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

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## FRONT MATTER

### Title

- *Full title:* Escaping the perfect storm of simultaneous climate change impacts on agriculture and marine fisheries
- *Short title:* Climate change impact on agriculture and fisheries

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## 29 **Abstract**

30 Climate change can alter conditions that sustain food production and availability, with  
31 cascading consequences for human food security and [countries?'] economies. Yet, food  
32 production sectors are rarely examined together, which may lead to misleading policy  
33 recommendations depending on how gains or losses in one sector are balanced by losses  
34 or gains in another. Here, we evaluate global vulnerability to climate change impacts on  
35 agriculture and marine fisheries. Under a business-as-usual scenario (RCP8.5), ~90% of  
36 the world's human population –mostly living in the most sensitive and least adaptive  
37 countries– are projected to be exposed to productivity losses in both sectors, while less  
38 than 3% are projected to live in regions experiencing simultaneous productivity GAINS?  
39 by 2100. Most countries –including the most vulnerable and many of the largest CO<sub>2</sub>  
40 producers– would experience concomitant greater wins or lower losses on both food  
41 production sectors if greenhouse gas emissions are reduced (RCP2.6). Reducing societies'  
42 vulnerability to future climate impacts requires prompt mitigation actions led by major  
43 CO<sub>2</sub> emitters which should be coupled with strategic adaptation [programs?'] within and  
44 across sectors in regions where negative impacts seem inevitable.

## 46 **MAIN TEXT**

### 48 **Introduction**

49 The impact of climate change on the world's ecosystems and the cascading consequences  
50 for human societies is one of the grand challenges of our time (1–3). Agriculture and  
51 marine fisheries are key food production sectors that sustain global food security, human  
52 health, economic growth, and employment worldwide (4–6), but are significantly and  
53 heterogeneously affected by climatic change (7, 8), with these impacts being projected to  
54 accelerate as greenhouse gas emissions rise (9–12). Policy decisions on mitigation and  
55 adaptation strategies require understanding, anticipating, and synthesizing these climate  
56 change impacts. Central to these decisions are assessments of: (i) the extent to which  
57 impacts in different food production sectors can be compensated, (ii) the consequences for  
58 human societies, and (iii) the potential benefits of mitigation actions. In that regard, global  
59 vulnerability assessments that consider countries' exposure of food production sectors to  
60 climate-induced changes in productivity, their socioeconomic sensitivity to impacted  
61 productivity, as well as their adaptive capacity are certainly useful to define the  
62 opportunity space for climate policy, provided that food production sectors are analyzed  
63 together. Building on previous multi-sector assessments of exposure (13, 14) and

64 vulnerability (*II*), our purpose is to move toward a global scale analysis of human  
65 vulnerability to climate change on two major food sectors: agriculture and marine fisheries.

66 We draw from the vulnerability framework developed in the Intergovernmental Panel on  
67 Climate Change (IPCC)'s (Fig. 1) to assess human vulnerability to climate change impacts  
68 on agriculture and marine fisheries for, respectively, 240 and 194 countries, states or  
69 territories (hereafter "countries"). We evaluated exposure by projecting changes in  
70 productivity of agriculture (maize, rice, soy and wheat) and marine fisheries to the end of  
71 the century relative to contemporary values under two contrasting greenhouse gas  
72 emission scenarios (exposure): a 'business-as-usual' scenario (RCP8.5) and a strong  
73 mitigation scenario (RCP2.6). To generate a comprehensive index of vulnerability for  
74 agriculture and marine fisheries, we then integrated these models with socioeconomic data  
75 on countries' dependency on each sector for food, economy and employment (sensitivity),  
76 and the capacity to respond to climate impacts by mobilizing future assets (adaptive  
77 capacity) (Fig. 1; Table S1).

78 In contrast to previous global studies on vulnerability that are focused on a single sector,  
79 our approach seeks to uncover how the different vulnerability dimensions (exposure,  
80 sensitivity and adaptive capacity) of agriculture and marine fisheries interact and co-occur  
81 under future climate scenarios to derive priority areas for policy interventions and identify  
82 potential synergies or trade-offs. We examine the impacts of climate change on two global  
83 food systems sectors that are key for livelihoods and food security globally (15, 16) and  
84 for which data were available with an acceptable degree of confidence. The likely impacts  
85 on other food sectors (aquaculture, freshwater fisheries and livestock production), for  
86 which global climate change projections are less developed, are discussed only  
87 qualitatively but will be an important future research priority as climate projections on  
88 these sectors become more refined.

## 89 **Results and discussion**

### 90 **A "perfect storm" in the tropics**

91 Spatial heterogeneity of predicted climate change impacts on agriculture and fisheries,  
92 coupled with varying degrees of human sensitivity and adaptive capacity on these sectors,  
93 suggest that for multi-sector countries (i.e. countries engaged in both sectors, as opposed  
94 to landlocked countries with no or negligible marine fisheries), climate change may induce  
95 situations of 'win-win' (i.e. both sectors are favored by climate change), 'win-lose' (i.e.  
96 losses in one sector and gains in the other) or 'lose-lose' (i.e. both sectors are negatively

97 impacted). Under future climate projections, tropical areas, particularly in Latin America,  
98 Central and Southern Africa and South-East Asia, would disproportionately face lose-lose  
99 situations with exposure to lower agriculture productivity and lower maximum fisheries  
100 catch potential by 2100 (Fig. 2A-B; Fig. S1). These areas are generally highly dependent  
101 on agriculture and fisheries for employment, food security, or revenue (Fig. 2C-D).

102 Conversely, countries situated at high latitudes (e.g. Europe, North America) –where food,  
103 jobs and revenue dependences upon domestic agriculture and seafood production are  
104 generally lower– will experience losses of lower magnitude, or even gains in some cases  
105 (e.g. Canada or Russia) under future climate conditions (Fig. 2A). This latitudinal pattern  
106 of exposure is consistent across both climate change scenarios (Fig. S1) and is mostly due  
107 to the combined effects of increased temperature, rainfall changes, water demand, and CO<sub>2</sub>  
108 effects on photosynthesis and transpiration (agriculture), and temperature-induced shifts in  
109 species' distribution ranges due to changes in suitable habitat and primary production  
110 (marine fisheries), as reported in other studies (10, 12, 17–19).

111 The different dimensions of vulnerability generally merge to create a “perfect tropical  
112 storm” where the most vulnerable countries to climate change impacts on agriculture are  
113 also the most vulnerable to climate impacts on their fisheries ( $\rho=0.67$ ;  $p\text{-value}<0.001$   
114 under RCP8.5, and  $\rho=0.68$ ;  $p\text{-value}<0.001$  and RCP2.6; Fig. 3; Fig. S2). For agriculture  
115 and, to a lesser extent, fisheries, sensitivity is negatively correlated with adaptive capacity  
116 ( $\rho=-0.79$ ;  $p\text{-value}<0.001$  for agriculture;  $\rho=-0.12$ ;  $p\text{-value}=0.07$ , respectively; Fig. S2),  
117 indicating that countries that are most dependent on food production sectors generally  
118 have the lowest adaptive capacity (Fig. 2). The potential impacts (i.e. the combination of  
119 exposure and sensitivity) of climate change on agriculture or fisheries will be exacerbated  
120 in the tropics, where most developing countries with lower capacity to respond to and  
121 recover from climate change impacts are located. Overall, vulnerability remains consistent  
122 across scenarios, with countries most vulnerable under RCP8.5 also ranking high under  
123 RCP2.6 for both sectors, and vice-versa ( $\rho= 0.98$ ;  $p\text{-value}<0.001$  and  $\rho= 0.96$ ;  $p\text{-}$   
124  $\text{value}<0.001$  for agriculture and fisheries vulnerability, respectively).

### 125 **Challenges and opportunities for sectorial adaptation**

126 The most vulnerable countries will require transformative changes focusing on adjusting  
127 practices, processes, and capital within and across sectors. For example, within-sector  
128 strategies such as diversification towards crops with good nutritional value can improve  
129 productivity and food security if they match with the future climate conditions (20).

130 Although many opportunities for strategic crop diversification seem to be available under  
131 RCP2.6, few options would remain under RCP8.5 (Figs. S3-4).

132 In some cases, cross-sector adaptation may be an option by diversifying away from  
133 negatively impacted sectors and into positively impacted ones (i.e. moving out of the loss  
134 and into the win sector in win-lose conditions). For example, some countries projected to  
135 experience losses in fisheries productivity by 2100 would experience gains in agriculture  
136 productivity (Fig. 4; Fig. S1), indicating potential opportunities for national-scale  
137 reconfiguration of food production systems. By contrast, few countries are projected to  
138 experience gains in fisheries and losses in agriculture (n=28 under RCP2.6, n=14 under  
139 RCP8.5; Fig. 4).

140 Opportunities for cross-sector diversification may be constrained not only by climate  
141 change policy (see section below) but also by poor environmental governance. Indeed,  
142 any identified potential gains in productivity are under the assumption of good  
143 environmental management (i.e. crops and fisheries being sustainably managed). Fish  
144 stocks and crops in many tropical countries are currently unsustainably harvested (21, 22),  
145 which may constrain any potential climate-related gains and increase the global burden,  
146 unless major investments in sectorial governance and sustainable intensification are made  
147 (20, 23, 24).

### 148 **Reducing exposure through climate mitigation**

149 Vulnerability of both agriculture and fisheries to climate change can be greatly reduced if  
150 measures to mitigate greenhouse gas emissions are taken rapidly. Under a business-as-  
151 usual emission scenario (RCP8.5), almost the entire world's human population (~97%) is  
152 projected to be directly exposed to high levels of change in at least one food production  
153 sector by 2100 (outer ring in Fig. 4A; Fig. S1). Additionally, 7.2 billion people (~90% of  
154 the world's future population) would live in countries projected to be exposed to lose-lose  
155 conditions (i.e. productivity losses in both sectors). These countries generally have high  
156 sensitivity and weak adaptive capacity (Fig. S1). In contrast, only 0.2 billion people (<3%  
157 of the world's projected population) would live in regions projected to experience a win-  
158 win situation under RCP8.5 (i.e. productivity gains in both sectors) by the end of this  
159 century (outer ring in Fig. 4B; Fig. S1). With drastic reductions of greenhouse gas  
160 emissions (so scenario RCP2.6), however, lose-lose situations would be reduced by a third,  
161 so ~60% of the world's population, while win-win situations would increase by a third so

up to 5% of the world's population, mostly because of improved agricultural productivity (Fig. 4).

Although productivity losses would be inevitable in many cases, the magnitude of these losses would be considerably lower under RCP2.6, notably for countries facing lose-lose conditions whose average change in productivity would move from about -25% to -5% for agriculture and from -60% to 15% for fisheries (see change in inner rings in Fig. 4A-B). Main improvements would occur in Africa (all crops and marine fisheries), Asia (mostly marine fisheries and wheat), and South America (mostly wheat and soy) but also in Europe (mostly marine fisheries) and North America (mostly wheat and marine fisheries; Fig S6). Hence, although negative consequences of climate change cannot be fully avoided in some regions of the world such as Africa, Asia and Oceania, they have the potential to be drastically lowered if mitigation actions are taken rapidly.

Pathways for reducing exposure to the impacts of climate change through reduced greenhouse gas emissions should include global action and be long-lasting to achieve the Paris Agreement targets (a pathway similar to RCP2.6) which can massively reduce human vulnerability to climate change impact on food production systems. Overwhelmingly, net gains (i.e. higher gains, lower losses or losses to gains) from a successful climate mitigation strategy would prevail over net losses (i.e. higher losses, lower gains or gains to losses) (Fig. 5A). Most vulnerable countries, in particular, would experience the highest net productivity gains (mostly through lower losses), while least vulnerable countries would benefit the least from emission reductions as they would generally experience lower net productivity gains, and in some cases net productivity losses (Fig. 5A; Fig. S7).

Although this may appear as a bleak outlook for global climate mitigation, we show that among the 15 countries currently contributing to ~80% of the global greenhouse gas production, most would experience net productivity gains (lower losses or losses to gains) in agriculture (n=10) and fisheries (n=13), from moving from RCP8.5 to RCP2.6. These include countries with large per capita emissions such as USA, China and Saudi Arabia. Conversely, countries projected to experience mitigation-induced net losses in productivity would do so via lower gains, regardless of the sector considered (Fig. 5B; Table S2). These results strongly suggest that committing to reduced emissions can dramatically reduce the burden of climate change, in particular on the most vulnerable regions, while benefitting agricultural and fisheries sectors of most of the largest CO<sub>2</sub>

195 producers, thus providing additional incentives for advancing the climate mitigation  
196 agenda.

### 198 **Caveats and future directions**

199 Although we present a new, integrated vision on the challenges faced by two globally  
200 significant food production sectors, many gaps of knowledge remain. First, the above  
201 estimates of people experiencing win-win, win-lose or lose-lose situations are quite  
202 uncertain to the climate impact models that are used to estimate exposure ((10, 12); Fig.  
203 S5). In addition, long-term trends in productivity changes overlook extreme or ‘black  
204 swan’ events (e.g. pest and diseases, extreme weather, political crises, etc.) that can play a  
205 critical role in food (in)stability and therefore food security (25). Although these caveats  
206 may weaken the robustness of the conclusions (26), they should not hinder action at this  
207 point, as the results remain broadly similar to other assessments that used different  
208 modelling approaches, assumptions and data (17–19).

209 Second, our metric of agriculture exposure adds together various globally significant crops  
210 out of which a significant proportion (36%) is used to feed animals (27). While projections  
211 for other crops such as ground nuts, roots, peas and other cereals suggest similar  
212 geographical patterns of change (Fig. S4 and Fig. S8), on changes for other locally and/or  
213 nutritionally significant crops (28) (e.g. fruits, legumes, etc.) remain largely unknown,  
214 highlighting an important area for future model development.

215 Third, each vulnerability dimension interacts with global forces that remain largely  
216 unpredictable. These include how governments will prioritize these sectors in the future,  
217 changes in trade policies, shifting dietary preferences, changes in technologies, advances  
218 in gene editing techniques increasing crop yields, and changes in arable land and cropping  
219 density due to the interactions between arable land extension, production intensification,  
220 and soil erosion and degradation eliminating areas for cultivation, among others. Together,  
221 these gaps provide a strong motivation for more detailed integration of insights from  
222 several disciplines (29, 30).

223 Fourth, while we decided to limit the scope of our analysis to food production sectors for  
224 which global climate change projections were well developed, it is worth noting that  
225 different patterns of vulnerability may emerge if different sectors were included.  
226 Considering freshwater fisheries, for instance, would provide valuable insights into new

opportunities (or challenges) in vulnerable countries that have a significant inland fishery sector (e.g. Malawi, Sierra Leone, Uganda, Guyana or Bangladesh). The evidence so far seems to suggest that there is not much potential for increased inland fisheries productivity due to increased competition for waters and the current high proportion (90 %) of inland catch coming from already stressed systems (31). Low-value freshwater species cultured domestically –an important component of food security globally and in many food-insecure regions (in particular in East and Southeast Asia; (32))– may be subject to the same constraints. The global potential of marine aquaculture production that does not rely on inputs from wild capture feeds (i.e. shellfish) is expected to decline under climate change, although regions such as Southeast Asia may become more suitable in the future (Fig. S9; (33)). For the livestock sector, decline in pasture productivity in many regions with significant broad care grazing industry (e.g. Australia, South America; see relative changes in managed grass in Fig. S4) combined with additional stresses (e.g. stock heat and water stress low-latitude regions, pests and rainfall events) is likely to outweigh potential benefits, while disruption of major feed crops (e.g. maize, Fig. S3) and marine fish stocks (Fig. 2B) used for fishmeal would affect the intensive livestock industries (34). Overall, climate change impacts on other food production sectors indicate the potential for further negative impacts on global food systems, although analyses that integrations among sectors are still nascent and sorely needed (35).

## Conclusion

The goal of this analysis has been to consider the many dimensions of multi-sector vulnerability in order to inform a transition toward more integrated climate policy. On the basis of our approach and models, we conclude that although lose-lose situations will be pervasive and profound, affecting several billion people in the most food-insecure regions, climate action can dramatically minimize future impacts and benefit the overwhelming majority of the world’s population. We have shown that climate action can benefit both the most vulnerable countries but also large greenhouse gas emitters to provide substantial incentives to collectively reduce global CO<sub>2</sub> emissions. The future will nevertheless entail societal adaptation, which could include adjustments within and across food production sectors.

## Materials and Methods

### Overview

260 Each vulnerability dimension (exposure, sensitivity and adaptive capacity) was evaluated  
261 using a set of quantitative indicators at the country-level. Exposure was projected to the  
262 end of the century (2090-2099) using two emission scenarios (RCP2.6 and RCP8.5),  
263 which provided insights into exposure levels in the case of highly successful reduction of  
264 greenhouse gas emissions (RCP2.6) and a continued business-as-usual scenario (RCP8.5).  
265 We also accounted for future development trends by incorporating GDP per capita (an  
266 indicator of adaptive capacity) projected for 2090-2100 under a “middle of the road”  
267 scenario in which social, economic, and technological trends do not shift markedly from  
268 historical patterns (SSP2). Projections were unfortunately not available for other indicators.  
269 Hence, we use multiple present-day indicators in order to capture important aspects of the  
270 *sensitivity* dimension. This works under the assumption that no major turnover would  
271 occur in the rankings (e.g. most dependent countries at present remain the most dependent  
272 in 2100), which is reasonable considering historical trends (Fig. S10). Table S1  
273 summarizes sources and coverage of data for each indicator. In the sections bellow, we  
274 describe each dimension and their underlying indicators but do not elaborate methods as  
275 they are fully described in each data source.

### 276 **Agriculture exposure**

278 To assess exposure of countries’ agricultural sector to climate change, we used yield  
279 projections from Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) Fast  
280 Track experiment dataset of global gridded crop models (GGCM) simulations (36). We  
281 considered relative yield changes across four major rainfed crop types (maize, rice, soy  
282 and wheat) between two 10-year periods: 2001-2010 and 2090-2099. Outputs from five  
283 global 0.5° resolution crop models (EPIC, GEPIC, pDSSAT, IMAGE and PEGASUS)  
284 based on five general circulation models (GCM; GFDL-ESM2M, HadGEM2-ES, IPSL-  
285 CM5ALR, MIROC-ESM-CHEM and NorESM1-M) were used. Models assume that soil  
286 quality, depth, and hydraulic properties are sufficient for sustained agricultural production.  
287 Crop models are described in full detail in (12). Model uncertainties are available in Fig.  
288 S5.

289 The methods to summarize change in agriculture productivity globally is adapted from  
290 previous work (11, 12, 37, 38). First, we calculated each country’s total productivity for  
291 each crop averaged over each period, and measured country-level relative changes as the  
292 log ratio of total productivity projected in the 2090-2099 period to baseline total  
293 productivity of 2001-2010. We repeated this process for every pair of crop model-GCM,

294 with and without CO<sub>2</sub> fertilization effects, for both RCPs, and assumed present-day  
295 distributions of farm management and production area. All models included explicit  
296 nitrogen, temperature and water stresses on each crop, except PEGASUS for which results  
297 on rice were not available. Only experiments that were available for both RCP scenarios  
298 were included. We then obtained the median yield changes for each crop type and  
299 calculated the average yield change across the four crops to create the final relative change  
300 per country (i.e. our measure of agriculture exposure). Average yield changes for  
301 individual crops are presented in Fig. S3 along with six additional crops (cassava, millet,  
302 ground nut, sorghum, peas and managed grass) modelled according to the same process  
303 (Figs. S4).

304 Impact of climate mitigation on agriculture (Fig. 5) was measured for each country as the  
305 difference between projected changes in agriculture productivity under RCP2.6 and  
306 projected changes in agriculture productivity under 8.5 averaged across all crops (maize,  
307 rice, soy and wheat). Positive values thus indicate that climate mitigation would benefit  
308 agriculture (greater gains, lower losses, or loss-to-gain), and negative values indicate that  
309 climate mitigation would affect agriculture (lower gains, greater losses, or gains-to-losses).

### 310 **Marine fisheries exposure**

311 To assess exposure of countries' marine fisheries sector to climate change, we used  
312 projections of a proxy of maximum sustainable yield of the fish stocks, Maximum Catch  
313 Potential (MCP), from the Dynamic Bioclimate Envelope Model (DBEM) (39). Contrary  
314 to other available global projections (19), the DBEM focuses largely on exploited marine  
315 fishes and invertebrates, which makes projections directly relevant to vulnerability  
316 assessment in relation to seafood production. MCP is dependent on changes in body size,  
317 carrying capacity of each spatial cell for fish stocks (dependent on the environmental  
318 suitability for their growths as well as primary productivity), and spatial population  
319 dynamics as a result of temperature, oxygen, salinity, advection, sea ice and net primary  
320 production. Catches from each fish stock are calculated by applying a fishing mortality  
321 needed to achieve maximum sustainable yield. The DBEM thus assumes that the  
322 environmental preferences of species can be inferred from their biogeography, and that the  
323 carrying capacity of the population is dependent on the environmental conditions in  
324 relation to the species' inferred environmental preferences. It also assumes that species'  
325 environmental preferences will not evolve in response to climate change. Finally, it does  
326 not account for inter-specific interactions. More detailed list of assumptions in DBEM are  
327 provided in (39). Model uncertainties are available in Fig. S5.

328 We considered relative MCP changes between two 10-year periods: 2001-2010 and 2090-  
329 2099 using the DBEM outputs driven by three GCM (GFDP, IPSL and MPI). We  
330 evaluated marine fisheries exposure by summing MCP across each country's Exclusive  
331 Economic Zones (EEZs) over each period, and measured country-level relative changes as  
332 the log ratio of total MCP projected in the 2090-2099 period to baseline total MCP of  
333 2001-2010. We repeated this process for each GCM and used the average MCP change as  
334 a final relative change per country (i.e. our measure of fisheries exposure).

335 Impact of climate mitigation on fisheries (Fig. 5) was measured for each country as the  
336 difference between projected changes in MCP under RCP2.6 and projected changes in  
337 MCP under 8.5. Positive values thus indicate that climate mitigation will benefit fisheries  
338 (greater gains, lower losses, or loss-to-gain), and negative values indicate that climate  
339 mitigation will affect fisheries (lower gains, greater losses, or gains-to-losses).

### 340 **Agriculture sensitivity**

342 Sensitivity in the context of agriculture was assessed by combining metrics reflecting the  
343 contribution of agriculture to countries' economy (economic dependency), employment  
344 (job dependency) and food security (food dependency). We calculated the percentage of  
345 GDP contributed by agricultural revenue based on the World Bank's World Development  
346 Indicators (40) for our metric of economic dependency to agriculture. Employment data  
347 from FAOSTAT (41) was used to measure job dependency on the agricultural sector  
348 (*sensu* ISIC divisions 1-5). Since this data includes fishing, we subtracted the number of  
349 people employed in fisheries (see Fisheries sensitivity section) to calculate the percentage  
350 of the workforce employed by land-based agriculture as a metric of job dependency.  
351 Finally, we used the share of dietary energy supply derived from plants (2011-2013  
352 average) from FAOSTAT's Suite of Food Security Indicators (41) to evaluate food  
353 dependency on agriculture.

### 354 **Fisheries sensitivity**

356 Similar to agriculture sensitivity, and in accordance with previous global assessment of  
357 human dependence on marine ecosystems (42), sensitivity in the context of fisheries was  
358 assessed by combining indicators of the country-level contribution of fisheries to the  
359 economy (economic dependency), employment (job dependency) and food security (food  
360 dependency). We obtained the percentage of GDP contributed by reported and unreported  
361 seafood landings in 2014 from the Sea Around Us project (43) to estimate economic  
362 dependency. We used a database of marine fisheries employment compiled by (5) to

363 calculate the percentage of the workforce employed in fisheries and thus measure  
364 countries' dependency on this sector for employment. Finally, we used the food supply  
365 dataset from FAOSTAT (41) to compute the fraction of consumed animal protein supplied  
366 by seafood and evaluate food dependency on fisheries.

### 367 **Adaptive capacity**

369 We considered that adaptive capacity was not differentiated by sector, and thus evaluated  
370 each country's future adaptive capacity using the average per capita GDP for the years  
371 2090-2100 using GDP and population projections (44). We used the intermediate  
372 development scenario for purpose of comparability between RCP scenarios. In countries  
373 where projected GDP per capita was not available (mostly small island nations), we used  
374 the gridded (0.5°) population and GDP version developed by (45) based on data from (44).  
375 GDP per capita is a commonly used metric to estimate countries' ability to mobilize  
376 resources to adapt to climate change. GDP per capita was strongly and positively  
377 correlated with other indicators of adaptive capacity that could not be projected to 2100  
378 including key dimensions of governance (voice and accountability, political stability and  
379 lack of violence, government effectiveness, regulatory quality, rule of law, and control  
380 of corruption) and economic flexibility (Fig. S11).

### 381 **Missing data**

383 The main data sources (Table S1) allowed estimation of vulnerability for 84.8% of the  
384 world's population. Territories and dependencies with missing data were assigned their  
385 sovereign's values, which increased the total proportion of the population represented to  
386 98.4%. Finally, the remaining 1.6% was imputed using boosted regression trees to predict  
387 each individual indicator using all other indicators, with the exception of a few areas  
388 (<0.1% of total population) for which one indicator (agriculture exposure) was not  
389 imputed because it could not be treated as a regression problem; i.e. it depends on future  
390 climatic conditions rather than on current countries' socioeconomic and governance  
391 indicators.

### 392 **Aggregated vulnerability index**

394 In order to combine each vulnerability dimension (exposure, sensitivity and adaptive  
395 capacity) into a single, country-level metric of vulnerability per sector and per emission  
396 scenario, we first standardized all the indicators to a scale ranging from 0 to 100 using the  
397 following formula (46, 47):

$$\text{Indicator}_i = 100 * \exp[\ln(0.5) * (F_i/F_{50})] \quad (\text{Eq. 1})$$

where  $F_i$  is the factor (e.g. % of workforce employed in fisheries, percentage of GDP contributed by agriculture, governance status) for the  $i^{\text{th}}$  unit (e.g. a country, state, or territory) under consideration, and  $F_{50}$  is the median of the full range of values for this factor across all units. When needed, indicators were reversed so that high values convey high levels of a given vulnerability dimension (e.g. highly negative changes in agriculture productivity relate to high exposure). Each normalized indicator was then aggregated into its corresponding vulnerability dimension (e.g. job, revenue and food dependency combined into a single metric of sensitivity) by averaging the standardized indicators. Finally, the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) aggregation method was employed to calculate the country-level vulnerability index:

$$V_{i,s} = d^+_{i,s} / (d^+_{i,s} + d^-_{i,s}) * 100 \quad (\text{Eq. 2})$$

where  $V_{i,s}$  is the composite index of vulnerability of the country  $i$  for the sector  $s$  (agriculture or marine fisheries),  $d^+_{i,s}$  is the distance to the positive ideal solution (i.e. minimum exposure and sensitivity, and maximum adaptive capacity;  $A^+$ ) of the  $i^{\text{th}}$  country's sector  $s$  in the Euclidean space, and  $d^-_{i,s}$  is the distance to the negative ideal solution (i.e. maximum exposure and sensitivity, and minimum adaptive capacity;  $A^-$ ) of the  $i^{\text{th}}$  country's sector  $s$  in the Euclidean space. The vulnerability index may range between 0 when the vulnerability dimensions correspond and  $A^+$ , to 100 when they correspond to  $A^-$ . This approach assumes that exposure, sensitivity and adaptive capacity equally determine overall vulnerability (unweighted). Given that vulnerability dimensions are highly correlated (Fig. S2), an unequal weighting scheme would have little effect on the final vulnerability metric.

Overall, our dataset covers 240 and 194 countries/states/territories for agriculture and for fisheries, respectively, thus providing the most comprehensive assessment of vulnerability to climate change impacts on agriculture and marine fisheries to date. Analyses on the interactions between agriculture and fisheries vulnerability (e.g. Fig. 3) were only performed on multi-sector countries (i.e. landlocked countries were not considered). All data analyses were performed using R.

## Greenhouse gas emissions

429 The most up-to-date data available on countries' total amount of CO<sub>2</sub> emitted from the  
430 consumption of fossil-fuels (2014) were retrieved from Carbon Dioxide Information  
431 Analysis Center (48).

### 432 **Human population estimates**

434 Country-level projected human populations to 2090-2100 were obtained from the SSP  
435 Database 2.0 (49) using the intermediate shared socioeconomic pathway (SSP2) to allow  
436 comparison of population comparison between RCPs scenarios. Population projections  
437 under SSP2 assumes medium fertility, medium mortality, medium migration and the  
438 Global Education Trend (GET) education scenario for all countries. In countries where  
439 projected population was not available, we used the gridded (0.5°) population and GDP  
440 version developed by (45) based on data from (44).

## 442 H2: Supplementary Materials

443  
444 **Table S1:** Indicators and main data sources used to measure country-level metrics of  
445 agriculture and marine fisheries vulnerability to climate change.

446 **Table S2:** Effect of strong climate mitigation on top CO<sub>2</sub> producers and on the most  
447 vulnerable countries.

448 **Fig. S1:** Spatial variation in agriculture and marine fisheries exposure, and associated  
449 levels of sensitivity and adaptive capacity according to emission scenarios RCP 2.6 and  
450 RCP 8.5.

451 **Fig. S2:** Relationships between agriculture and marine fisheries vulnerability to climate  
452 change under RCP8.5 and RCP2.6.

453 **Fig. S3:** Changes in productivity for maize, rice, soy and wheat crops under RCP2.6 and  
454 RCP8.5.

455 **Fig. S4:** Changes in productivity for six other crops under RCP2.6 and RCP8.5.

456 **Fig. S5:** Uncertainty in projected changes in agriculture and marine fisheries productivity.

457 **Fig. S6:** Regional changes in agriculture and marine fisheries productivity under RCP2.6  
458 and RCP8.5.

459 **Fig. S7:** Net gains and losses in agriculture and fisheries productivity from climate  
460 mitigation.

461 **Fig. S8:** Spearman's rank correlations among pairs of agricultural crops changes in  
462 productivity under RCP2.6 and RCP8.5.

463 **Fig. S9:** Projected changes in finfish and bivalve aquaculture production potential under  
464 climate change.

465 **Fig. S10:** Correlations between historical and present-day indicators of sensitivity.

466 **Fig. S11:** Spearman's rank correlations among pairs of adaptive capacity indicators.

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581

## 582 Figures captions

583

584 **Figure 1 | IPCC vulnerability framework (AR4), adapted for our cross-sector analysis.** Exposure refers  
585 here to the extent to which a food production sector is subject to a driver of change. Sensitivity refers to the  
586 strength of reliance, or dependency, on this sector in terms of employment, revenue and food security.  
587 Adaptive capacity refers to the preconditions that enable a country to mobilize resources and adjust its food  
588 system in response to climate change-induced impacts of agriculture and fisheries. Note that IPCC now  
589 bridges AR4 definition of vulnerability with the concept of risk (AR5).

590 **Figure 2 | Dimensions of agriculture and marine fisheries vulnerability to climate change.** (A-B)  
591 Average relative changes in agriculture productivity (maize, rice, soy and wheat) and in maximum catch  
592 potential within Exclusive Economic Zones (EEZs) projected by 2100 (RCP8.5) were used to estimate  
593 exposure of agriculture and fishery, respectively. (C-D) Sensitivity on each sector is a composite metric of  
594 dependence for food, jobs and revenue. (E-F) Adaptive capacity is based on future GDP per capita and is not  
595 sector-specific. Socioeconomic indicators (C-F) are normalized between 0 (lowest possible value) and 100  
596 (largest possible value). The right panels are latitudinal trends. Class intervals are quantiles centered around  
597 zero but not symmetric for *exposure*.  
598

599 **Figure 3 | Vulnerability of agriculture and marine fisheries as a function of exposure, sensitivity and**  
600 **adaptive capacity to the impacts of climate change.** The bivariate map shows linked vulnerabilities of  
601 agriculture and fisheries for each country under RCP8.5. The 10 most vulnerable countries are indicated for  
602 agriculture (A) and marine fisheries (F). The right panel indicates latitudinal trends.

603 **Figure 4 | Magnitude of changes in agriculture and marine fisheries productivity, and impacted**  
604 **population size, according to two CO<sub>2</sub> emissions scenarios.** (A-B) Radial diagrams show projected  
605 concomitant changes in agriculture and marine fisheries productivity, where the angle describes the relative  
606 contribution of each sector to overall change (0°: gain in agriculture only; 90°: gain in fisheries only; 180°:  
607 loss in agriculture only; 270°: loss in fisheries only) and thus describe win-win (green), lose-lose (red) and  
608 win-lose (yellow and blue) exposure categories. Each diagram consists of two rings. The inner ring  
609 represents the overall magnitude of the projected changes, measured as the distance between each country's  
610 projected change and the origin (i.e. no change) in an orthogonal coordinate system. The outer ring indicates  
611 human population projected to be living at each bearing by 2100. (C) Alluvial diagram illustrates how the  
612 total number of people projected to experience win-win (green), win-lose (blue and orange) and lose-lose  
613 (red) situations varies according to the emission scenario. Numbers are in billions (summations may not be  
614 exact owing to rounding) and only account for the projected population by 2100. See Fig. S1 for global maps  
615 of each exposure category and Fig. S5 for model uncertainty surrounding these estimates.

616 **Figure 5 | Climate mitigation benefits for agriculture and marine fisheries productivity at the country-**  
617 **scale.** (A) Countries' net change in future agriculture and fisheries productivity induced by climate

618 mitigation plotted against their corresponding vulnerability under RCP8.5. Net change represents the  
619 projected differences in changes in productivity from RCP8.5 (business-as-usual) to RCP2.6 (highly  
620 successful reduction of greenhouse gas emissions). Negative and positive values thus indicate net loss (i.e.  
621 lower gains, higher losses, or gains-to-losses) and net gain (i.e. higher gains, lower losses, or losses-to-gains)  
622 from climate mitigation, respectively. The 15 most vulnerable countries are indicated. (B) Countries' net  
623 change in future agriculture and fisheries productivity plotted against annual CO<sub>2</sub> production with the top 15  
624 CO<sub>2</sub> producers indicated. Density plots show the distribution of the world's population, and values report net  
625 change in sectors' productivity at the 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup> and 90<sup>th</sup> percentiles of the distribution. See Fig. S7 for  
626 global estimates on mitigation benefits and Table S2 for details on top CO<sub>2</sub> producers and the most  
627 vulnerable countries.