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1 The potential impacts of climate change on agriculture and fisheries
2 production in 72 tropical coastal communities

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65 **Abstract**

66

67 Climate change is expected to profoundly affect key food production sectors, including
68 fisheries and agriculture. However, the potential impacts of climate change on these sectors
69 are rarely considered jointly, and when they are, it is often at a national scale, which can
70 mask substantial variability in how communities will be affected. Here, we combine
71 socioeconomic surveys and intersectoral multi-model simulation outputs to conduct a sub-
72 national analysis of the potential impacts of climate change on fisheries and agriculture in 72
73 coastal communities across five Indo-Pacific countries. Our study reveals three key findings:
74 First, we find that the overall potential losses to fisheries is higher than potential losses to
75 agriculture, but there is substantial within-country variability. Second, while more than two-
76 thirds of locations will bear a double burden of potential losses to both fisheries and
77 agriculture simultaneously, mitigation could reduce the proportion of places facing a double
78 burden. Third, lower socioeconomic status communities are more likely to experience
79 potential impacts than higher socioeconomic status communities.

80

81 **Introduction**

82

83 Climate change is expected to profoundly impact key food production sectors, with the
84 tropics expected to suffer losses in both fisheries and agriculture. For example, by 2100
85 tropical areas could lose up to 200 suitable plant growing days per year due to climate
86 change¹. Likewise, fishable biomass in the ocean could drop by up to 40% in some tropical
87 areas^{2,3}.

88

89 While understanding the magnitude of losses that climate change is expected to create in key
90 food production sectors is crucial, it is the social dimensions of vulnerability that determine
91 the degree to which societies are likely to be affected by these changes⁴⁻⁸. Vulnerability is the
92 degree to which a system is susceptible to and unable to cope with the effects of change. It is
93 comprised of exposure (the degree to which a system is stressed by environmental or social
94 conditions), and the social dimensions of sensitivity (the state of susceptibility to harm from
95 perturbations), and adaptive capacity (people's ability to anticipate, respond to, and recover
96 from the consequences of these changes)^{4,9}. Together, the exposure and sensitivity domains
97 are referred to as "potential impacts", which are the focus of this article.

98

99 Incorporating key social dimensions of vulnerability is particularly important because many
100 coastal communities simultaneously rely on both agriculture and fisheries to varying
101 degrees¹⁰, yet assessments of climate change impacts and the policy prescriptions that come
102 from them often consider these sectors in isolation^{1,5,11-14}. Recently, studies have begun to
103 look at the simultaneous impacts of climate change on both fisheries and agriculture at the
104 national level^{15,16}, but this coarse scale does not capture whether people simultaneously
105 engage with- and are likely to be affected by- changes in these sectors. Indeed, whether
106 households engage in both fisheries and agriculture¹⁰ will determine whether people have the
107 knowledge, skills, and capital to substitute sectors if one declines, or alternatively, make them
108 particularly susceptible to the potential 'perfect storm' of a combined decline across sectors¹⁵.
109 Thus, more localised analyses incorporating key social dimensions of vulnerability are
110 required to better understand how combined impacts to fisheries and agriculture may affect
111 coastal communities. Here, we combine a measure of exposure based on model projections of
112 losses to exploitable marine biomass (here dubbed "fisheries catch potential") and agriculture
113 from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) Fast Track phase 3
114 dataset with a measure of sensitivity based on survey data about material wealth and

115 engagement in fisheries, agriculture, and other occupational sectors from >3,000 households
116 across 72 tropical coastal communities in five countries (Table S1). We ask: “What are the
117 potential impacts of projected changes to fisheries catch potential and agriculture on coastal
118 communities?” “How much will mitigation measures reduce these potential impacts?” and
119 “Are lower socioeconomic status coastal communities facing more potential impacts from
120 climate change than their wealthier counterparts? “

121

122 **Results and Discussion**

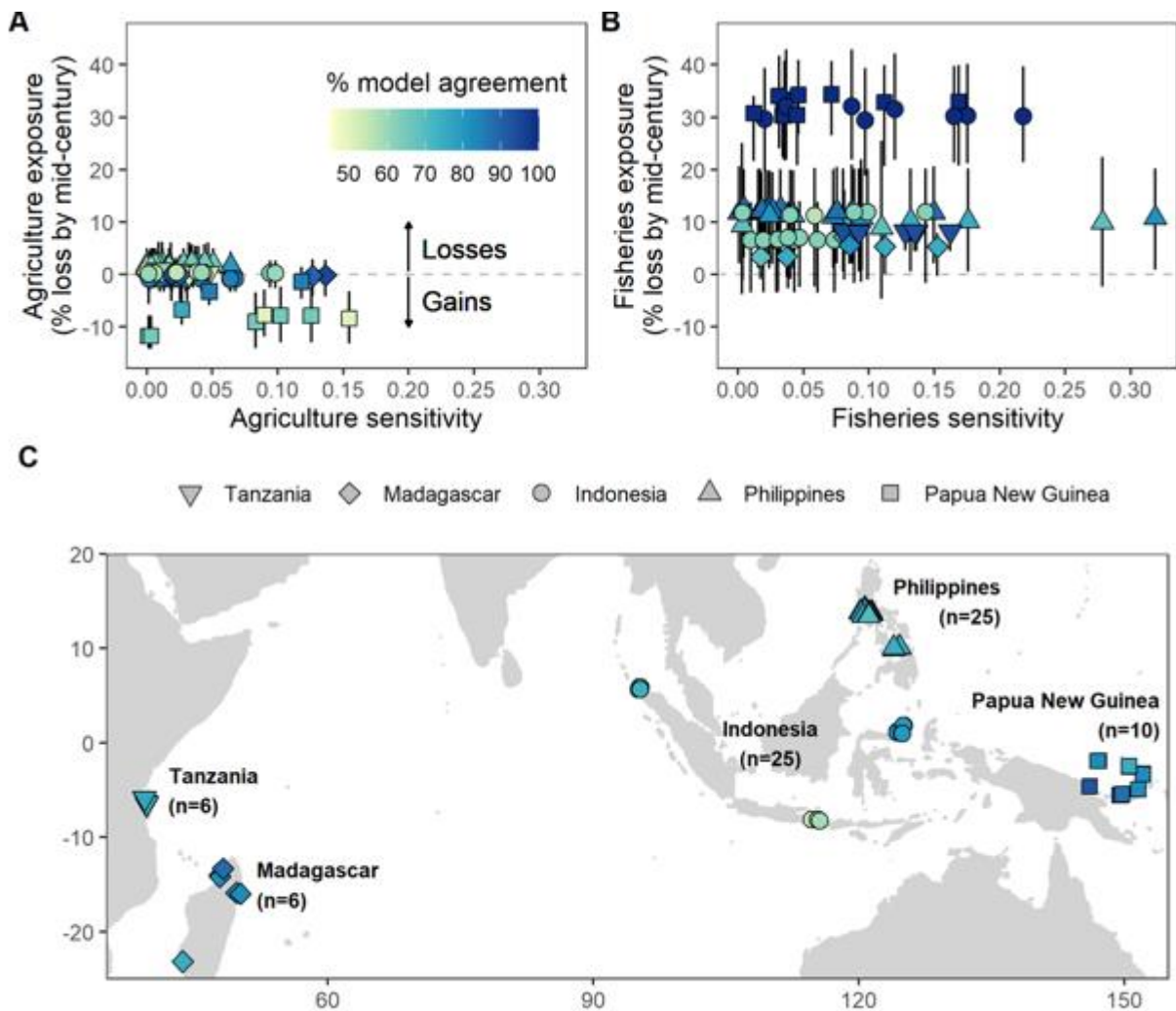
123 Our study has three key results. First, we find that overall possible impacts on fisheries catch
124 potential is higher than possible impacts on agriculture, but there can be substantial within-
125 country variability in both exposure and sensitivity (Fig. 1). Specifically, exposure under the
126 high-emissions Shared Socioeconomic Pathway 8.5 scenario (which has tracked historic
127 cumulative CO₂ emissions¹⁷, but has been recently critiqued for over-projecting CO₂
128 emissions and economic growth¹⁸) indicates substantive losses by mid-century to fisheries
129 catch potential [Fig. 1; 14.7% +/- 4.3% (SE) mean fisheries catch potential loss]. To put
130 these projected losses in perspective, Sala et al.¹⁹ found that strategically protecting 28% of
131 the ocean could increase food provisioning by 5.9 million tonnes, which is just 6.9% of the
132 84.4 million tons of marine capture globally in 2018²⁰. Thus, the mean expected fisheries
133 catch potential losses are approximately double that which could be buffered by strategic
134 conservation. Model run agreement about the directionality of change for projected impacts
135 to fisheries catch potential was high (SSP5-8.5: 84.7 +/- 4.5% (SE); SSP1-2.6: 89.2 +/-
136 4.06% (SE)). Interestingly, crop models projected that agricultural productivity (based on
137 rice, maize, and cassava- see methods) is expected to experience small average gains across
138 the 72 sites (1.2% +/- 1.5% (SE) mean agricultural gain), with a large response range
139 between sites and crops (Fig S1). However, the average gains are not significantly different
140 from zero (t = -0.80, df = 5.0, p=0.46), and model run agreement about directionality of
141 change was lower for agriculture (SSP5-8.5: 69.1 +/- 4.82% (SE); SSP1-2.6: 70.4 +/- 3.27%
142 (SE)). These projected agricultural gains are driven exclusively by rice (Supplemental Fig 1),
143 which has particularly large model disagreement^{14,21}. Excluding rice shows an average
144 decline in agricultural production by mid-century, since maize and cassava show consistent
145 median losses under both SSP1-2.6 and SSP5-8.5 climate scenarios (Supplemental Fig. 1).
146 Significantly greater losses in fisheries catch potential compared to agriculture productivity
147 are apparent not only for our study sites (i.e. 15.9 +/- 5.6% (SE) greater; t = 2.81, df = 4.97,
148 p = 0.0379), but also for a random selection of 4,746 (10% of) coastal locations in our study
149 countries with populations >25 people per km² (Fig. 2). Among those random sites, fisheries
150 catch potential losses are an average of 15.6 +/- 5.1% (SE) greater than agriculture
151 productivity changes (t = 3.06, df = 5.00, p=0.0282). Differences between expected losses at
152 our sites and the randomly selected sites are small for agriculture (Cohen’s D for SSP5-8.5=-
153 0.31, SSP1-2.6=-0.35) and negligible for fisheries catch potential (Cohen’s D for SSP5-8.5 =-
154 0.02, SSP1-2.6=-0.03), indicating that our sites are not particularly biased towards high or
155 low exposure for the study region. Not only is the level of exposure generally higher in
156 fisheries compared to agriculture, but the sensitivity is on average nearly twice as high (Fig.
157 1A,B; 0.077 +/- 0.007 mean fisheries sensitivity; 0.04 +/- 0.01 mean agricultural sensitivity; t
158 =3.0, df = 2.26, p-value =0.0815).

159

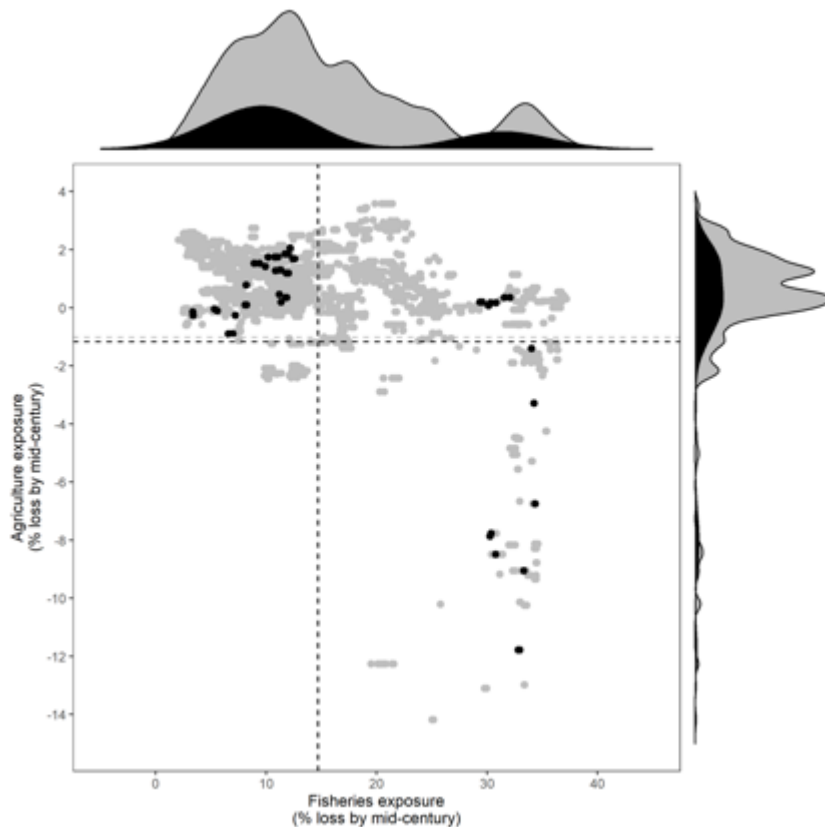
160 Our analysis also reveals high within-country variability in potential impacts (i.e. both
161 exposure and sensitivity), particularly for fisheries (Fig. 1) - a finding that may be masked in
162 studies looking at national-level averages^{15,16}. Looking only at the mean expected losses can
163 obscure the more extreme fisheries catch potential losses projected for many communities
164 (Figs. 1,2). For example, under SSP5-8.5, our Indonesian sites are projected to experience

165 very close to the average fisheries catch potential losses among our study sites (15.9 +/-
 166 2.1%SE), but individual sites range from 6.5-32% losses (Fig 1B). There is also substantial
 167 within-country variation in how communities are likely to experience climate change
 168 impacts, based on their sensitivity (Fig. 1A,B). For example, in the Philippines, exposure to
 169 fisheries is consistently moderate (range 8.9-12.6% loss), but sensitivity ranges from our
 170 lowest (0.001) to our highest recorded scores (0.32). There is also within-country variability
 171 in model agreement, particularly for the agricultural models in Indonesia, where agricultural
 172 model agreement ranges from 50-85% and fisheries model agreement ranges from 56-100%
 173 for SSP5-8.5, and 50-80% and 50-94%, respectively, for SSP1-2.6.

174
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 176



177
 178 **Figure 1. Potential Impacts for (A) agriculture and (B) fisheries under SSP5-8.5.**
 179 **Potential impacts comprise the exposure (y-axis, measured in potential losses) and**
 180 **sensitivity (x-axis, measured as level of dependence by households). Error bars show**
 181 **25th and 75th percentiles of exposure. (C) study site locations (n=72). Model run**
 182 **agreement highlights the proportion of (A) crop model runs (n=20), (B) fisheries model**
 183 **runs (n=16), and (C) average of agriculture and fisheries model runs that agree about**
 184 **the direction of change per site. Inset map in Supplemental Fig. 9.**
 185



186
187

188 **Figure 2. A comparison of expected fisheries catch potential and agriculture losses**
 189 **(exposure) by mid-century under SSP5-8.5. Black dots/histograms are our study sites.**
 190 **Grey dots/histograms are a random selection of 4,746 (10% of) coastal cells with**
 191 **population densities >25 people/km² from our study countries. Dotted lines represent**
 192 **mean exposure.**

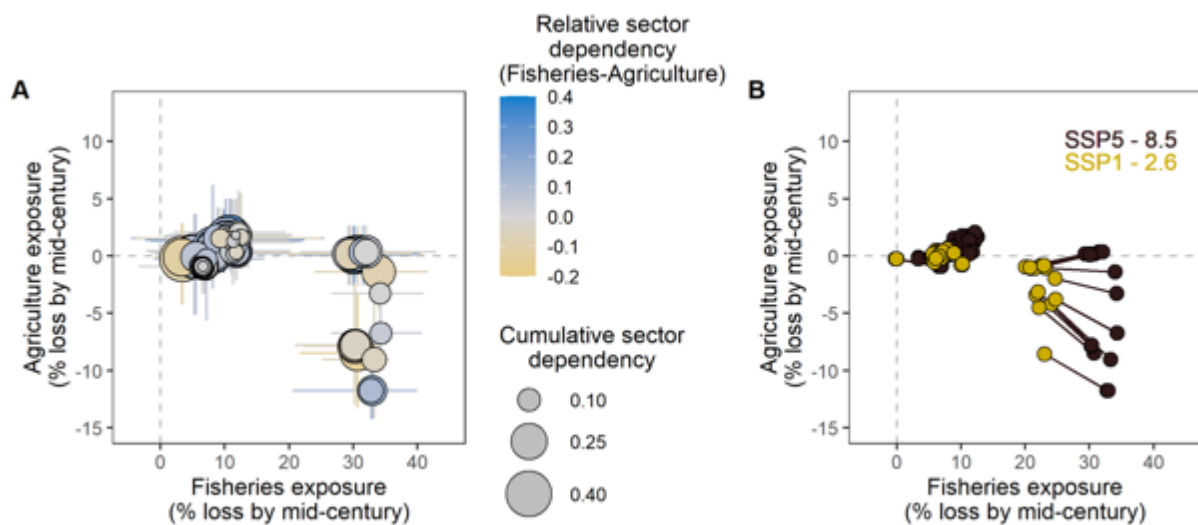
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194 The second key result from our integrated assessment reveals that some locations will bear a
 195 double burden of losses to fisheries and agriculture simultaneously, but mitigation efforts that
 196 reduce greenhouse gas emissions could curb these losses. Specifically, under SSP5-8.5, 64%
 197 of our study sites are expected to lose productivity in fisheries and agriculture simultaneously
 198 (Fig. 3A), but this would reduce to 37% of sites under the low emissions scenario SSP1-2.6
 199 (Fig. 3B). Again, the effect of mitigation is consistent in the random selection of 4,746 sites
 200 (Supplemental Figure 2), with 70% of randomly selected sites expected to experience a
 201 double burden under SSP5 8.5, and 47% under SSP1 2.6. Many of the sites expected to
 202 experience the highest losses to both fisheries catch potential and agriculture have moderate
 203 to high sensitivity (Fig 3A, Supplemental Fig.3), which means the impacts of these changes
 204 could be profoundly felt by coastal communities.

205

206 Over a third of our sites (36% under SSP5-8.5) are expected to experience increases in
 207 agriculture (due to CO₂ fertilization effects that fuel potential increases particularly in rice
 208 yields) while experiencing losses in fisheries catch potential. For these sites, a question of
 209 critical concern is whether the potential gains in agriculture could help offset the losses in
 210 fisheries catch potential. The answer to this lies in part in the degree of substitutability
 211 between sectors. Our survey of 3008 households reveals high variation among countries, and
 212 even within some countries in the degree of household occupational multiplicity
 213 incorporating both agriculture and fisheries sectors (Table 1). 31% of households in our study

214 engaged in both fishing and agriculture, though this ranged from 10% of households in the
 215 Philippines to 77% of households in Papua New Guinea. This means that the degree to which
 216 agricultural gains might possibly offset some fisheries losses at the household scale is very
 217 context dependent. Our survey also revealed that 17% of households were involved in
 218 agriculture but not fisheries, ranging from 33% in Madagascar to 3% in our Papua New
 219 Guinean study communities. Alternatively, more than a third of households surveyed in
 220 Indonesia and Philippines were involved in fisheries but not agriculture (36% and 37%
 221 respectively), compared to a low value of 16% in Madagascar. In 12% of the Philippines
 222 communities surveyed (n=3), not a single household was engaged in agriculture. Thus, for
 223 32% of households across our sample, including some entire communities, potential
 224 agricultural gains will not offset potential fisheries losses. In these locations building adaptive
 225 capacity to buffer change will be critical⁹.



226
 227 **Figure 3. The simultaneous potential losses to fisheries and agriculture in coastal**
 228 **communities. (A) Under SSP5-8.5 agricultural losses (y-axis) plotted against fisheries**
 229 **losses (x-axis) with bubble size revealing the overall sensitivity and the colour revealing**
 230 **the fisheries-agricultural relative sector dependency of each community's sensitivity.**
 231 **(B) The potential benefits of mitigation shown by the potential losses for each**
 232 **community change going from the high emissions scenario (SSP5-8.5) to a low emissions**
 233 **scenario (SSP1-2.6).**

234
 235
 236

COUNTRY	NUMBER OF HOUSEHOLDS	AGRICULTURE AND FISHERIES	AGRICULTURE, NO FISHERIES	FISHERIES, NO AGRICULTURE
INDONESIA	1140	0.25	0.18	0.36
MADAGASCAR	339	0.42	0.33	0.16
PAPUA NEW GUINEA	318	0.77	0.03	0.18
PHILIPPINES	973	0.11	0.18	0.37
TANZANIA	238	0.69	0.04	0.26

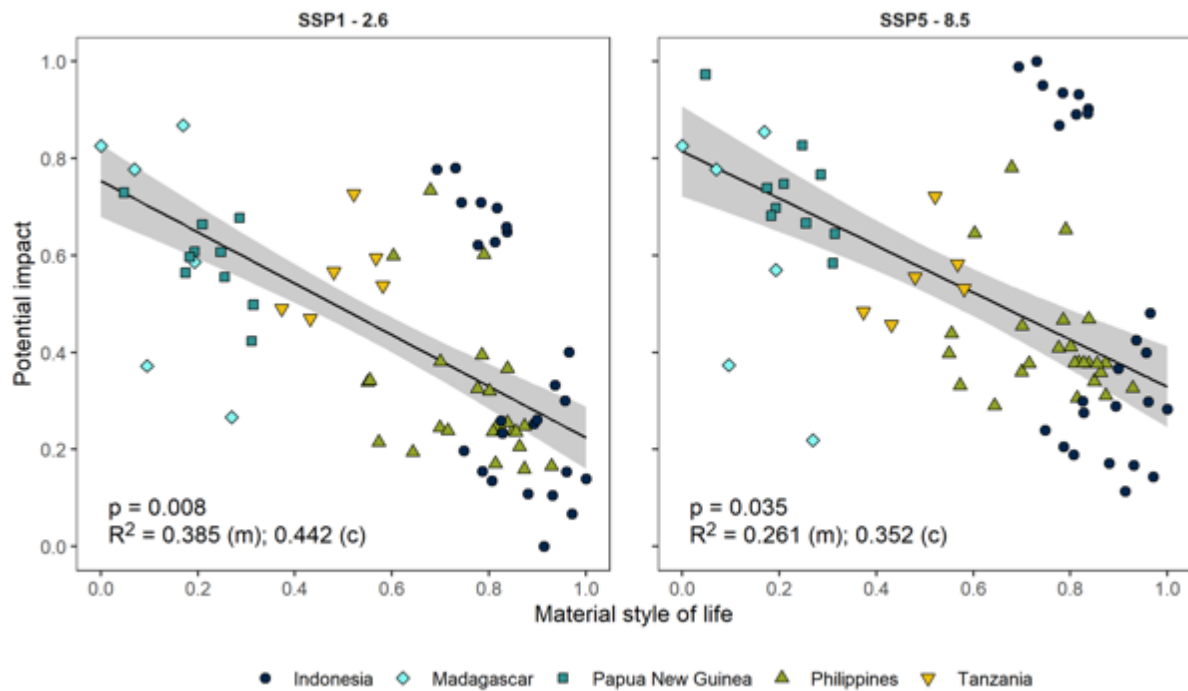
237 **Table 1. Proportion of surveyed households in each study country engaged in both**
 238 **agriculture and fisheries, agriculture but not fisheries, and fisheries but not agriculture.**

239 **Note, proportions do not add up to 1 because some households were not engaged in**
240 **agriculture or fisheries.**

241

242 Our third key result is that coastal communities with lower socioeconomic status are more
243 likely to experience potential impacts than communities of higher socioeconomic status
244 across the climate mitigation scenarios (SSP1-2.6 and SSP5-8.5; Fig. 4). Specifically, we
245 examined the relationship between the average material style of life (a metric of wealth based
246 on material assets; see methods) in a community and the relative potential impacts of
247 simultaneous fisheries catch potential and agriculture losses (measured as the Euclidean
248 distance of sensitivity and exposure from the origin). Importantly, socioeconomic status is
249 related to both sensitivity and exposure (Supplemental Fig. 4). In other words, low
250 socioeconomic status communities tend to have higher sensitivity to fisheries and agriculture
251 than the wealthy, and are significantly more likely to be exposed to climate change impacts.
252 Our findings regarding the relationship between socioeconomic status and sensitivity are
253 consistent with a broad body of literature that shows how people tend to move away from
254 natural resource dependent occupations as they become wealthier^{10,22–25}. One potential
255 interpretation of our findings is that alternative livelihood programs (e.g. jobs outside the
256 fisheries or agricultural sectors, such as the service industry) could reduce sensitivity in lower
257 socioeconomic status communities. However, decades of research on livelihood
258 diversification has highlighted a multitude of reasons why alternative livelihood projects
259 frequently fail²⁶, including that they do not provide high levels of non-economic satisfactions
260 (e.g., social, psychological, and cultural)^{27–29}, as well as cultural barriers to switching
261 occupations (e.g. caste systems)³⁰, and attachment to identity and place³¹. Alternative
262 occupations need to provide some of the same satisfactions, including basic needs (safety,
263 income), social and psychological needs (time away from home, community in which you
264 live, etc.), and self-actualization (adventure, challenge, opportunity to be own boss, etc.). For
265 example, fishing attracts individuals manifesting a personality configuration referred to as an
266 externalizing disposition, which is characterized by a need for challenges, adventure, and
267 risk. Fishing can be extremely satisfying for people with this personality complex, while
268 many alternative occupations can lead to job dissatisfaction, which has negative social and
269 psychological consequences^{32,33}. Research has shown that for fisheries, recreational fishing
270 captains or guides as alternative occupations produce some of the same satisfactions and have
271 been successful³³. Despite these limited successes, alternative livelihood programs frequently
272 fail and are not a viable substitute for mitigating climate change for the ~6 million coral reef
273 fishers globally³⁴.

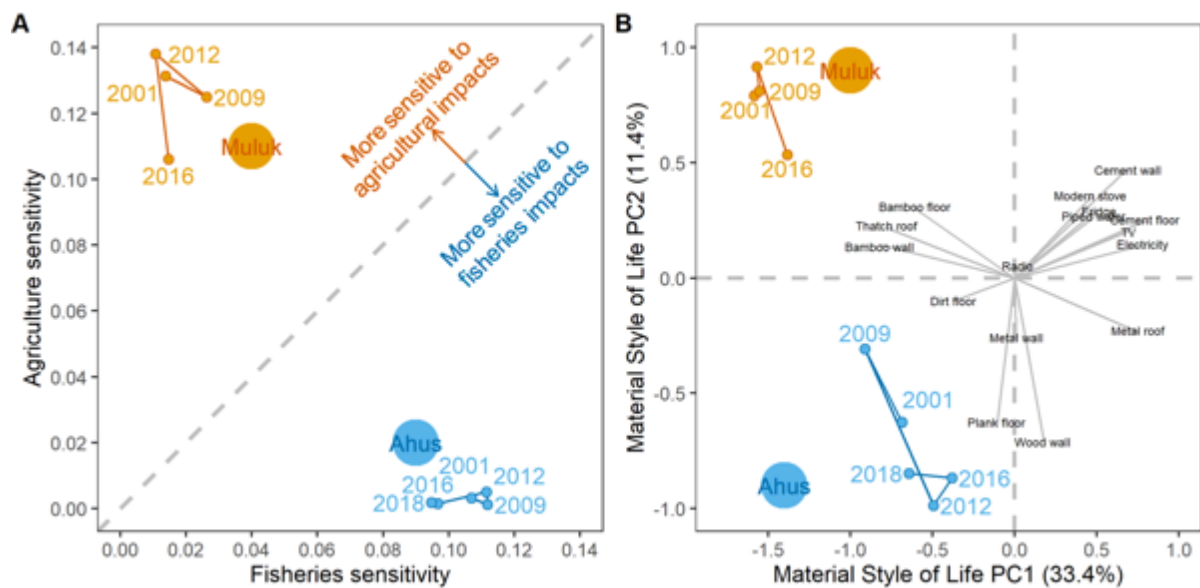
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277 **Figure 4. Relationships between potential impacts (calculated as the Euclidean distance**
 278 **of exposure and sensitivity) and material style of life (a metric of wealth based on**
 279 **material assets) under different mitigation strategies. Grey shading indicates 95%**
 280 **confidence intervals. (m)=marginal R^2 , (c)=conditional R^2 .**
 281

282 Our study is an important first step in examining the potential simultaneous impacts to
 283 fisheries catch potential and agriculture in coastal communities, but has some limitations,
 284 some of which could be addressed in future studies. First, our measure of exposure was
 285 dynamic (i.e., it was projected into the future), while our measures of sensitivity and material
 286 wealth were static (i.e., from a single point in time) and did not consider potential changes
 287 over time. Although there are projections of how national-scale measures of wealth (e.g.
 288 gross domestic product; GDP) may change in the future, there are no reliable projections for
 289 household- or community-scale changes to material wealth or livelihoods. As a supplemental
 290 analysis, we examined observed changes in sensitivity and material wealth over 15 and 16
 291 years, respectively, in two Papua New Guinean coastal communities (Fig. 5). We found that,
 292 over the observed time frame (2001-2016), which is approximately half that of the predicted
 293 time frame of exposure, sensitivity scores were extremely stable, particularly in Ahus (Fig.
 294 5). Similarly, material wealth was also reasonably stable over time, but did reflect a shift in
 295 both communities toward more houses being built out of sturdier material (e.g., wood plank
 296 walls and floor, metal roofs). Importantly, while there were absolute changes to material
 297 wealth in both communities, the relative position stayed very similar. Although these data do
 298 not allow us to make inferences about what will happen into the future, they do highlight that,
 299 at least in decadal timeframes, these indicators are reasonably stable. One alternative
 300 approach may have been to assume that projected national-scale changes to GDP would
 301 apply evenly across each coastal community within a country (i.e., adjust the intercept of
 302 both material wealth and correlated sensitivity for each country relative to the projected
 303 changes in GDP). However, given the wide spread of material wealth and sensitivity scores
 304 within countries, we ultimately were less comfortable with the assumptions inherent in the
 305 approach (i.e., that national-scale changes would affect all communities in a country equally)
 306 than with the caveat that our metrics were static.



308
 309 **Fig 5. Changes in sensitivity (A) and material wealth (B) over time in two Papua New**
 310 **Guinean communities. Panel B shows how the communities change along the first two**
 311 **axes of a principal component analysis based on 16 household-scale material items.**
 312

313 Second, there are key limitations and assumptions to the models we used. For example, many
 314 tropical small-scale fisheries target seagrass³⁵ and coral reef habitats³⁴, which are not
 315 represented in the global ensemble models. Additionally, the ensemble models were
 316 developed at relatively low spatial resolution (e.g. 1° cells), and are not designed to capture
 317 higher resolution structures and processes. Our approach for dealing with this was to make
 318 transparent the degree of ensemble model run agreement about the direction of change, which
 319 relies on the assumption that we have greater confidence in projections that have higher
 320 model run agreement. Another limitation is that there may be discrepancies between the total
 321 consumer biomass (see method) in the absence of fishing that is outputted by the models used
 322 here and what would actually be harvested by fishers since total consumer biomass can
 323 include both target and non-target species as well as other taxa entirely. Despite these
 324 limitations, we assumed that total consumer biomass is directly related to potential fisheries
 325 yields¹¹. Likewise, we included just 3 crops in the agricultural models (rice, maize, and
 326 cassava), which are key in the study region, with many study countries growing 2 or more of
 327 these crops. For example, Indonesia is the 3rd largest producer of rice in the world, and the 6th
 328 largest producer of maize and cassava³⁶. However, subsistence agriculture in Papua New
 329 Guinea is dominated by banana and yams, for which agricultural yield projections were not
 330 available. We used an unweighted average of projected changes in these three crops to
 331 represent a portfolio of small-scale agriculture, with a sensitivity test based on agricultural
 332 projections weighted by current yields/production area proportions of current yields
 333 (Supplemental Fig. 1). Finally, it is important to keep key model assumptions in mind when
 334 interpreting these data. For example, the agricultural models assumed no changes in farm
 335 management or climate change adaptation over time, while the fisheries models do not
 336 explicitly resolve predation impacts from higher trophic levels on phytoplankton.
 337

338 Third, our sensitivity metric examined a somewhat narrow aspect of what makes people
 339 sensitive to climate change. Sensitivity is thought to contain dimensions of economic,
 340 demographic, psychological, and cultural dependency³⁷. Our metric was based on people's

341 engagement in natural resource-based livelihoods, which primarily captures the economic
342 dimensions (although livelihoods do provide cultural and psychological contributions to
343 people^{26,28,29,31,38}).

344
345 Fourth, our study explicitly focused on the potential impacts of climate change in 72 Indo-
346 Pacific coastal communities by examining their sensitivity and exposure, but our
347 methodology did not enable us to incorporate adaptive capacity. Adaptive capacity is a latent
348 trait that enables people to adapt to and take advantage of the opportunities created by
349 change^{39,40}, and is critically important in determining the fate of coastal communities under
350 climate change. Adaptive capacity is thought to consist of dimensions of assets, flexibility,
351 social organisation, learning, socio-cognitive, and agency^{9,41,42}. Unfortunately, indicators of
352 these dimensions of adaptive capacity were not collected in a standardised manner across all
353 of the different projects comprising this study.

354
355 Fifth, we investigated the potential impacts of climate change on two key food production
356 sectors, but there may be other climate change impacts which have much more profound
357 impacts on people's wellbeing. For example, sea level rise may destroy homes and other
358 infrastructure⁴³, while heat waves may result in direct mortality⁴⁴. Lastly, we used shared
359 socioeconomic pathway exploratory scenarios that bracket the full range of scenario
360 variability (SSP5-8.5 and SSP1-2.6). At the time of publication, these were the only scenarios
361 available for both fisheries and agriculture using the ISIMIP Fastrack Phase 3 dataset. Future
362 publications may wish to explore additional scenarios.

363
364 Our study quantifies the potential impacts of climate change on key food production sectors
365 in tropical coastal communities across a broad swath of the Indo-Pacific. We find that both
366 exposure and sensitivity to fisheries is generally higher than to agriculture, but some places
367 may experience losses from both sectors simultaneously. These losses may be compounded
368 by other drivers of change, such as overfishing or soil erosion, which is already leading to
369 declining yields^{45,46}. Simultaneous losses to both fisheries catch potential and agriculture will
370 limit people's opportunity to adapt to changes through switching livelihoods between food
371 production sectors⁹. This will especially be the case in lower socioeconomic status
372 communities where dependence on natural resources is higher¹⁰. Together, our novel
373 integration of model projections and socioeconomic surveys highlight the importance of
374 assessing climate change impacts across sectors, but reveals important mismatches between
375 the scale at which people will experience the impacts of climate change and the scale at
376 which modelled projections about climate change impacts are currently available.

377
378 **Methods**

379 *Sampling of coastal communities*

380 Here, we integrated data from five different projects that had surveyed coastal communities
381 across five countries⁴⁷⁻⁵⁰. Between 2009 and 2015, we conducted socioeconomic surveys in
382 72 sites from Indonesia (n=25), Madagascar (n=6), Papua New Guinea (n=10), the
383 Philippines (n=25), and Tanzania (Zanzibar) (n=6). Site selection was for broadly similar
384 purposes- to evaluate the effects of various coastal resource management initiatives
385 (collaborative management, integrated conservation and development projects, recreational
386 fishing projects) on people's livelihoods in rural and peri-urban villages. Within each project,
387 sites were purposively selected to be representative of the broad range of socioeconomic
388 conditions (e.g., population size, levels of development, integration to markets) experienced
389 within the region. We did not survey strictly urban locations (i.e., major cities). Because our

390 sampling was not strictly random, care should be taken when attempting to make inferences
391 beyond our specific study sites.

392

393 We surveyed between 13 and 150 households per site, depending on the population of the
394 communities and the available time to conduct interviews per site. All projects employed a
395 comparable sampling design: households were either systematically (e.g., every third house),
396 randomly sampled, or in the case of three villages, every household was surveyed (a census)
397 (Table S1). Respondents were generally the household head, but could have been other
398 household members if the household head was not available during the study period (i.e. was
399 away). In the Philippines, sampling protocol meant that each village had an even number of
400 male and female respondents. Respondents gave verbal consent to be interviewed.

401

402 A standard methodology was employed to assess material style of life, a metric of material
403 assets-based wealth^{48,51}. Interviewers recorded the presence or absence of 16 material items
404 in the household (e.g., electricity, type of walls, type of ceiling, type of floor). We used a
405 Principal Component Analysis on these items and kept the first axis (which explained 34.2%
406 of the variance) as a material wealth score. Thus, each community received a mean material
407 style of life score, based on the degree to which surveyed households had these material
408 items, which we then scaled from 0-1. We also conducted an exploratory analysis of how
409 material style of life has changed in two sites in Papua New Guinea (Muluk and Ahus
410 villages) over fifteen and sixteen year time span across four and five time periods (2001,
411 2009, 2012, 2016 and 2002, 2009, 2012, 2016, 2018), respectively, that have been surveyed
412 since 2001/2⁵². These surveys were semi-panel data (i.e. the community was surveyed
413 repeatedly, but we did not track individuals over each sampling interval) and sometimes
414 occurred in different seasons. For illustrative purposes, we plotted how these villages
415 changed over time along the first two principal components.

416

417 *Sensitivity*

418 We asked each respondent to list all livelihood activities that bring in food or income to the
419 household and rank them in order of importance. Occupations were grouped into the
420 following categories: farming, cash crop, fishing, mariculture, gleaning, fish trading, salaried
421 employment, informal, tourism, and other. We considered fishing, mariculture, gleaning, fish
422 trading together as the ‘fisheries’ sector, farming and cash crop as the ‘agriculture’ sector and
423 all other categories into an ‘off-sector’.

424

425 We then developed three distinct metrics of sensitivity based on the level of dependence on
426 agriculture, fisheries, and both sectors together. Each metric incorporates the proportion of
427 households engaged in a given sector (e.g., fisheries), whether these households also engage
428 in occupations outside of this sector (agriculture and salaried/formal employment; referred to
429 as ‘linkages’ between sectors), and the directionality of these linkages (e.g., whether
430 respondents ranked fisheries as more important than other agriculture and salaried/formal
431 employment) (Eq. 1-3)

432

$$433 S_A = \frac{A}{A+NA} \times \frac{N}{A+NA} \times \frac{\left(\frac{r_a}{2}\right) + 1}{r_a + r_{na} + 1} \quad (1)$$

434

$$435 S_F = \frac{F}{F+NF} \times \frac{N}{F+NF} \times \frac{\left(\frac{r_f}{2}\right) + 1}{r_f + r_{nf} + 1} \quad (2)$$

436

$$S_{AF} = \frac{AF}{AF+NAF} \times \frac{N}{AF+NAF} \times \frac{\left(\frac{r_{af}}{2}\right) + 1}{r_{af} + r_{naf} + 1} \quad (3)$$

438
439

440 where S_A , S_F and S_{AF} are a community's sensitivity in the context of agriculture, fisheries
441 and both sectors, respectively. A , F and AF are the number of households relying on
442 agriculture-related occupations within that community, fishery-related and agriculture- and
443 fisheries-related occupations within the community, respectively. NA , NF and NAF are the
444 number of households relying on non-agriculture-related, non-fisheries-related, and non-
445 agriculture-or-fisheries-related occupations within the community, respectively. N is the
446 number of households within the community. r_a , r_f and r_{af} are the number of times
447 agriculture-related, fisheries-related and agriculture-and-fisheries-related occupations were
448 ranked higher than their counterpart, respectively. r_{na} , r_{nf} and r_{naf} are the number of times
449 non-agriculture, non-fisheries, and non-agriculture-and-fisheries-related occupations were
450 ranked higher than their counterparts. As with the material style of life, we also conducted an
451 exploratory analysis of how joint agriculture-fisheries sensitivity has changed over time in a
452 subset of sites (Muluk and Ahus villages in Papua New Guinea) that have been sampled since
453 2001/2002⁵². Although our survey methodology has the potential for bias (e.g. people might
454 provide different rankings based on the season, or there might be gendered differences in how
455 people rank the importance of different occupations⁵³), our time-series analysis suggest that
456 seasonal and potential respondent variation do not dramatically alter our community-scale
457 sensitivity metric.

458

459 *Exposure*

460 To evaluate the exposure of communities to the impact of future climates on their agriculture
461 and fisheries sectors, we used projections of production potential from the Inter-Sectoral
462 Impact Model Intercomparison Project (ISIMIP) Fast Track phase 3 experiment dataset of
463 global simulations. Production potential of agriculture and fisheries for each of the 72
464 community sites and 4,746 randomly selected sites from our study countries with coastal
465 populations >25 people/km² were projected to the mid-century (2046-2056) under two
466 emission scenarios (SSP1-2.6, and SSP5-8.5) and compared with values from a reference
467 historical period (1983-2013).

468

469 For fisheries exposure (E_F), we considered relative change in simulated total consumer
470 biomass (all modelled vertebrates and invertebrates with a trophic level >1). For each site, the
471 twenty nearest ocean grid cells were determined using the Haversine formula (Supplemental
472 Fig. 5). We selected twenty grid cells after a sensitivity analysis to determine changes in
473 model agreement based on different numbers of cells used (1, 3, 5, 10, 20, 50, 100;
474 Supplemental Figs. 6-7), which we balanced off with the degree to which larger numbers of
475 cells would reduce the inter-site variability (Supplemental Fig. 8). 25th and 75th percentiles
476 for the change in marine animal biomass across the model ensemble were also reported.
477 Projections of the change in total consumer biomass for the 72 sites were extracted from
478 simulations conducted by the Fisheries and marine ecosystem Model Intercomparison Project
479 (FishMIP^{3,54}). FishMIP simulations were conducted under historical, SSP1-2.6 (low
480 emissions) and SSP5-8.5 (high emissions) scenarios forced by two Earth System Models
481 from the most recent generation of the Coupled Model Intercomparison project (CMIP6)⁵⁵;
482 GFDL-ESM4⁵⁶ and IPSL-CM6A-LR⁵⁷. The historical scenario spanned 1950-2014, and the
483 SSP scenarios spanned 2015-2100. Nine FishMIP models provided simulations:
484 APECOSM^{58,59}, BOATS^{60,61}, DBEM^{2,62}, DBPM⁶³, EcoOcean^{64,65}, EcoTroph^{66,67}, FEISTY⁶⁸,
485 Macroecological⁶⁹, and ZooMSS¹¹. Simulations using only IPSL-CM6A-LR were available

486 for APECOSM and DBPM, while the remaining 7 FishMIP models used both Earth System
487 Model forcings. This resulted in 16 potential model runs for our examination of model
488 agreement, albeit with some of these runs being the same model forced with two different
489 ESMs. Thus, the range of model agreement could range from 8 (half model runs indicating
490 one direction of change, and half indicating the other) to 16 (all models agree in direction of
491 change). Model outputs were saved with a standardised 1° spatial grid, at either a monthly or
492 annual temporal resolution.

493

494 For agriculture exposure (E_A), we used crop model projections from the Global Gridded Crop
495 model Intercomparison Project (GGCMI) Phase 3¹⁴, which also represents the agriculture
496 sector in ISIMIP. We used a window of 11x11 cells centred on the site and removed non-land
497 cells (Fig S5). The crop models use climate inputs from 5 CMIP6 ESMs (GFDL-ESM4,
498 IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL), downscaled and
499 bias-adjusted by ISIMIP and use the same simulation time periods. We considered relative
500 yield change in three rain-fed and locally relevant crops: rice, maize, and cassava, using
501 outputs from 4 global crop models (EPIC-IIASA, LPJmL, pDSSAT, and PEPIC), run at 0.5°
502 resolution. These 4 models with 5 forcings generate 20 potential model runs for our
503 examination of model agreement. Yield simulations for cassava were only available from the
504 LPJmL crop model. All crop model simulations assumed no adaptation in growing season
505 and fertilizer input remained at current levels. Details on model inputs, climate data, and
506 simulation protocol are provided in ref¹⁴. At each site, and for each crop, we calculated the
507 average change (%) between projected vs. historical yield within 11x11 cell window. We
508 then averaged changes in rice, maize and cassava to obtain a single metric of agriculture
509 exposure (E_A).

510

511

512 We also obtained a composite metric of exposure (E_{AF}) by calculating each community's
513 average change in both agriculture and fisheries:

514

$$515 \quad E_{AF} = \frac{E_A + E_F}{2} \quad (4)$$

516

517 *Potential Impact*

518 We calculated relative potential impact as the Euclidian distance from the origin (0) of
519 sensitivity and exposure.

520

521 *Sensitivity Test*

522 To determine whether our sites displayed a particular exposure bias, we compared the
523 distributions of our sites and 4,746 sites that were randomly selected from 47,460 grid cells
524 within 1 km of the coast of the 5 countries we studied which had population densities >25
525 people/km², based on the SEDAC gridded populating density of the world dataset
526 (<https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11/data-download>).
527 We used Cohen's D to determine the size of the difference between our sites and the
528 randomly selected sites.

529

530 *Validating ensemble models*

531 We attempted a two-stage validation of the ensemble model projections. First, we reviewed
532 the literature on downscaling of ensemble models to examine whether downscaling validation
533 had been done for the ecoregions containing our study sites.

534

535 While no fisheries ensemble model downscaling had been done specific to our study regions,
536 most of the models of the ensemble have been independently evaluated against separate
537 datasets aggregated at scales down to Large Marine Ecosystems (LMEs) or Exclusive
538 Economic Zones (EEZs) (see ¹¹). For example, the DBEM was created with the objective of
539 understanding the effects of climate change on exploited marine fish and invertebrate
540 species^{2,71}. This model roughly predicts species' habitat suitability; and simulates spatial
541 population dynamics of fish stocks to output biomass and maximum catch potential (MCP), a
542 proxy of maximum sustainable yield^{2,62,70}. Compared with spatially explicit catch data from
543 the Sea Around Us Project (SAUP; www.seaaroundus.org)⁷¹ there were strong similarities in
544 the responses to warming extremes for several EEZs in our current paper (Indonesia and
545 Philippines) and weaker for the EEZs of Madagascar, Papua New Guinea, and Tanzania. At
546 the LME level, DBEM MCP simulations explained about 79% of the variation in the SAUP
547 catch data across LMEs⁷². The four LMEs analyzed in this paper (Agulhas Current; Bay of
548 Bengal; Indonesian Sea; and Sulu-Celebes Sea) fall within the 95% confidence interval of the
549 linear regression relationship⁶². Another example, BOATS, is a dynamic biomass size-
550 spectrum model parameterised to reproduce historical peak catch at the LME scale and
551 observed catch to biomass ratios estimated from the RAM legacy stock assessment database
552 (in 8 LMEs with sufficient data). It explained about 59% of the variability of SAUP peak
553 catch observation at the LME level with the Agulhas Current, Bay of Bengal, and Indonesian
554 Sea catches reproduced within +/-50% of observations⁶¹. The EcoOcean model validation
555 found that all four LMEs included in this study fit very close to the 1:1 line for overserved
556 and predicted catches in 2000^{64,65}. DBPM, FEISTY, and APECOSM have also been
557 independently validated by comparing observed and predicted catches. While the models of
558 this ensemble have used different climate forcings when evaluated independently, when
559 taken together the ensemble multi-model mean reproduces global historical trends in relative
560 biomass, that are consistent with the long term trends and year-on-year variation in relative
561 biomass change (R^2 of 0.96) and maximum yield estimated from stock assessment models
562 (R^2 of 0.44) with and without fishing respectively¹¹.

563
564 Crop yield estimates simulated by GGCM crop models have been evaluated against
565 FAOSTAT national yield statistics^{14,73,74}. These studies show that the models, and especially
566 the multi-model mean, capture large parts of the observed inter-annual yield variability across
567 most main producer countries, even though some important management factors that affect
568 observed yield variability (e.g., changes in planting dates, harvest dates, cultivar choices, etc.)
569 are not considered in the models. While GCM-based crop model results are difficult to
570 validate against observations, Jägermeyr et al.¹⁴ show that the CMIP6-based crop model
571 ensemble reproduces the variability of observed yield anomalies much better than CMIP5-
572 based GGCM simulations. In an earlier crop model ensemble of GGCM, Müller et al.⁷⁴
573 show that most crop models and the ensemble mean are capable of reproducing the weather-
574 induced yield variability in countries with intensely managed agriculture. In countries where
575 management introduces strong variability to observed data, which cannot be considered by
576 models for lack of management data time series, the weather-induced signal is often low⁷⁵,
577 but crop models can reproduce large shares of the weather-induced variability, building trust
578 in their capacity to project climate change impacts⁷⁴.

579
580
581 We then attempted to validate the models in our study regions. For the crop models, we
582 examined production-weighted agricultural projections weighted by current yields/production
583 area (Supplemental Fig. 1). We used an observational yield map (SPAM2005) and multiplied
584 it with fractional yield time series simulated by the models to calculate changes in crop

585 production over time, which integrates results in line with observational spatial patterns. The
586 weighted estimates were not significantly different to the unweighted ones ($t=0.17$, $df=5$,
587 $p=0.87$). For the fisheries models, our study regions were data poor and lacked adequate
588 stock assessment data to extend the observed global agreement of the sensitivity of fish
589 biomass to climate during our reference period (1983-2013). Instead, we provide the degree
590 of model run agreement about the direction of change in the ensemble models to ensure
591 transparency about the uncertainty in this downscaled application.

592

593 *Analyses*

594 To account for the fact that communities were from five different countries we used linear
595 mixed effects models (with country as a random effect) for all analyses. All averages
596 reported (i.e. exposure, sensitivity, and model agreement) are estimates from these models. In
597 both our comparison of fisheries and agriculture exposure and test of differences between
598 production-weighted and unweighted agriculture exposure we wanted to maintain the paired
599 nature of the data while also accounting for country. To accomplish this we used the
600 differences between the exposure metrics as the response variable (e.g. fisheries exposure
601 minus agriculture exposure), testing whether these differences are different from zero. We
602 also used linear mixed effects models to quantify relationships between material style of life
603 and potential impacts under different mitigation scenarios (SSP1-2.6 and 8.5), estimating
604 95% confidence intervals from 1000 bootstrap replications. To further explore whether these
605 relationships between material style of life and potential impacts were driven by exposure or
606 sensitivity, we conducted a supplemental analysis to quantify relationships between material
607 style of life and: 1) joint fisheries and agricultural sensitivity; 2) joint fisheries and
608 agricultural exposure under different mitigation scenarios. We present both the conditional R^2
609 (i.e., variance explained by both fixed and random effects) and the marginal R^2 (i.e., variance
610 explained by only the fixed effects) to help readers compare among the material style of life
611 relationships.

612

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623

624

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628 JS, TE, JE, DG, JG, RFH, CN, JPA, CP, and DT contributed fisheries model simulations. LT,
629 JJ, RFH, TE, and IC analysed the data and all authors contributed to the writing of the
630 manuscript.

631

632 **Competing interest statement.** The authors have no competing interests.

633

634 **Data availability**

635 All outputs from the FishMIP model ensemble are available via ISIMIP
636 (<https://www.isimip.org/gettingstarted/data-access/>).

637

638 Data and code available at:

639 https://github.com/ircaldwell/Cinneretal_ImpactClimateChangeAgricultureFisheries

640

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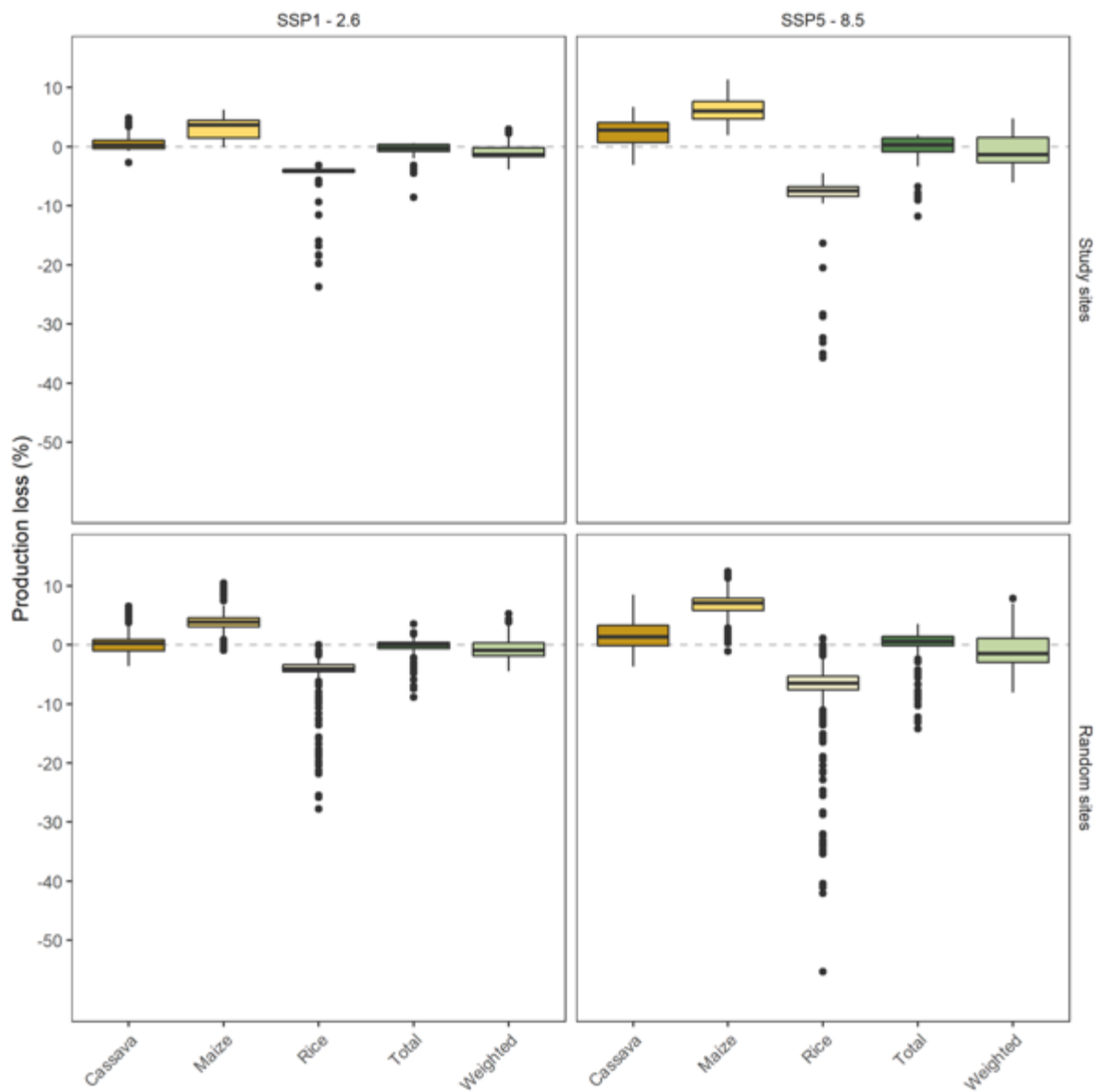
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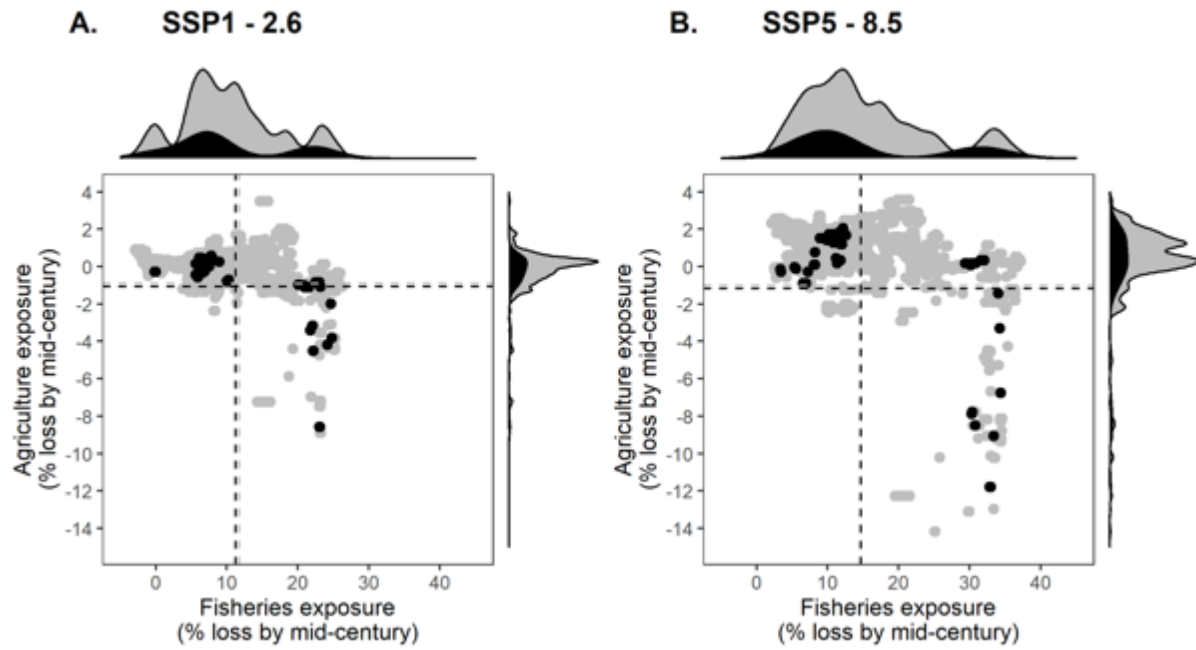
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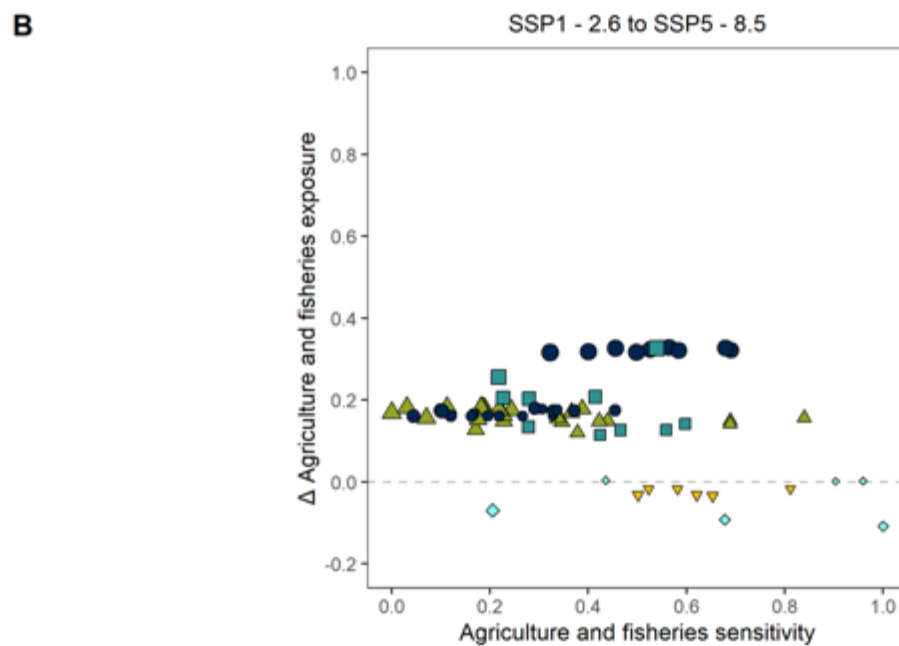
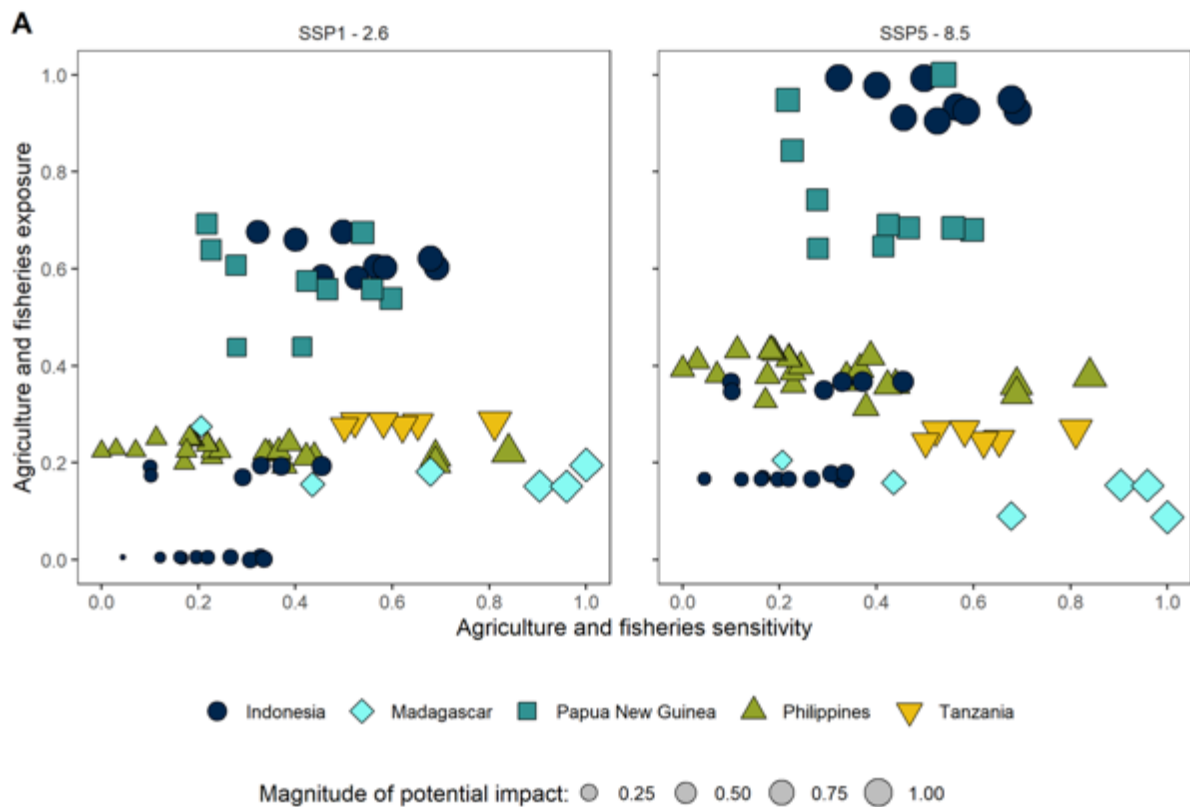
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Figure S1. Projected agricultural changes by crop for SSP1-2.6 and 8.5. Top row are projections for our study sites, while the bottom row examines projected changes for 4,746 randomly selected sites from our study region. Weighted average is based on agricultural projections weighted by current yields/production area.



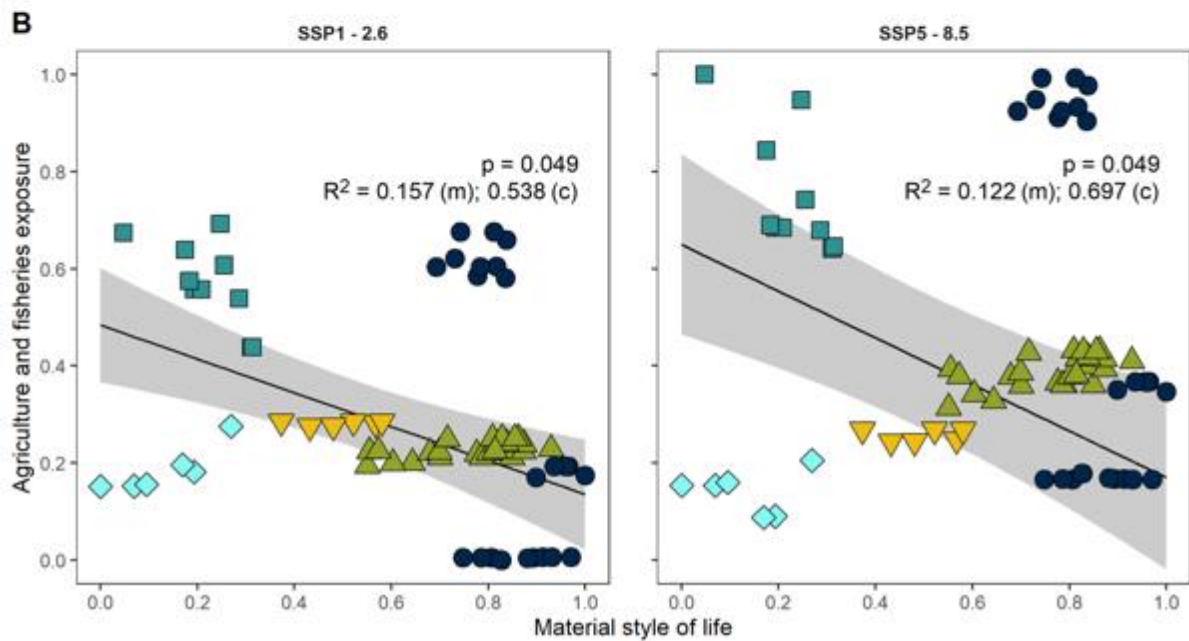
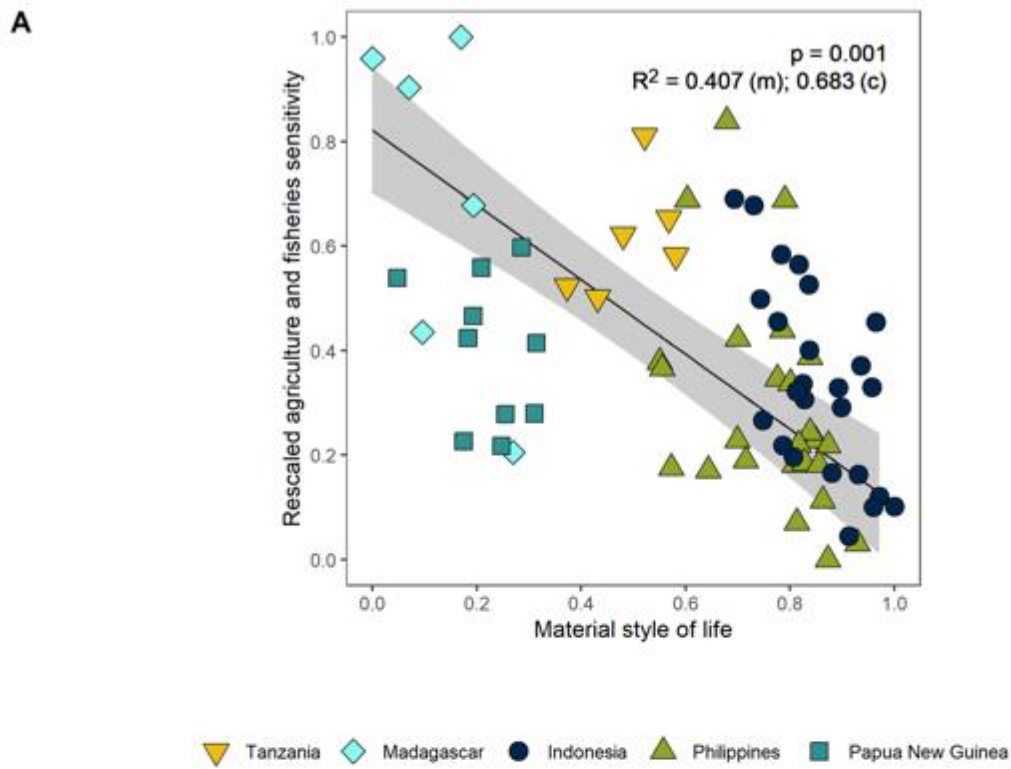
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 830 Figure S2. A comparison of expected fisheries and agriculture losses (exposure). A) SSP1-
 831 2.6, B) SSP5-8.5. Black dots/histograms are our study sites. Grey dots/histograms are a
 832 random selection of 4,746 (10% of) coastal cells with population densities >25 people/km².
 833 Dotted lines represent the mean exposure. Differences between expected losses in our sites
 834 and the randomly selected sites are generally small to negligible (Cohen's D for agricultural
 835 losses SSP5-8.5=0.31, SSP1-2.6= 0.35, fisheries losses SSP5-8.5 =-0.02, RCP2.6=-0.03),
 836 indicating that our sites are not particularly biased.
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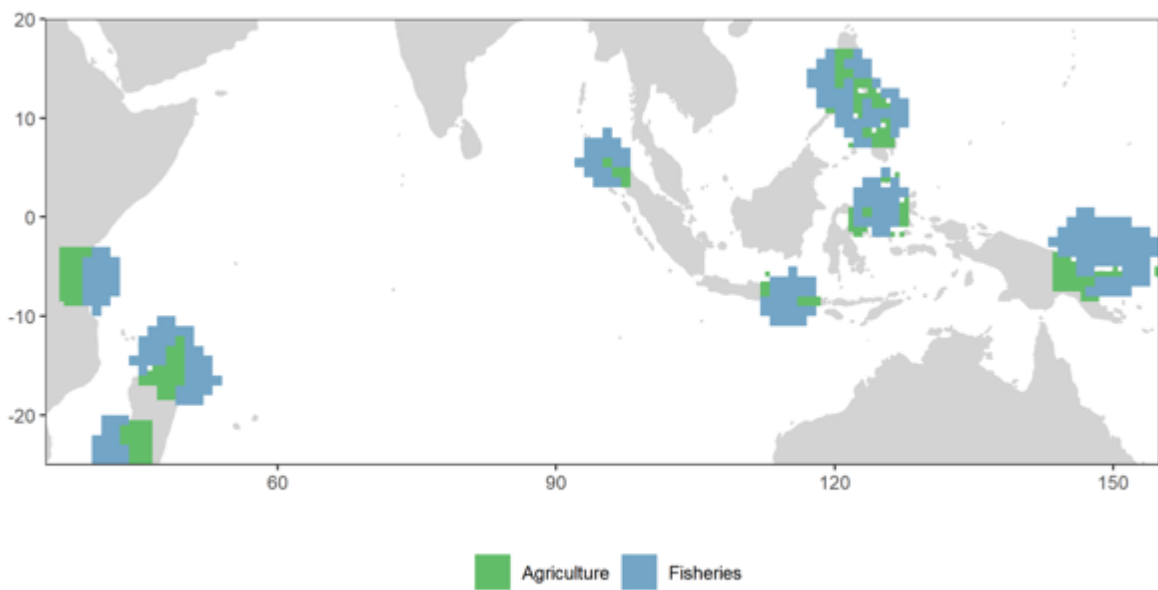
Fig S3. Potential impacts of changes to agriculture and fisheries by scenario. A) SSP1-2.6, B) SSP5-8.5. Both exposure and sensitivity to fisheries and agriculture are integrated. The potential impact is calculated as the Euclidian distance to the origin. C) The change in potential impact from mitigation (i.e. the difference between SSP5-8.5 and SSP1-2.6).

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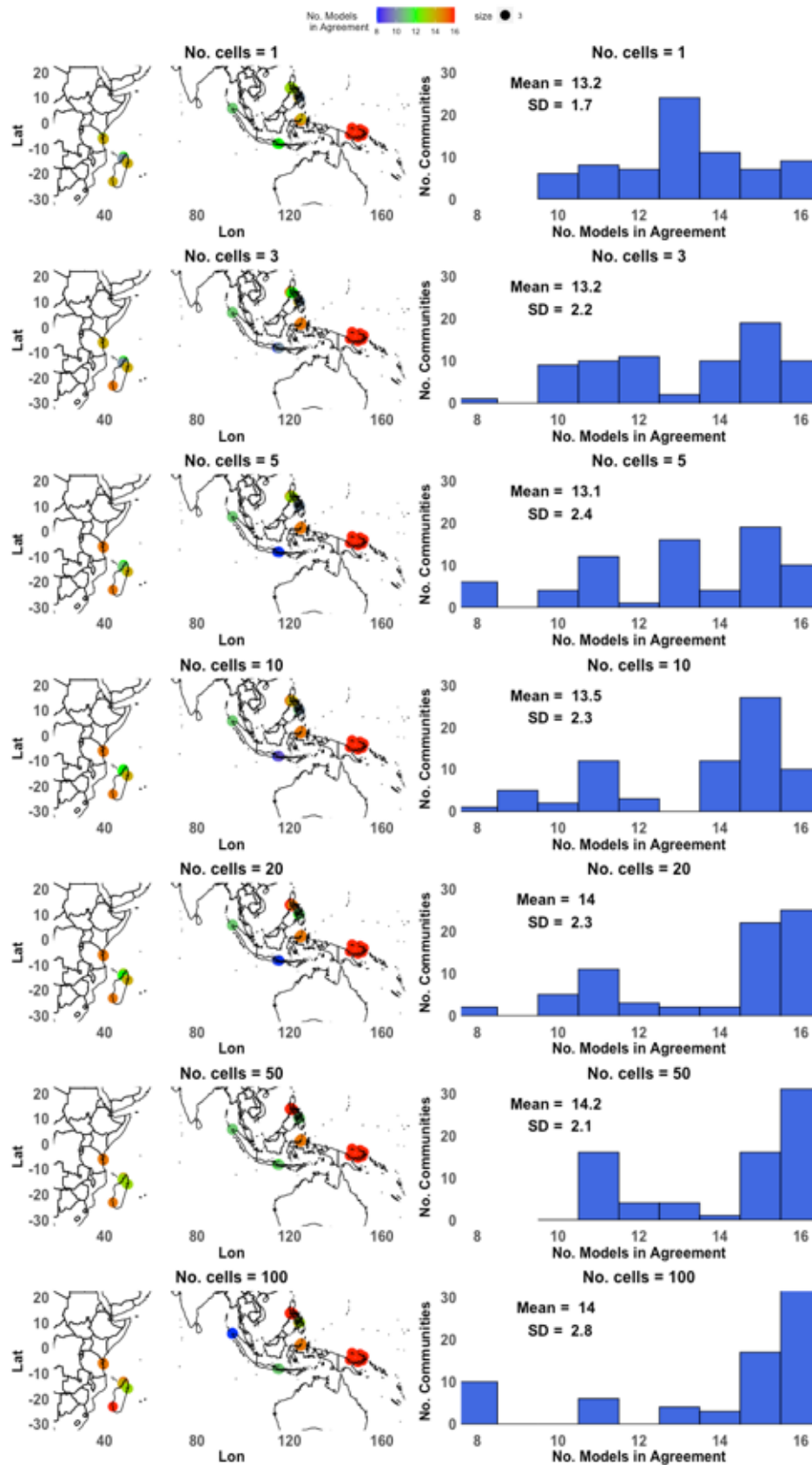
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Fig S4. Relationships between MSL and (A) Ag-Fish sensitivity, (B) Ag-Fish exposure under SSP1-2.6 and (C) SSP5-8.5. (m)=marginal R^2 , (c)=conditional R^2



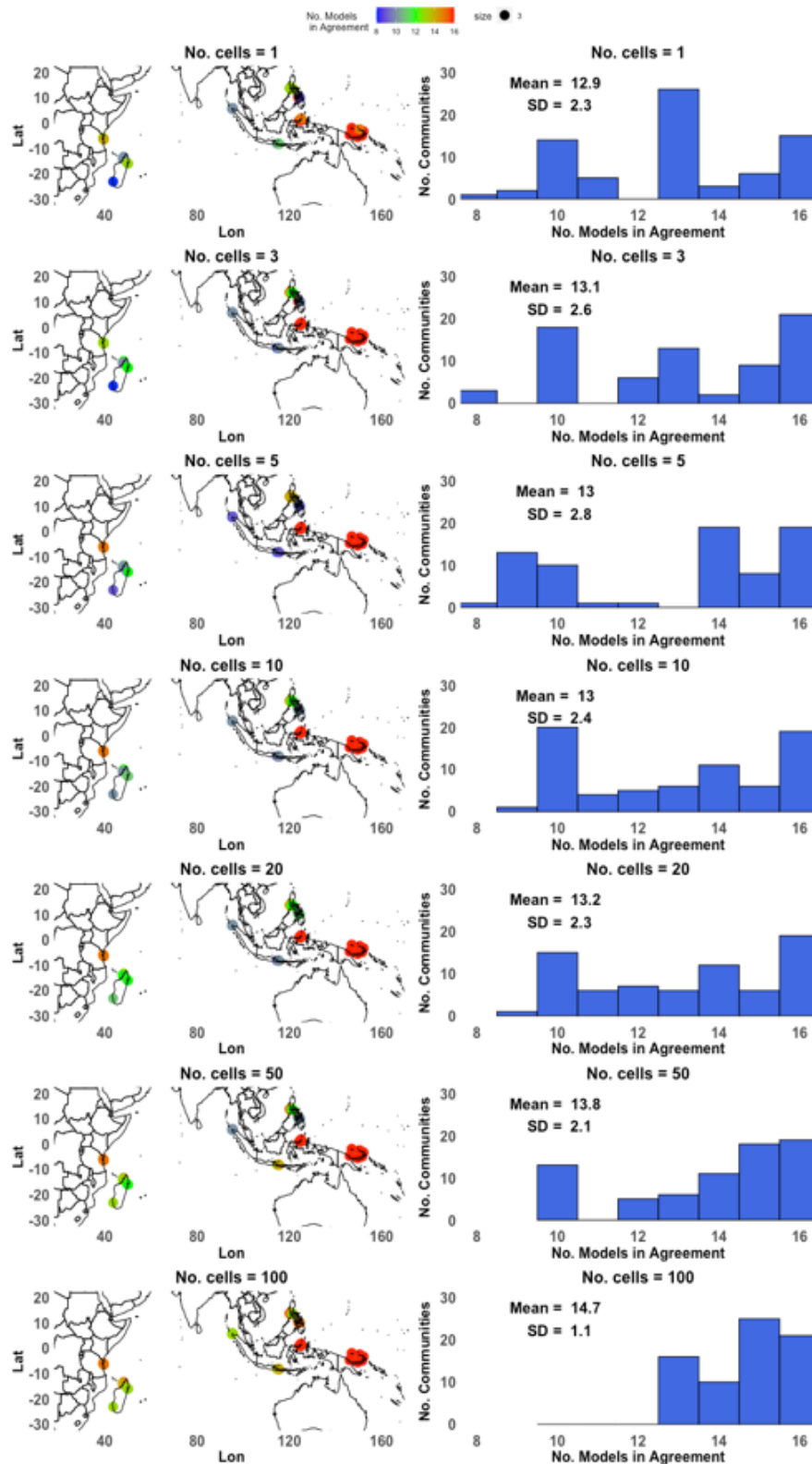
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Fig. S5. The cells used in determining fisheries and agriculture exposure.



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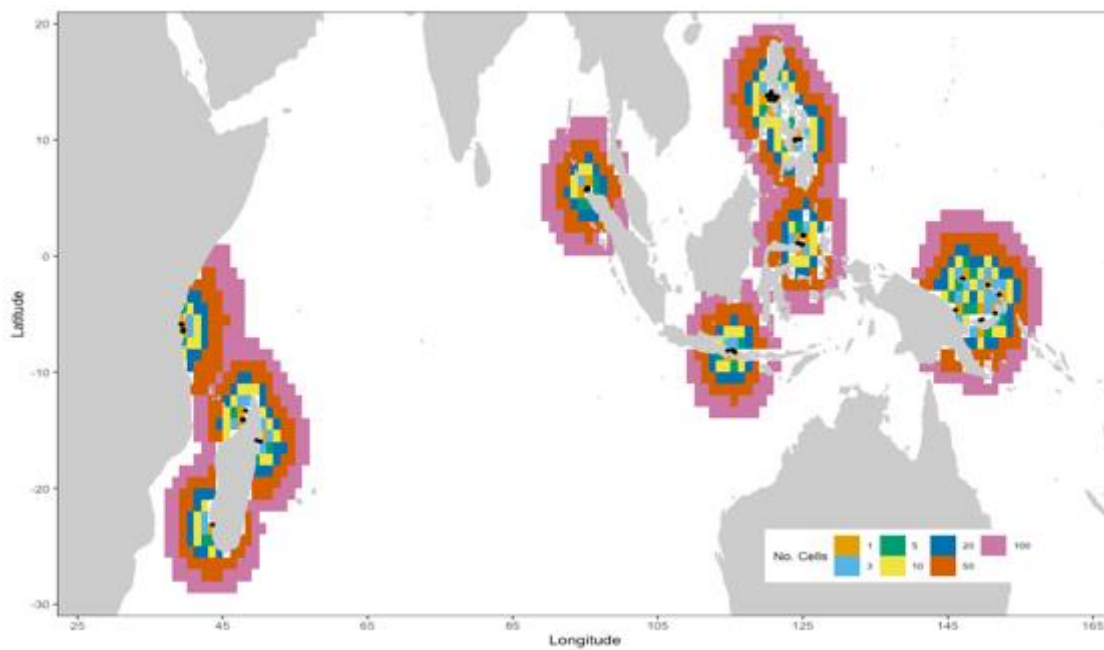
Figure S6. Trade-off between model agreement and number of cells used for fisheries SSP1-2.6. A model run agreement of 50%, the lowest possible value, indicates that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree on the direction of change.



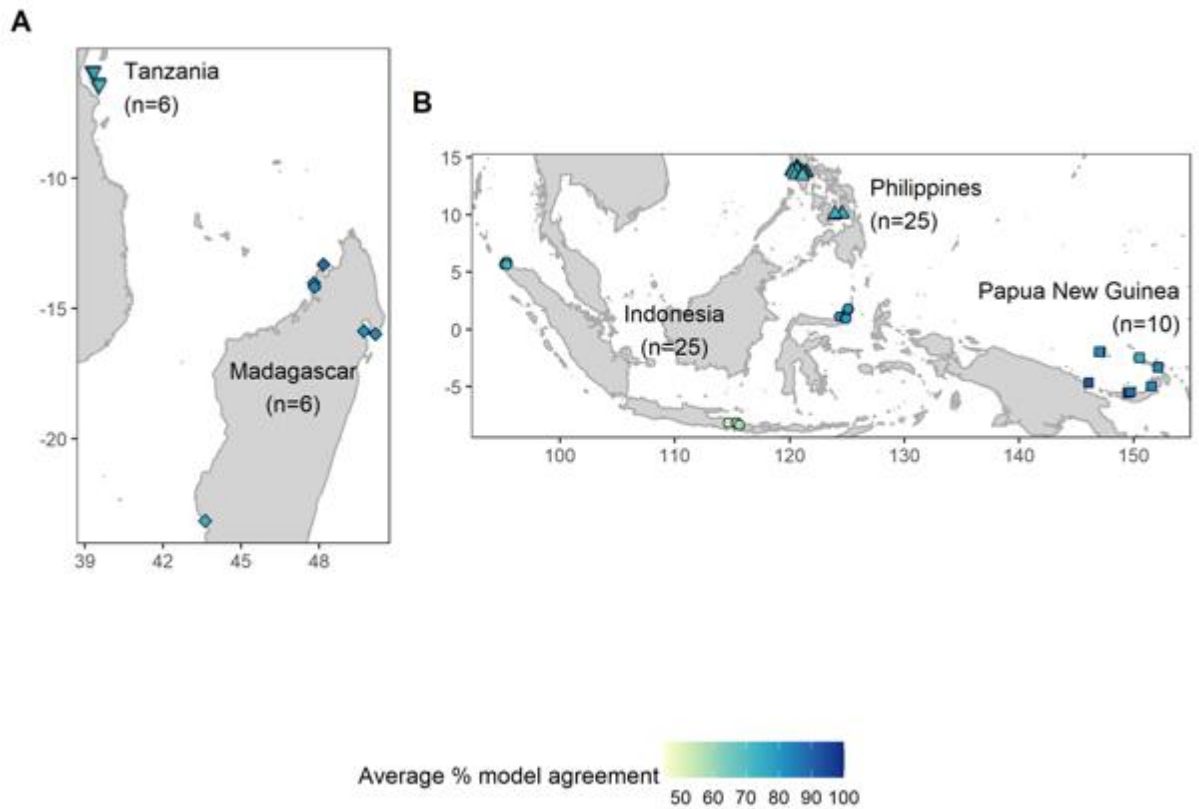
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Fig S7. Trade-off between model agreement and number of cells used for fisheries SSP5-8.5. A model run agreement of 50%, the lowest possible value, indicates that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree on the direction of change.

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890 Figure S8. Spatial extent covered by using different numbers of grid cells to determine
891 fisheries exposure. Black dots are coastal study sites associated with each?
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Fig. S9. Inset map of study sites and average agriculture-fisheries model run agreement at each site. A model run agreement of 50% means that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree on the direction of change.

901 Table S1. Sample size and proportion of social surveys
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COMMUNITY	COUNTRY	NUMBER HOUSEHOLDS SURVEYED	NUMBER HOUSEHOLDS TOTAL	SAMPLING PROPORTION	SAMPLING STRATEGY
ANOI ITAM	indonesia	29	158	0.18	Systematic
BAHOI	indonesia	22	100	0.22	Systematic
BALOHANVILLAGE	indonesia	47	577	0.08	Systematic
BENTANAN	indonesia	40	355	0.11	Systematic
BLONGKO	indonesia	56	1827	0.03	Systematic
BONDALEM	indonesia	48	333	0.14	Systematic
BOYONG PANTE	indonesia	18	2505	0.01	Systematic
BUERAWANG	indonesia	51	344	0.15	Systematic
IBOIH	indonesia	21	92	0.23	Systematic
IEU MEULEE	indonesia	30	228	0.13	Systematic
JABOI	indonesia	50	1269	0.04	Systematic
KAHUKU	indonesia	27	180	0.15	Systematic
KEUNEUKAI	indonesia	44	196	0.22	Systematic
LAMPUYANG	indonesia	36	241	0.15	Systematic
MINANGA	indonesia	27	203	0.13	Systematic
PASIRAN	indonesia	58	480	0.12	Systematic
PEMUTERAN	indonesia	49	1651	0.03	Systematic
PENUKTUKAN	indonesia	26	133	0.20	Systematic
PRIA LAOT	indonesia	22	1986	0.01	Systematic
RUMBIA	indonesia	20	902	0.02	Systematic
SAMBIRENTENG	indonesia	61	278	0.22	Systematic
TALISE	indonesia	30	1024	0.03	Systematic
TEJAKULA	indonesia	52	630	0.08	Systematic
TULAMBEN	indonesia	24	2366	0.01	Systematic
TUMBAK	indonesia	21	1799	0.01	Systematic
AMBODIPAKA	madagascar	115	835	0.14	Systematic
DAUPHIN	madagascar	55	90	0.61	Systematic
FIMIHARA	madagascar	43	900	0.05	Systematic
MASOALA	madagascar	63	142	0.44	Systematic
NOSY VALIHA	madagascar	29	41	0.71	Systematic
RASIS	madagascar	34	58	0.59	Systematic

AHUS	papua new guinea	38	122	0.31	Systematic
ANDRA	papua new guinea	23	95	0.24	Systematic
BAIA	papua new guinea	35	35	1	Census
DABANOT	papua new guinea	19	25	0.76	Systematic
KAVULIK	papua new guinea	24	51	0.47	Systematic
MULUK	papua new guinea	20	66	0.30	Systematic
SILOM 1	papua new guinea	13	23	0.57	Systematic
SOMALANI	papua new guinea	67	67	1	Census
UNGAKUM	papua new guinea	24	56	0.43	Systematic
VESSE	papua new guinea	55	55	1	Census
MATABAO	philippines	40	999	0.04	Random
MOCABAC ISLAND	philippines	40	119	0.34	Random
TIPOLO	philippines	28	585	0.05	Random
AGUINING	philippines	30	480	0.06	Random
CALUBCUB II	philippines	40	912	0.04	Random
BATAAN	philippines	41	435	0.09	Random
LAIYA APLAYA	philippines	41	1,202	0.03	Random
SAWANG	philippines	40	438	0.09	Random
LAGADLARIN	philippines	40	753	0.05	Random
BALIBAGO	philippines	40	635	0.06	Random
ANILAO PROPER	philippines	40	600	0.07	Random
SAN AGUAPITO IV	philippines	40	352	0.11	Random
PAPAYA	philippines	40	508	0.08	Random
PANTALAN	philippines	40	643	0.06	Random
WAWA	philippines	40	4,662	0.01	Random
BUCAL	philippines	40	212	0.19	Random
BAHA	philippines	40	200	0.20	Random

TALIBAYOG	philippines	40	411	0.10	Random
NINIKAT NG PAG-ASA	philippines	39	133	0.29	Random
MALIGAYA	philippines	40	207	0.19	Random
KANLURAN	philippines	40	133	0.30	Random
BRGY 6	philippines	40	151	0.26	Random
BRGY 4	philippines	40	110	0.36	Random
POBLACION	philippines	40	404	0.10	Random
PUTICAN	philippines	34	102	0.33	Random
JAMBIANI	tanzania	40	600	0.07	Systematic
MATEMWE	tanzania	39	378	0.10	Systematic
MKOKOTONI	tanzania	39	500	0.08	Systematic
MTENDE	tanzania	39	400	0.10	Systematic
MZURI	tanzania	40	217	0.18	Systematic
PWANI MCHANGANI	tanzania	41	200	0.21	Systematic

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