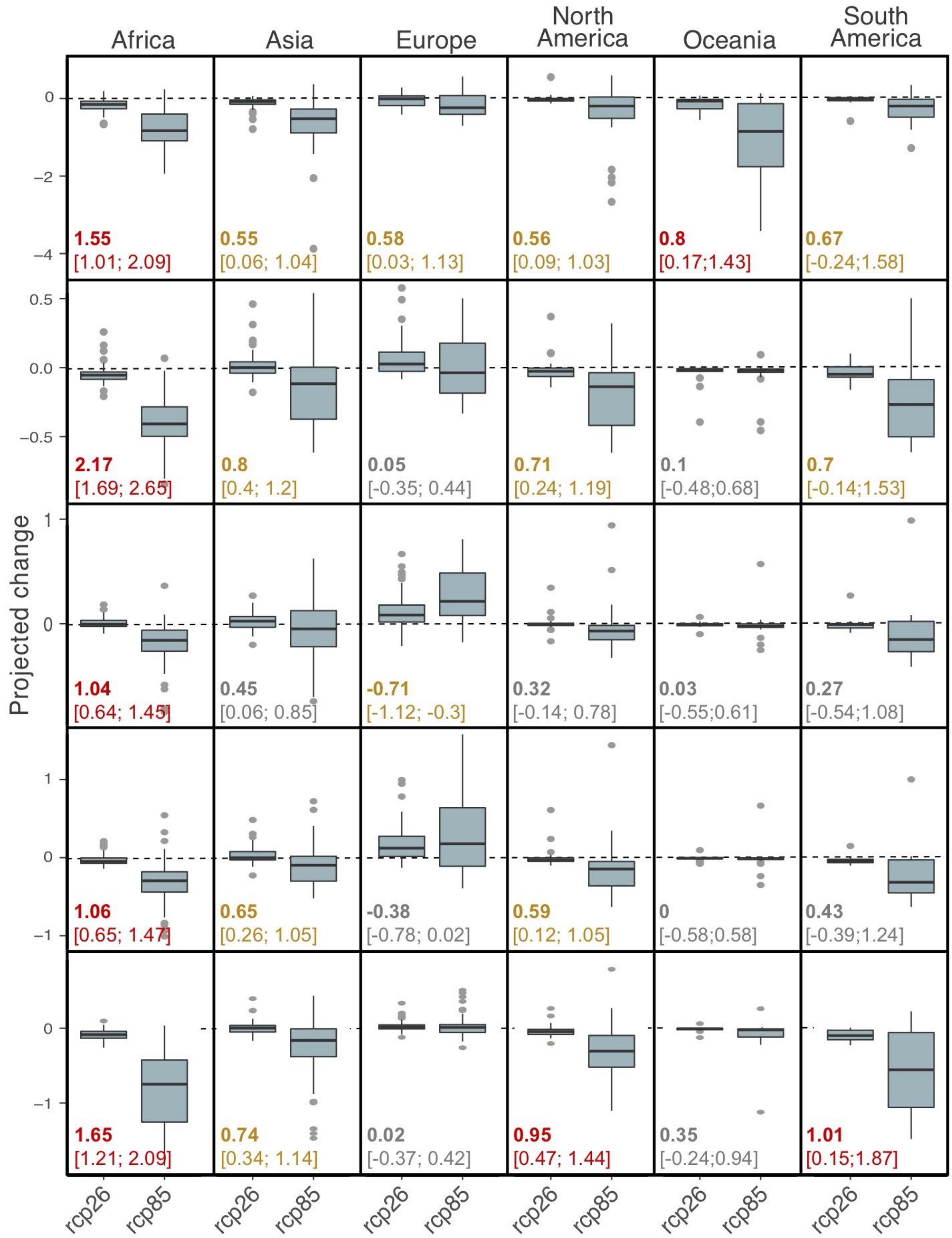

Fig. S6. Regional changes in agriculture and marine fisheries productivity under RCP2.6 and RCP8.5. Numbers in each box indicate the Cohen's d effect sizes [95% confidence interval] for paired samples between the two RCP scenarios. Negative and positive values thus indicate net loss (i.e., lower gains, higher losses, gain-to-loss) and net gain (i.e., higher gains, lower losses, loss-to-gain) from climate mitigation, respectively. Large, medium and small effect sizes are indicated in red, orange and grey, respectively.

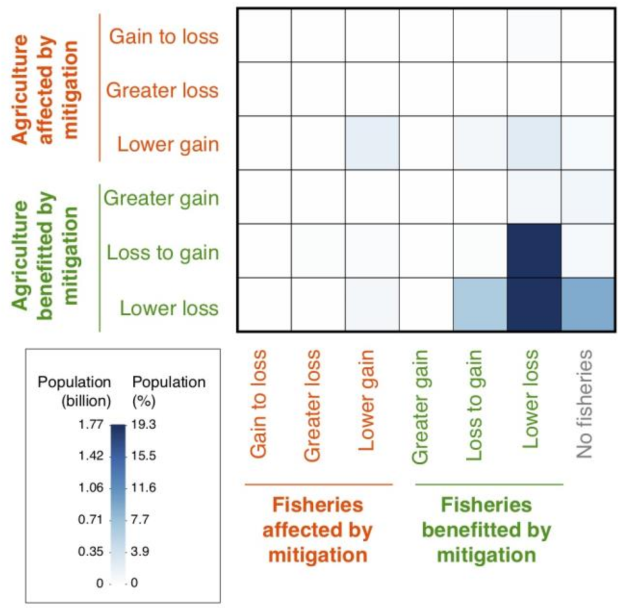

Fig. S7. Net gains and losses in agriculture and fisheries productivity from climate mitigation.

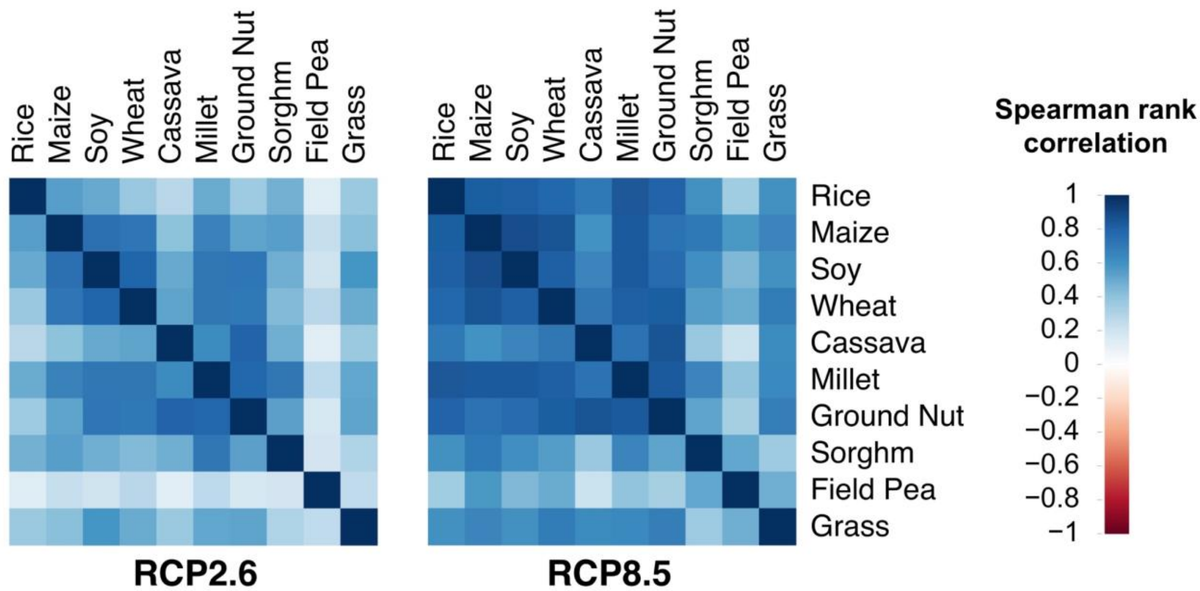

Fig. S8. Spearman's rank correlations among pairs of agricultural crop changes in productivity under RCP2.6 and RCP8.5.

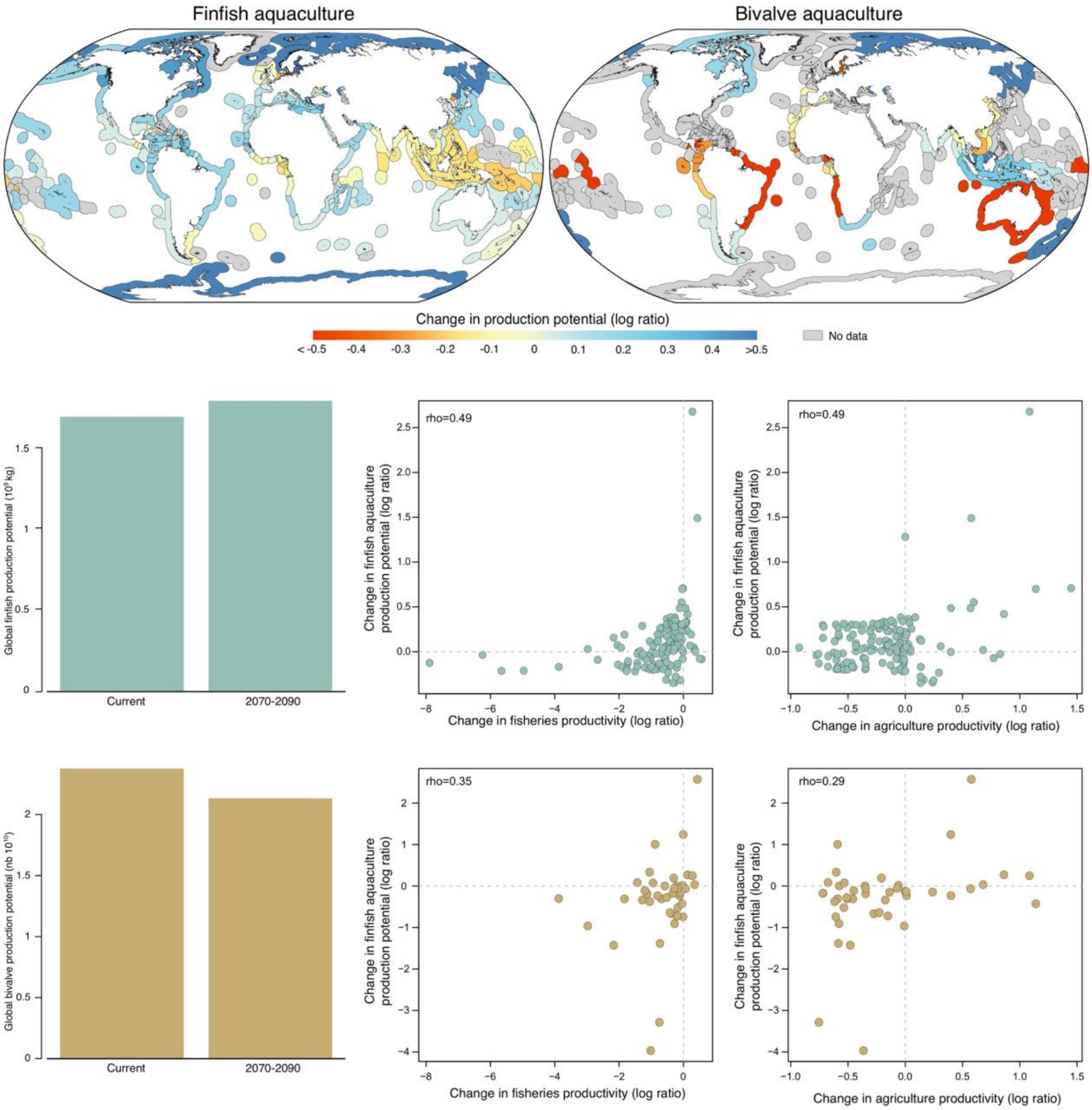

Fig. S9. Projected changes in finfish and bivalve aquaculture production potential under climate change. Maps show average change in finfish and bivalve aquaculture production potential (2070-90 in comparison to 1985-2005 baseline) under RCP8.5. Barplots indicate total global finfish (bermuda color) and bivalve (harvest gold color) aquaculture production potential for 1985-2005 and 2070-90. Biplots show changes in aquaculture production potential against changes in agriculture and marine fisheries productivity under RCP8.5. Changes are the results of temperature, chlorophyll and aragonite saturation. Note that finfish aquaculture assumes unlimited food supply. Data and details on the methods from (*33*, *51*).

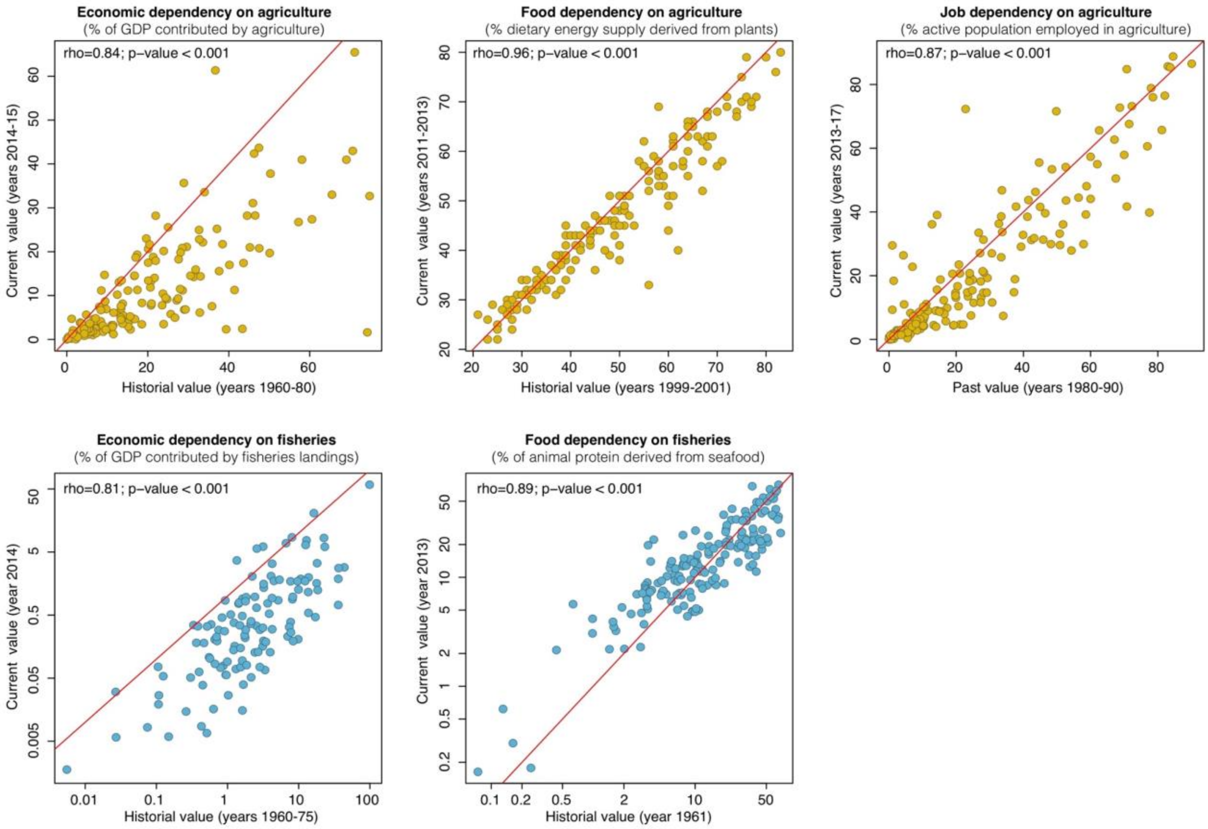

Fig. S10. Correlations between historical and present-day indicators of sensitivity. The year range defining each period is indicated on the axes. Each point represents a country and the red line indicates the 1:1 relationship (i.e. no change). Spearman's rank correlation coefficients and associated p-values are indicated. Historical data for job dependency on fisheries was not available.

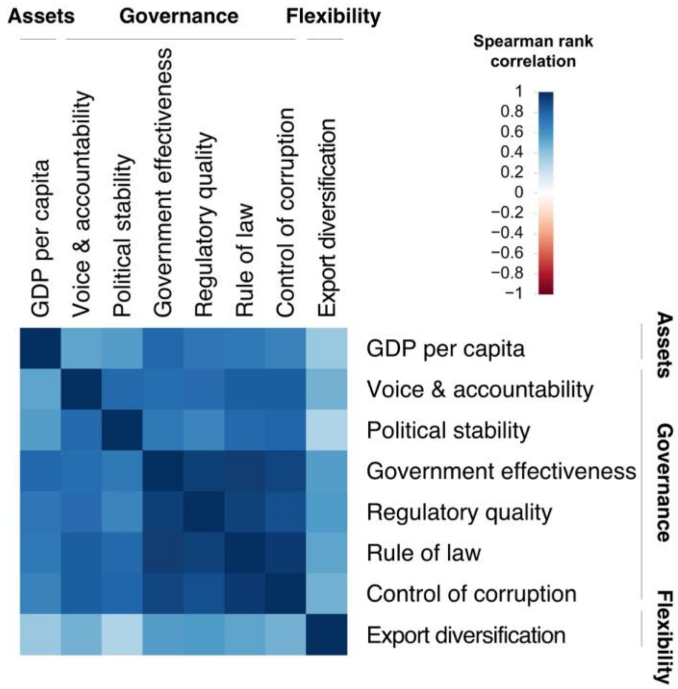

Fig. S11. Spearman's rank correlations among pairs of adaptive capacity indicators. Governance status includes six indicators developed by the Worldwide Governance Indicators (WGI) project (*52*): voice accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption. Each of these indicators was measured by combining 30 data sources ranging from public and private sectors to NGOs and households surveys (*52*). Although margins of error and temporal trend were available for each governance indicator, we only incorporated the 2016 average estimates. The export diversification index developed by IMF (*53*) is used to evaluate economic flexibility. This index computes the overall Theil's entropy index (*54*) and reflects how the structure of exports by product of a given country differ from the structure of product of the world. Export diversification index was rescaled so that a value of 0 indicates lowest flexibility and a value of 1 indicates highest flexibility. All indicators are positively and significantly correlated, indicating that GDP per capita can broadly capture domains of adaptive capacity.

Table S1. Indicators and main data sources used to measure country-level metrics of agriculture and marine fisheries vulnerability to climate change. Year (Y) and number of countries (N) covered in the original datasets are indicated.

Sector	Dimension	Component	Indicator	Source	Coverage
Agriculture					
	Exposure	Change in agriculture productivity by 2100	Average change (log ratio) in maize, rice, soy and wheat productivity (RCP8.5+RCP2.6)	AgMIP (*12*, *37*)	Y: 2090-99 N: 221
	Sensitivity	Job dependency	% of workforce employed by agriculture	FAO (*42*)	Y: 2013-17 N: 241
		Economic dependency	% of GDP contributed by agricultural revenue	World Bank (*41*)	Y: 2014-15 N: 216
		Food dependency	% of dietary energy supply derived from plants	FAO (*42*)	Y: 2011-13 N : 227
	Adaptive capacity	Assets	Projected GDP per capita (SSP2)	SSP Database (*45*)	Y: 2090-2100 N: 227
Fisheries					
	Exposure	Change in fisheries productivity by 2100	Change (log ratio) in maximum catch potential within each country's EEZ (RCP8.5+RCP2.6)	Cheung et al. (*10*)	Y: 2090-99 N:194
	Sensitivity	Job dependency	% of the workforce employed by marine fisheries	Teh & Sumaila (*5*)	Y: 2003 N: 144
		Economic dependency	% of GDP contributed by seafood landings	SAU (*44*)	Y: 2014 N: 162
		Food dependency	% of consumed animal protein supplied by seafood	FAO (*42*)	Y: 2013 N: 176
	Adaptive capacity	Assets	Projected GDP per capita (SSP2)	SSP Database (*45*)	Y: 2090-2100 N: 227

Table S2. Effect of strong climate mitigation on top CO_2 producers and on the most vulnerable countries. Win situations (highlighted in bold) indicate a net gain from moving from RCP8.5 to RCP2.6, which may occur via lower losses, higher gains, or losses-to-gains. Lose situations indicate a net loss from moving from RCP8.5 to RCP2.6, which may occur via lower gains, higher losses, or gains-to-losses. See main text Fig. 5 for magnitude.

Category	Country	Impact of mitigation on agriculture	Impact of mitigation on fisheries
Top C02 producers	China	**Win (losses to gains)**	**Win (lower losses)**
	USA	**Win (losses to gains)**	**Win (lower losses)**
	India	**Win (lower losses)**	**Win (lower losses)**
	Russia	Lose (lower gains)	Lose (lower gains)
	Japan	Lose (lower gains)	**Win (losses to gains)**
	Germany	Lose (lower gains)	Win (lower losses)
	Iran	**Win (losses to gains)**	**Win (lower losses)**
	Saudi Arabia	**Win (losses to gains)**	**Win (lower losses)**
	South Korea	**Win (losses to gains)**	**Win (losses to gains)**
	Canada	Lose (lower gains)	Lose (lower gains)
	Brazil	**Win (lower losses)**	**Win (lower losses)**
	South Africa	**Win (lower losses)**	**Win (lower losses)**
	Mexico	**Win (lower losses)**	**Win (lower losses)**
	Indonesia	**Win (lower losses)**	**Win (lower losses)**
	United Kingdom	Lose (lower gains)	**Win (lower losses)**
Most vulnerable through agriculture impacts (RCP8.5)	Mali	**Win (lower losses)**	-
	Niger	**Win (lower losses)**	-
	Chad	**Win (lower losses)**	-
	Burkina Faso	**Win (lower losses)**	-
	Sierra Leone	**Win (lower losses)**	**Win (lower losses)**
	Togo	**Win (lower losses)**	**Win (lower losses)**
	Malawi	**Win (lower losses)**	-
	Ethiopia	**Win (lower losses)**	-
	Madagascar	**Win (lower losses)**	**Win (lower losses)**
	Burundi	**Win (lower losses)**	-
	Guinea Bissau	**Win (lower losses)**	**Win (lower losses)**
	Somalia	**Win (lower losses)**	**Win (lower losses)**
	Liberia	**Win (losses to gains)**	**Win (lower losses)**
	Sudan	**Win (lower losses)**	**Win (lower losses)**
	Mozambique	**Win (lower losses)**	**Win (lower losses)**
Most vulnerable through fisheries impacts (RCP8.5)	Kiribati	**Win (losses to gains)**	**Win (lower losses)**
	Federated States of Micronesia	**Win (lower losses)**	**Win (lower losses)**
	Sao Tome and Principe	**Win (lower losses)**	**Win (lower losses)**
	Guyana	**Win (lower losses)**	**Win (losses to gains)**
	Suriname	**Win (lower losses)**	**Win (losses to gains)**
	Solomon Islands	**Win (lower losses)**	**Win (lower losses)**
	Marshall Islands	**Win (lower losses)**	**Win (lower losses)**
	Guinea Bissau	**Win (lower losses)**	**Win (lower losses)**
	Tuvalu	Lose (gains to losses)	**Win (lower losses)**
	Comoros	**Win (lower losses)**	**Win (lower losses)**
	Sierra Leone	**Win (lower losses)**	**Win (lower losses)**
	Palau	**Win (lower losses)**	**Win (lower losses)**
	Myanmar	**Win (lower losses)**	**Win (losses to gains)**
	Saint Vincent and the Grenadines	**Win (lower losses)**	**Win (lower losses)**