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

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Abstract

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

Introduction

Climate change is expected to profoundly impact key food production sectors, with the tropics expected to suffer losses in both fisheries and agriculture. For example, by 2100 tropical areas could lose up to 200 suitable plant growing days per year due to climate change[1]. Likewise, fishable biomass in the ocean could drop by up to 40% in some tropical areas[2,3].

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

Incorporating key social dimensions of vulnerability is particularly important because many coastal communities simultaneously rely on both agriculture and fisheries to varying degrees[10], yet assessments of climate change impacts and the policy prescriptions that come from them often consider these sectors in isolation[1,5,11–14]. Recently, studies have begun to look at the simultaneous impacts of climate change on both fisheries and agriculture at the national level[15,16], but this coarse scale does not capture whether people simultaneously engage with- and are likely to be affected by- changes in these sectors. Indeed, whether households engage in both fisheries and agriculture[10] will determine whether people have the knowledge, skills, and capital to substitute sectors if one declines, or alternatively, make them particularly susceptible to the potential 'perfect storm' of a combined decline across sectors[15]. Thus, more localised analyses incorporating key social dimensions of vulnerability are required to better understand how combined impacts to fisheries and agriculture may affect coastal communities. Here, we combine a measure of exposure based on model projections of losses to exploitable marine biomass (here dubbed "fisheries catch potential") and agriculture from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) Fast Track phase 3 dataset with a measure of sensitivity based on survey data about material wealth and engagement in fisheries, agriculture, and other occupational sectors from >3,000 households across 72 tropical coastal communities in five countries (Table S1). We ask: "What are the potential impacts of projected changes to fisheries catch potential and agriculture on coastal communities?" "How much will mitigation measures reduce these potential impacts?" and "Are lower socioeconomic status coastal communities facing more potential impacts from climate change than their wealthier counterparts? "

Results and Discussion

Our study has three key results. First, we find that overall possible impacts on fisheries catch potential is higher than possible impacts on agriculture, but there can be substantial within-country variability in both exposure and sensitivity (Fig. 1). Specifically, exposure under the high-emissions Shared Socioeconomic Pathway 8.5 scenario (which has tracked historic cumulative CO_2 emissions[17], but has been recently critiqued for over-projecting CO_2 emissions and economic growth[18]) indicates substantive losses by mid-century to fisheries catch potential [Fig. 1; 14.7% +/- 4.3% (SE) mean fisheries catch potential loss]. To put these projected losses in perspective, Sala et al.[19] found that strategically protecting 28% of the ocean could increase food provisioning by 5.9 million tonnes, which is just 6.9% of the 84.4 million tons of marine capture globally in 2018[20]. Thus, the mean expected fisheries catch potential losses are approximately double that which could be buffered by strategic conservation. Model run agreement about the directionality of change for projected impacts to fisheries catch potential was high (SSP5-8.5: 84.7 +/- 4.5% (SE); SSP1-2.6: 89.2 +/- 4.06% (SE)). Interestingly, crop models projected that agricultural productivity (based on rice, maize, and cassava- see methods) is expected to experience small average gains across the 72 sites (1.2% +/- 1.5% (SE) mean agricultural gain), with a large response range between sites and crops (Fig S1). However, the average gains are not significantly different from zero ($t = -0.80$, $df = 5.0$, $p=0.46$), and model run agreement about directionality of change was lower for agriculture (SSP5-8.5: 69.1 +/- 4.82% (SE); SSP1-2.6: 70.4 +/- 3.27% (SE)). These projected agricultural gains are driven exclusively by rice (Supplemental Fig 1), which has particularly large model disagreement[14,21]. Excluding rice shows an average decline in agricultural production by mid-century, since maize and cassava show consistent median losses under both SSP1-2.6 and SSP5-8.5 climate scenarios (Supplemental Fig. 1). Significantly greater losses in fisheries catch potential compared to agriculture productivity are apparent not only for our study sites (i.e. 15.9 +/- 5.6% (SE) greater; $t = 2.81$, $df = 4.97$, $p = 0.0379$), but also for a random selection of 4,746 (10% of) coastal locations in our study countries with populations >25 people per km^2 (Fig. 2). Among those random sites, fisheries catch potential losses are an average of 15.6 +/- 5.1% (SE) greater than agriculture productivity changes ($t = 3.06$, $df = 5.00$, $p=0.0282$). Differences between expected losses at our sites and the randomly selected sites are small for agriculture (Cohen's D for SSP5-8.5=-0.31, SSP1-2.6=-0.35) and negligible for fisheries catch potential (Cohen's D for SSP5-8.5 =-0.02, SSP1-2.6=-0.03), indicating that our sites are not particularly biased towards high or low exposure for the study region. Not only is the level of exposure generally higher in fisheries compared to agriculture, but the sensitivity is on average nearly twice as high (Fig. 1A,B; 0.077 +/- 0.007 mean fisheries sensitivity; 0.04+/-0.01 mean agricultural sensitivity; $t =3.0$, $df = 2.26$, p-value =0.0815).

Our analysis also reveals high within-country variability in potential impacts (i.e. both exposure and sensitivity), particularly for fisheries (Fig. 1) - a finding that may be masked in studies looking at national-level averages[15,16]. Looking only at the mean expected losses can obscure the more extreme fisheries catch potential losses projected for many communities (Figs. 1,2). For example, under SSP5-8.5, our Indonesian sites are projected to experience very close to the average fisheries catch potential losses among our study sites (15.9 +/- 2.1%SE), but individual sites range from 6.5-32% losses (Fig 1B). There is also substantial within-country variation in how communities are likely to experience climate change impacts, based on their sensitivity (Fig. 1A,B). For example, in the Philippines, exposure to fisheries is consistently moderate (range 8.9-12.6% loss), but sensitivity ranges from our lowest (0.001) to our highest recorded scores (0.32). There is also within-country variability in model agreement, particularly for the agricultural models in Indonesia, where agricultural model agreement ranges from 50-85% and fisheries model agreement ranges from 56-100% for SSP5-8.5, and 50-80% and 50-94%, respectively, for SSP1-2.6.

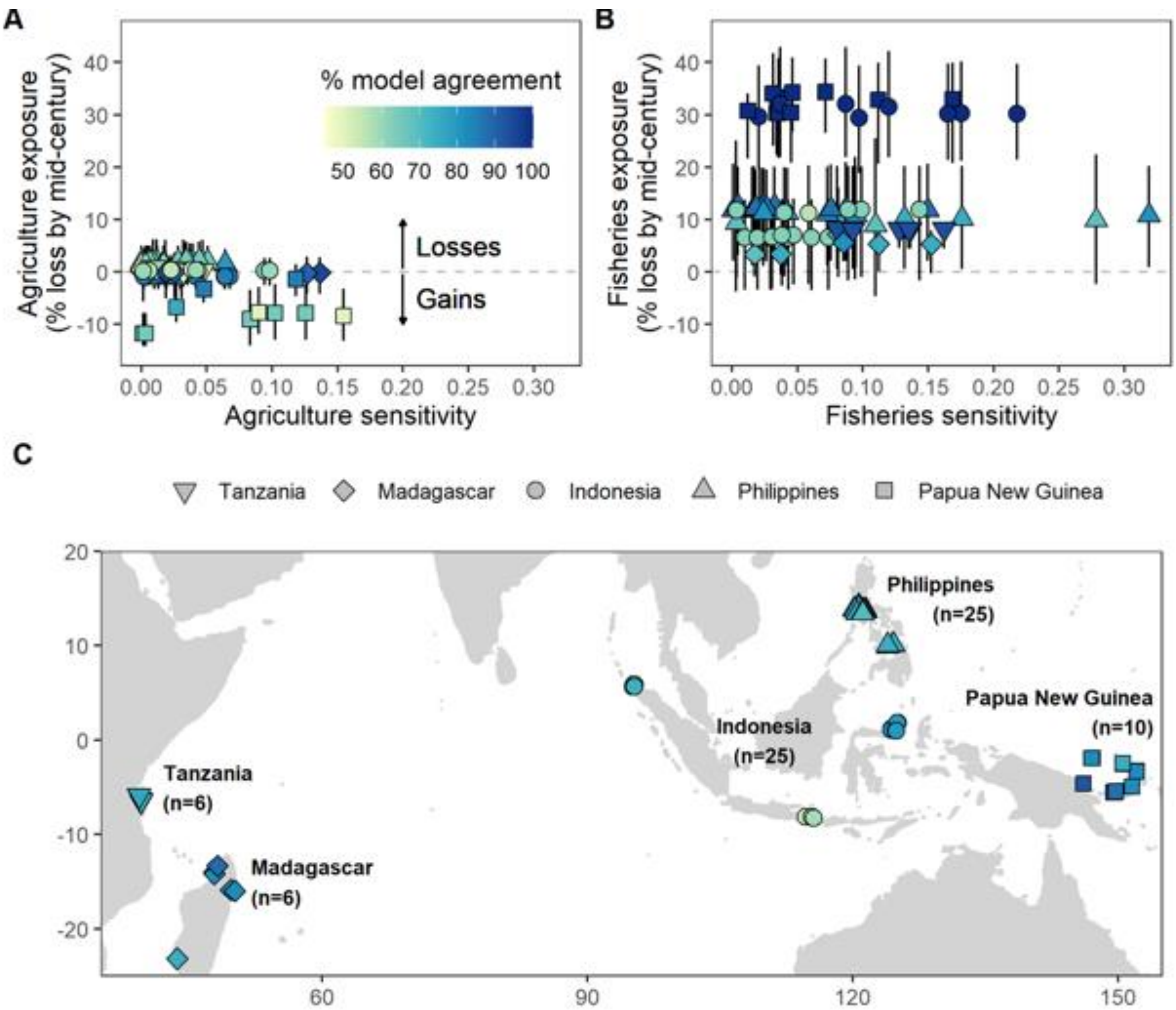

Figure 1. Potential Impacts for (A) agriculture and (B) fisheries under SSP5-8.5. Potential impacts comprise the exposure (y-axis, measured in potential losses) and sensitivity (x-axis, measured as level of dependence by households). Error bars show 25th and 75th percentiles of exposure. (C) study site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

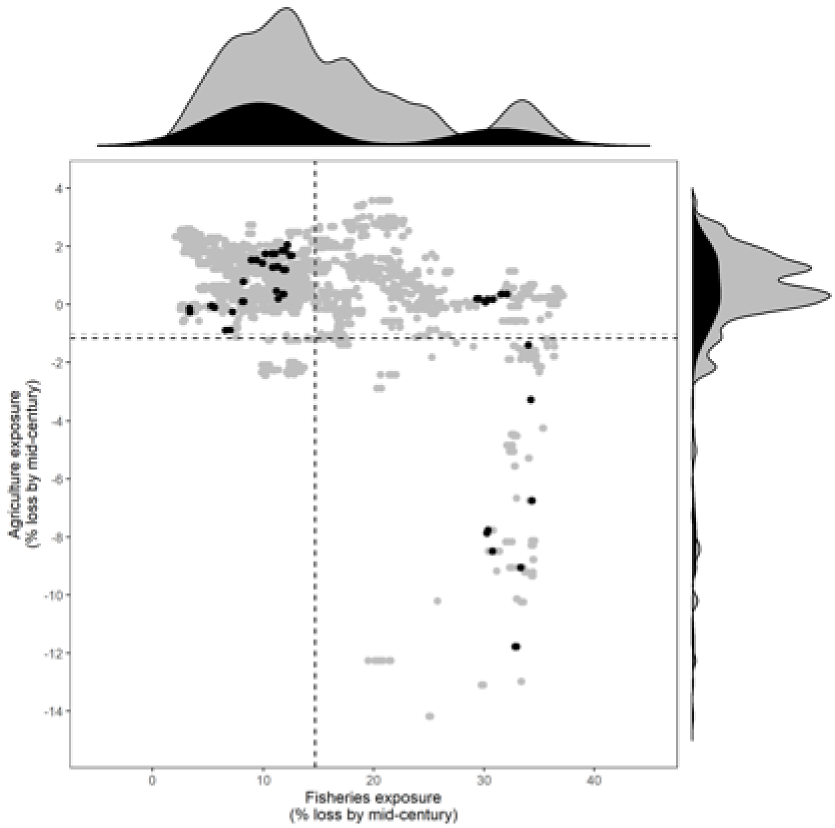

Figure 2. A comparison of expected fisheries catch potential and agriculture losses (exposure) by mid-century under SSP5-8.5. Black dots/histograms are our study sites. Grey dots/histograms are a random selection of 4,746 (10% of) coastal cells with population densities >25 people/km^2 from our study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

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

Over a third of our sites (36% under SSP5-8.5) are expected to experience increases in agriculture (due to CO_2 fertilization effects that fuel potential increases particularly in rice yields) while experiencing losses in fisheries catch potential. For these sites, a question of critical concern is whether the potential gains in agriculture could help offset the losses in fisheries catch potential. The answer to this lies in part in the degree of substitutability between sectors. Our survey of 3008 households reveals high variation among countries, and even within some countries in the degree of household occupational multiplicity incorporating both agriculture and fisheries sectors (Table 1). 31% of households in our study engaged in both fishing and agriculture, though this ranged from 10% of households in the Philippines to 77% of households in Papua New Guinea. This means that the degree to which agricultural gains might possibly offset some fisheries losses at the household scale is very context dependent. Our survey also revealed that 17% of households were involved in agriculture but not fisheries, ranging from 33% in Madagascar to 3% in our Papua New Guinean study communities. Alternatively, more than a third of households surveyed in Indonesia and Philippines were involved in fisheries but not agriculture (36% and 37% respectively), compared to a low value of 16% in Madagascar. In 12% of the Philippines communities surveyed (n=3), not a single household was engaged in agriculture. Thus, for 32% of households across our sample, including some entire communities, potential agricultural gains will not offset potential fisheries losses. In these locations building adaptive capacity to buffer change will be critical[9].

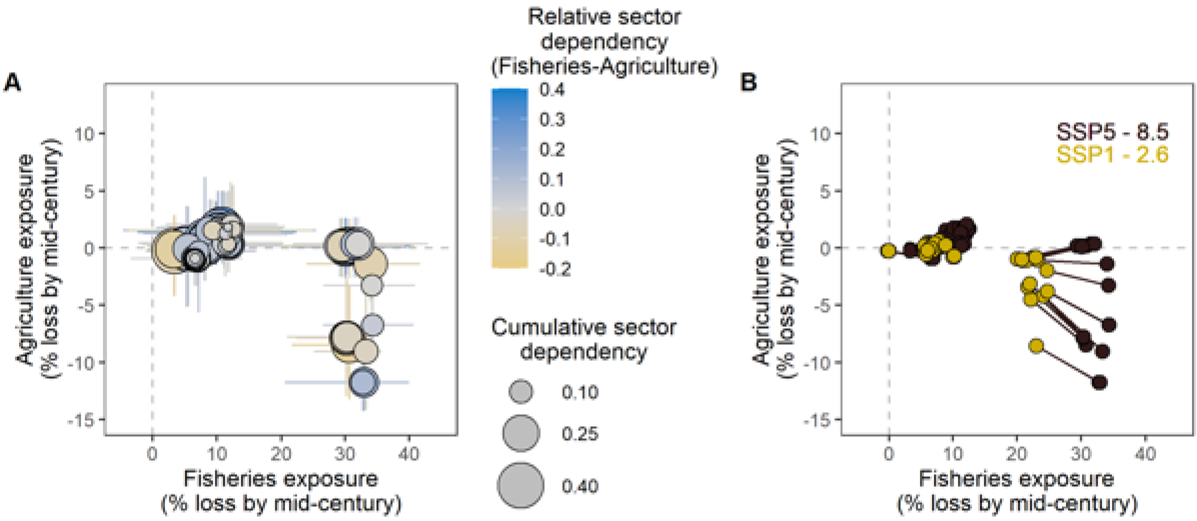

Figure 3. The simultaneous potential losses to fisheries and agriculture in coastal communities. (A) Under SSP5-8.5 agricultural losses (y-axis) plotted against fisheries losses (x-axis) with bubble size revealing the overall sensitivity and the colour revealing the fisheries-agricultural relative sector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

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

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

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

Our third key result is that coastal communities with lower socioeconomic status are more likely to experience potential impacts than communities of higher socioeconomic status across the climate mitigation scenarios (SSP1-2.6 and SSP5-8.5; Fig. 4). Specifically, we examined the relationship between the average material style of life (a metric of wealth based on material assets; see methods) in a community and the relative potential impacts of simultaneous fisheries catch potential and agriculture losses (measured as the Euclidean distance of sensitivity and exposure from the origin). Importantly, socioeconomic status is related to both sensitivity and exposure (Supplemental Fig. 4). In other words, low socioeconomic status communities tend to have higher sensitivity to fisheries and agriculture than the wealthy, and are significantly more likely to be exposed to climate change impacts. Our findings regarding the relationship between socioeconomic status and sensitivity are consistent with a broad body of literature that shows how people tend to move away from natural resource dependent occupations as they become wealthier[10,22–25]. One potential interpretation of our findings is that alternative livelihood programs (e.g. jobs outside the fisheries or agricultural sectors, such as the service industry) could reduce sensitivity in lower socioeconomic status communities. However, decades of research on livelihood diversification has highlighted a multitude of reasons why alternative livelihood projects frequently fail[26], including that they do not provide high levels of non-economic satisfactions (e.g., social, psychological, and cultural)[27–29], as well as cultural barriers to switching occupations (e.g. caste systems)[30], and attachment to identity and place[31]. Alternative occupations need to provide some of the same satisfactions, including basic needs (safety, income), social and psychological needs (time away from home, community in which you live, etc.), and self-actualization (adventure, challenge, opportunity to be own boss, etc.). For example, fishing attracts individuals manifesting a personality configuration referred to as an externalizing disposition, which is characterized by a need for challenges, adventure, and risk. Fishing can be extremely satisfying for people with this personality complex, while many alternative occupations can lead to job dissatisfaction, which has negative social and psychological consequences[32,33]. Research has shown that for fisheries, recreational fishing captains or guides as alternative occupations produce some of the same satisfactions and have been successful[33]. Despite these limited successes, alternative livelihood programs frequently fail and are not a viable substitute for mitigating climate change for the ~6 million coral reef fishers globally[34].

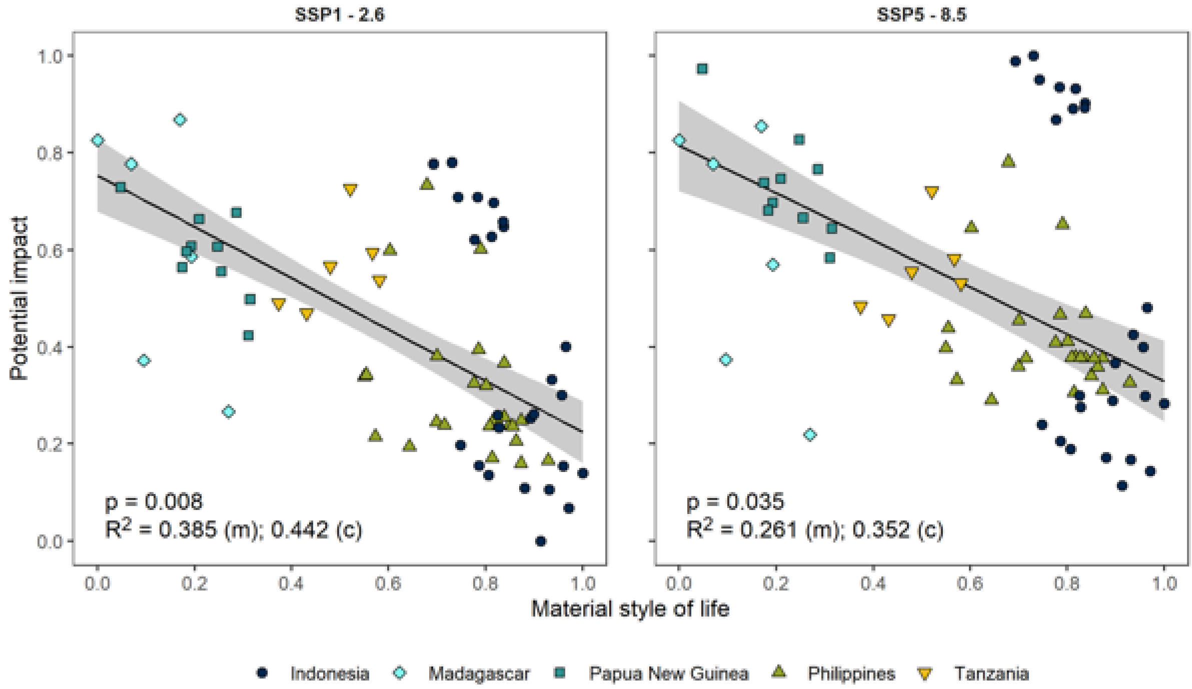

Figure 4. Relationships between potential impacts (calculated as the Euclidean distance of exposure and sensitivity) and material style of life (a metric of wealth based on material assets) under different mitigation strategies. Grey shading indicates 95% confidence intervals. (m)=marginal R^2, (c)=conditional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

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

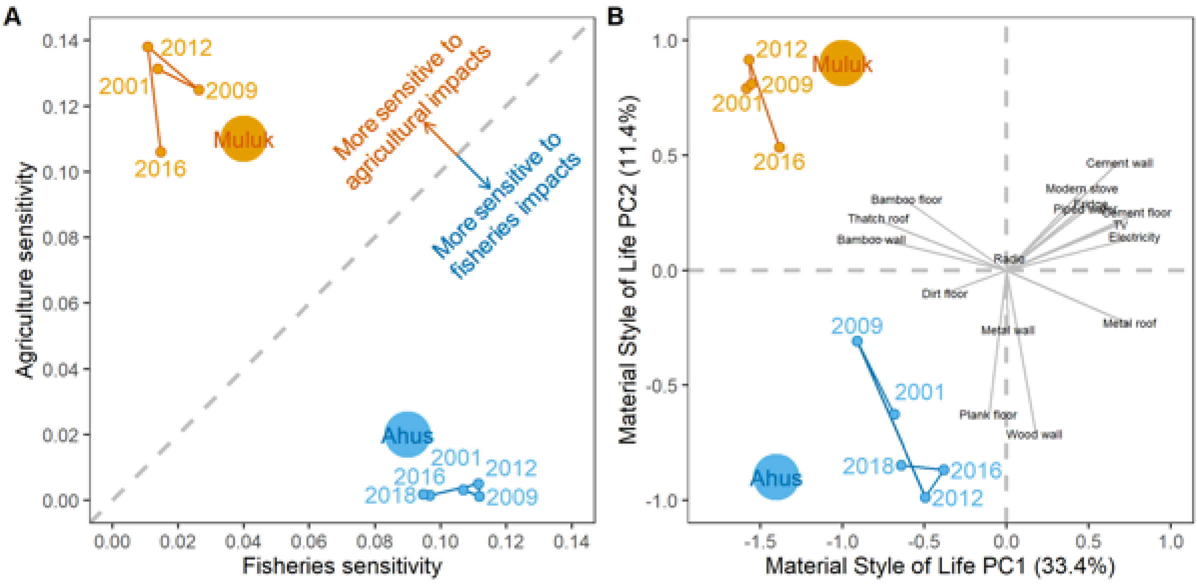

Fig 5. Changes in sensitivity (A) and material wealth (B) over time in two Papua New Guinean communities. Panel B shows how the communities change along the first two axes of a principal component analysis based on 16 household-scale material items.

Second, there are key limitations and assumptions to the models we used. For example, many tropical small-scale fisheries target seagrass[35] and coral reef habitats[34], which are not represented in the global ensemble models. Additionally, the ensemble models were developed at relatively low spatial resolution (e.g. 1° cells), and are not designed to capture higher resolution structures and processes. Our approach for dealing with this was to make transparent the degree of ensemble model run agreement about the direction of change, which relies on the assumption that we have greater confidence in projections that have higher model run agreement. Another limitation is that there may be discrepancies between the total consumer biomass (see method) in the absence of fishing that is outputed by the models used here and what would actually be harvested by fishers since total consumer biomass can include both target and non-target species as well as other taxa entirely. Despite these limitations, we assumed that total consumer biomass is directly related to potential fisheries yields[11]. Likewise, we included just 3 crops in the agricultural models (rice, maize, and cassava), which are key in the study region, with many study countries growing 2 or more of these crops. For example, Indonesia is the 3rd largest producer of rice in the world, and the 6th largest producer of maize and cassava[36]. However, subsistence agriculture in Papua New Guinea is dominated by banana and yams, for which agricultural yield projections were not available. We used an unweighted average of projected changes in these three crops to represent a portfolio of small-scale agriculture, with a sensitivity test based on agricultural projections weighted by current yields/production area proportions of current yields (Supplemental Fig. 1). Finally, it is important to keep key model assumptions in mind when interpreting these data. For example, the agricultural models assumed no changes in farm management or climate change adaptation over time, while the fisheries models do not explicitly resolve predation impacts from higher trophic levels on phytoplankton.

Third, our sensitivity metric examined a somewhat narrow aspect of what makes people sensitive to climate change. Sensitivity is thought to contain dimensions of economic, demographic, psychological, and cultural dependency[37]. Our metric was based on people's engagement in natural resource-based livelihoods, which primarily captures the economic dimensions (although livelihoods do provide cultural and psychological contributions to people[26,28,29,31,38]).

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

Fifth, we investigated the potential impacts of climate change on two key food production sectors, but there may be other climate change impacts which have much more profound impacts on people's wellbeing. For example, sea level rise may destroy homes and other infrastructure[43], while heat waves may result in direct mortality[44]. Lastly, we used shared socioeconomic pathway exploratory scenarios that bracket the full range of scenario variability (SSP5-8.5 and SSP1-2.6). At the time of publication, these were the only scenarios available for both fisheries and agriculture using the ISIMIP Fastrack Phase 3 dataset. Future publications may wish to explore additional scenarios.

Our study quantifies the potential impacts of climate change on key food production sectors in tropical coastal communities across a broad swath of the Indo-Pacific. We find that both exposure and sensitivity to fisheries is generally higher than to agriculture, but some places may experience losses from both sectors simultaneously. These losses may be compounded by other drivers of change, such as overfishing or soil erosion, which is already leading to declining yields[45,46]. Simultaneous losses to both fisheries catch potential and agriculture will limit people's opportunity to adapt to changes through switching livelihoods between food production sectors[9]. This will especially be the case in lower socioeconomic status communities where dependence on natural resources is higher[10]. Together, our novel integration of model projections and socioeconomic surveys highlight the importance of assessing climate change impacts across sectors, but reveals important mismatches between the scale at which people will experience the impacts of climate change and the scale at which modelled projections about climate change impacts are currently available.

Methods

Sampling of coastal communities

Here, we integrated data from five different projects that had surveyed coastal communities across five countries[47–50]. Between 2009 and 2015, we conducted socioeconomic surveys in 72 sites from Indonesia (n=25), Madagascar (n=6), Papua New Guinea (n=10), the Philippines (n=25), and Tanzania (Zanzibar) (n=6). Site selection was for broadly similar purposes- to evaluate the effects of various coastal resource management initiatives (collaborative management, integrated conservation and development projects, recreational fishing projects) on people's livelihoods in rural and peri-urban villages. Within each project, sites were purposively selected to be representative of the broad range of socioeconomic conditions (e.g., population size, levels of development, integration to markets) experienced within the region. We did not survey strictly urban locations (i.e., major cities). Because our sampling was not strictly random, care should be taken when attempting to make inferences beyond our specific study sites.

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

A standard methodology was employed to assess material style of life, a metric of material assets-based wealth[48,51]. Interviewers recorded the presence or absence of 16 material items in the household (e.g., electricity, type of walls, type of ceiling, type of floor). We used a Principal Component Analysis on these items and kept the first axis (which explained 34.2% of the variance) as a material wealth score. Thus, each community received a mean material style of life score, based on the degree to which surveyed households had these material items, which we then scaled from 0-1. We also conducted an exploratory analysis of how material style of life has changed in two sites in Papua New Guinea (Muluk and Ahus villages) over fifteen and sixteen year time span across four and five time periods (2001, 2009, 2012, 2016 and 2002, 2009, 2012, 2016, 2018), respectively, that have been surveyed since 2001/2[52]. These surveys were semi-panel data (i.e. the community was surveyed repeatedly, but we did not track individuals over each sampling interval) and sometimes occurred in different seasons. For illustrative purposes, we plotted how these villages changed over time along the first two principal components.

Sensitivity

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

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

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

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

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

where S_A , S_F and S_{AF} are a community's sensitivity in the context of agriculture, fisheries and both sectors, respectively. A, F and AF are the number of households relying on agriculture-related occupations within that community, fishery-related and agriculture- and fisheries-related occupations within the community, respectively. NA, NF and NAF are the number of households relying on non-agriculture-related, non-fisheries-related, and non-agriculture-or-fisheries-related occupations within the community, respectively. N is the number of households within the community. r_a, r_f and r_{af} are the number of times agriculture-related, fisheries-related and agriculture-and-fisheries-related occupations were ranked higher than their counterpart, respectively. r_{na}, r_{nf} and r_{naf} are the number of times non-agriculture, non-fisheries, and non-agriculture-and-fisheries-related occupations were ranked higher than their counterparts. As with the material style of life, we also conducted an exploratory analysis of how joint agriculture-fisheries sensitivity has changed over time in a subset of sites (Muluk and Ahus villages in Papua New Guinea) that have been sampled since 2001/2002[52]. Although our survey methodology has the potential for bias (e.g. people might provide different rankings based on the season, or there might be gendered differences in how people rank the importance of different occupations[53]), our time-series analysis suggest that seasonal and potential respondent variation do not dramatically alter our community-scale sensitivity metric.

Exposure

To evaluate the exposure of communities to the impact of future climates on their agriculture and fisheries sectors, we used projections of production potential from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) Fast Track phase 3 experiment dataset of global simulations. Production potential of agriculture and fisheries for each of the 72 community sites and 4,746 randomly selected sites from our study countries with coastal populations >25 people/km^2 were projected to the mid-century (2046-2056) under two emission scenarios (SSP1-2.6, and SSP5-8.5) and compared with values from a reference historical period (1983-2013).

For fisheries exposure (E_F), we considered relative change in simulated total consumer biomass (all modelled vertebrates and invertebrates with a trophic level >1). For each site, the twenty nearest ocean grid cells were determined using the Haversine formula (Supplemental Fig. 5). We selected twenty grid cells after a sensitivity analysis to determine changes in model agreement based on different numbers of cells used (1, 3, 5, 10, 20, 50, 100; Supplemental Figs. 6-7), which we balanced off with the degree to which larger numbers of cells would reduce the inter-site variability (Supplemental Fig. 8). 25th and 75th percentiles for the change in marine animal biomass across the model ensemble were also reported. Projections of the change in total consumer biomass for the 72 sites were extracted from simulations conducted by the Fisheries and marine ecosystem Model Intercomparison Project (FishMIP[3,54]). FishMIP simulations were conducted under historical, SSP1-2.6 (low emissions) and SSP5-8.5 (high emissions) scenarios forced by two Earth System Models from the most recent generation of the Coupled Model Intercomparison project (CMIP6)[55]; GFDL-ESM4[56] and IPSL-CM6A-LR[57]. The historical scenario spanned 1950-2014, and the SSP scenarios spanned 2015-2100. Nine FishMIP models provided simulations: APECOSM[58,59], BOATS[60,61], DBEM[2,62], DBPM[63], EcoOcean[64,65], EcoTroph[66,67], FEISTY[68], Macroecological[69], and ZooMSS[11]. Simulations using only IPSL-CM6A-LR were available for APECOSM and DBPM, while the remaining 7 FishMIP models used both Earth System Model forcings. This resulted in 16 potential model runs for our examination of model agreement, albeit with some of these runs being the same model forced with two different ESMs. Thus, the range of model agreement could range from 8 (half model runs indicating one direction of change, and half indicating the other) to 16 (all models agree in direction of change). Model outputs were saved with a standardised 1° spatial grid, at either a monthly or annual temporal resolution.

For agriculture exposure (E_A), we used crop model projections from the Global Gridded Crop model Intercomparison Project (GGCMI) Phase 3[14], which also represents the agriculture sector in ISIMIP. We used a window of 11x11 cells centred on the site and removed non-land cells (Fig S5). The crop models use climate inputs from 5 CMIP6 ESMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL), downscaled and bias-adjusted by ISIMIP and use the same simulation time periods. We considered relative yield change in three rain-fed and locally relevant crops: rice, maize, and cassava, using outputs from 4 global crop models (EPIC-IIASA, LPJmL, pDSSAT, and PEPIC), run at 0.5° resolution. These 4 models with 5 forcings generate 20 potential model runs for our examination of model agreement. Yield simulations for cassava were only available from the LPJmL crop model. All crop model simulations assumed no adaptation in growing season and fertilizer input remained at current levels. Details on model inputs, climate data, and simulation protocol are provided in ref[14]. At each site, and for each crop, we calculated the average change (%) between projected vs. historical yield within 11x11 cell window. We then averaged changes in rice, maize and cassava to obtain a single metric of agriculture exposure (E_A).

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

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

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

Sensitivity Test
To determine whether our sites displayed a particular exposure bias, we compared the distributions of our sites and 4,746 sites that were randomly selected from 47,460 grid cells within 1 km of the coast of the 5 countries we studied which had population densities >25 people/km^2, based on the SEDAC gridded populating density of the world dataset (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11/data-download). We used Cohen's D to determine the size of the difference between our sites and the randomly selected sites.

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

While no fisheries ensemble model downscaling had been done specific to our study regions, most of the models of the ensemble have been independently evaluated against separate datasets aggregated at scales down to Large Marine Ecosystems (LMEs) or Exclusive Economic Zones (EEZs) (see [11]). For example, the DBEM was created with the objective of understanding the effects of climate change on exploited marine fish and invertebrate species[2,71]. This model roughly predicts species' habitat suitability; and simulates spatial population dynamics of fish stocks to output biomass and maximum catch potential (MCP), a proxy of maximum sustainable yield[2,62,70]. Compared with spatially explicit catch data from the Sea Around Us Project (SAUP; www.seaaroundus.org)[71] there were strong similarities in the responses to warming extremes for several EEZs in our current paper (Indonesia and Philippines) and weaker for the EEZs of Madagascar, Papua New Guinea, and Tanzania. At the LME level, DBEM MCP simulations explained about 79% of the variation in the SAUP catch data across LMEs[72]. The four LMEs analyzed in this paper (Agulhas Current; Bay of Bengal; Indonesian Sea; and Sulu-Celebes Sea) fall within the 95% confidence interval of the linear regression relationship[62]. Another example, BOATS, is a dynamic biomass size-spectrum model parameterised to reproduce historical peak catch at the LME scale and observed catch to biomass ratios estimated from the RAM legacy stock assessment database (in 8 LMEs with sufficient data). It explained about 59% of the variability of SAUP peak catch observation at the LME level with the Agulhas Current, Bay of Bengal, and Indonesian Sea catches reproduced within +/-50% of observations[61]. The EcoOcean model validation found that all four LMEs included in this study fit very close to the 1:1 line for overserved and predicted catches in 2000[64,65]. DBPM, FEISTY, and APECOSM have also been independently validated by comparing observed and predicted catches. While the models of this ensemble have used different climate forcings when evaluated independently, when taken together the ensemble multi-model mean reproduces global historical trends in relative biomass , that are consistent with the long term trends and year-on-year variation in relative biomass change (R^2 of 0.96) and maximum yield estimated from stock assessment models (R^2 of 0.44) with and without fishing respectively[11].

Crop yield estimates simulated by GGCMI crop models have been evaluated against FAOSTAT national yield statistics [14,73,74]. These studies show that the models, and especially the multi-model mean, capture large parts of the observed inter-annual yield variability across most main producer countries, even though some important management factors that affect observed yield variability (e.g., changes in planting dates, harvest dates, cultivar choices, etc.) are not considered in the models. While GCM-based crop model results are difficult to validate against observations, Jägermeyr et al.[14] show that the CMIP6-based crop model ensemble reproduces the variability of observed yield anomalies much better than CMIP5-based GGCMI simulations. In an earlier crop model ensemble of GGCMI, Müller et al.[74] show that most crop models and the ensemble mean are capable of reproducing the weather-induced yield variability in countries with intensely managed agriculture. In countries where management introduces strong variability to observed data, which cannot be considered by models for lack of management data time series, the weather-induced signal is often low[75], but crop models can reproduce large shares of the weather-induced variability, building trust in their capacity to project climate change impacts[74].

We then attempted to validate the models in our study regions. For the crop models, we examined production-weighted agricultural projections weighted by current yields/production area (Supplemental Fig. 1). We used an observational yield map (SPAM2005) and multiplied it with fractional yield time series simulated by the models to calculate changes in crop production over time, which integrates results in line with observational spatial patterns. The weighted estimates were not significantly different to the unweighted ones (t=0.17, df=5, p=0.87). For the fisheries models, our study regions were data poor and lacked adequate stock assessment data to extend the observed global agreement of the sensitivity of fish biomass to climate during our reference period (1983-2013). Instead, we provide the degree of model run agreement about the direction of change in the ensemble models to ensure transparency about the uncertainty in this downscaled application.

Analyses

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

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Competing interest statement. The authors have no competing interests.

Data availability

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

Data and code available at: https://github.com/ircaldwell/Cinneretal_ImpactClimateChangeAgricultureFisheries

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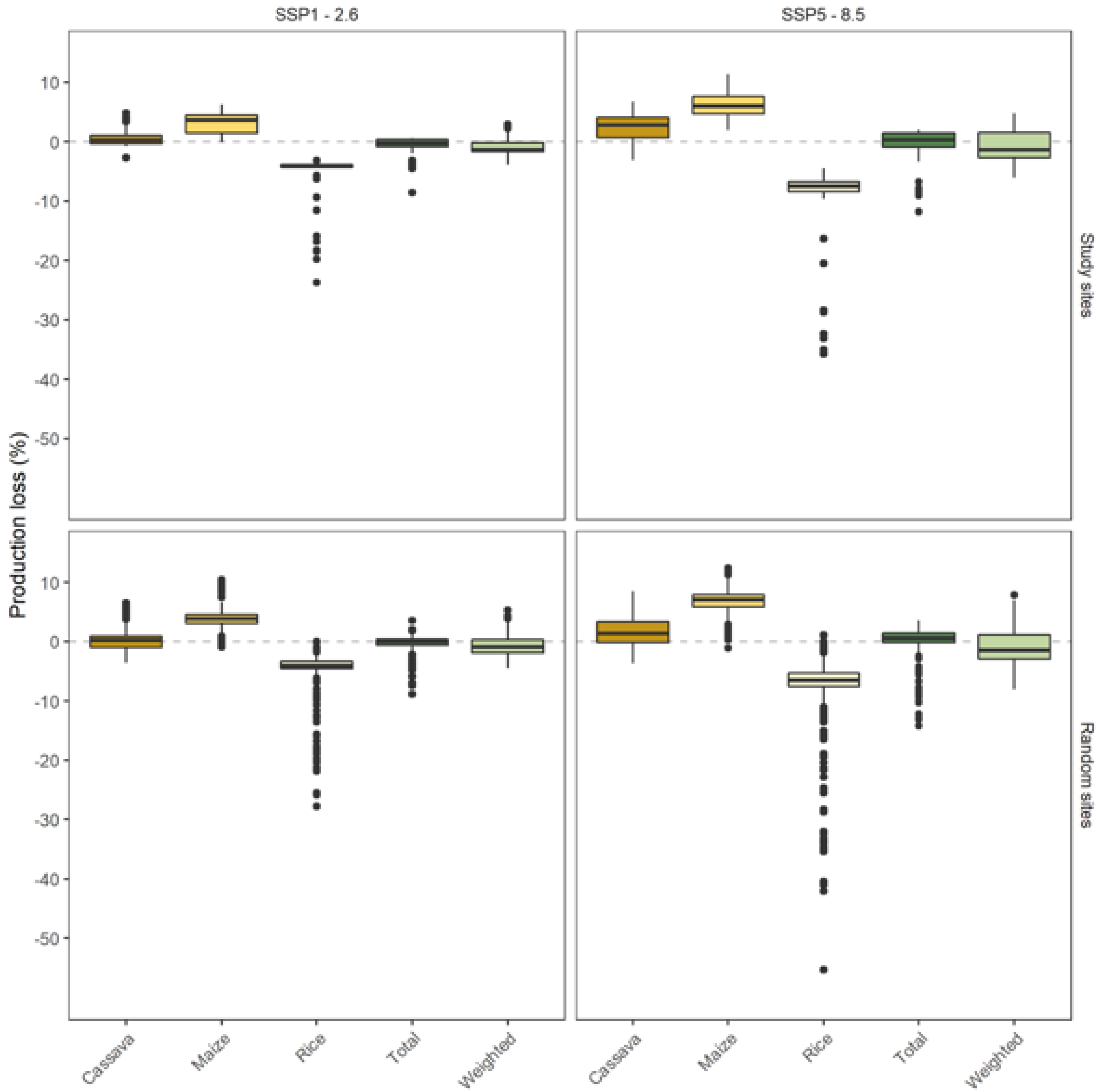

Figure S1. Projected agricultural changes by crop for SSP1-2.6 and 8.5. Top row are projections for our study sites, while the bottom row examines projected changes for 4,746 randomly selected sites from our study region. Weighted average is based on agricultural projections weighted by current yields/production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

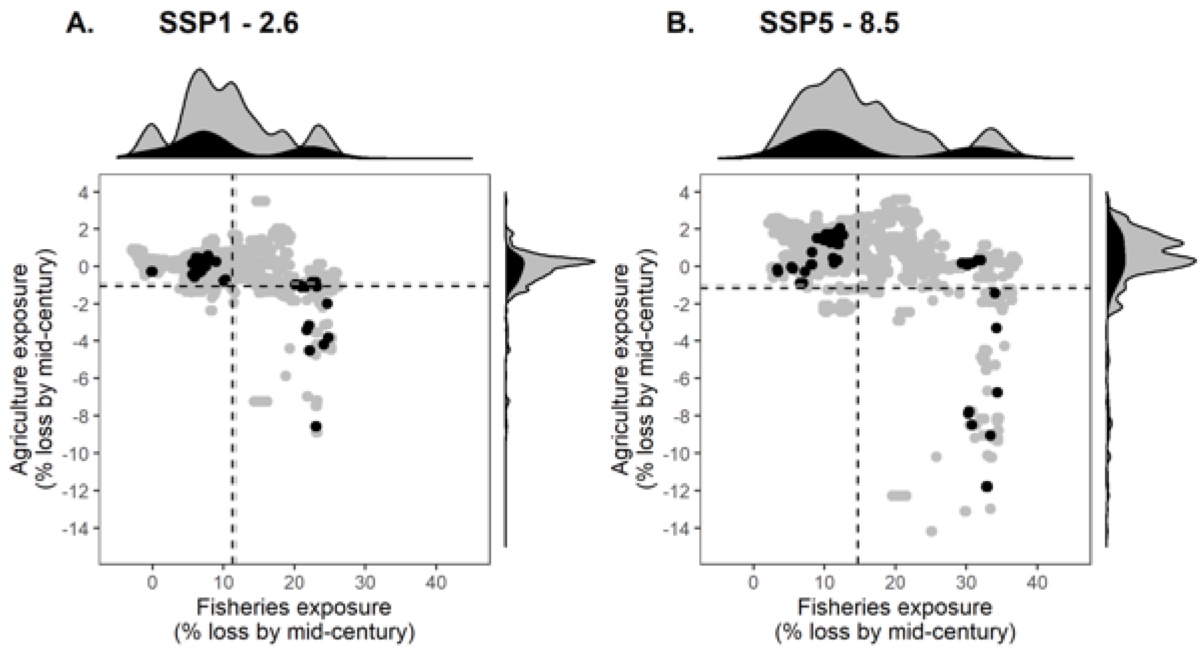

Figure S2. A comparison of expected fisheries and agriculture losses (exposure). A) SSP1-2.6, B) SSP5-8.5. Black dots/histograms are our study sites. Grey dots/histograms are a random selection of 4,746 (10% of) coastal cells with population densities >25 people/km^2. Dotted lines represent the mean exposure. Differences between expected losses in our sites and the randomly selected sites are generally small to negligible (Cohen's D for agricultural losses SSP5-8.5=0.31, SSP1-2.6= 0.35, fisheries losses SSP5-8.5 =-0.02, RCP2.6=-0.03), indicating that our sites are not particularly biased.

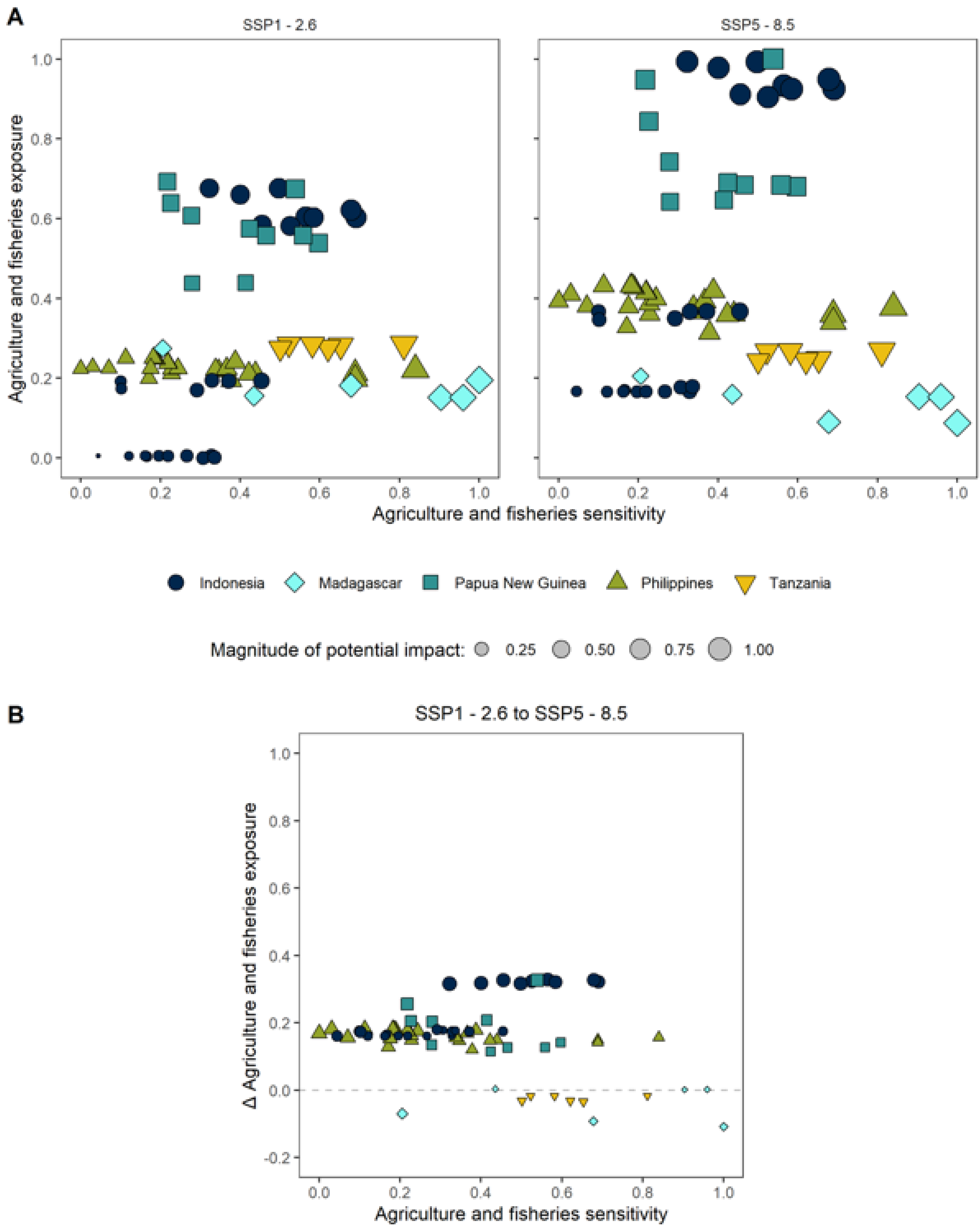

Fig S3. Potential impacts of changes to agriculture and fisheries by scenario. A) SSP1-2.6, B) SSP5-8.5. Both exposure and sensitivity to fisheries and agriculture are integrated. The potential impact is calculated as the Euclidian distance to the origin. C) The change in potential impact from mitigation (i.e. the difference between SSP5-8.5 and SSP1-2.6).

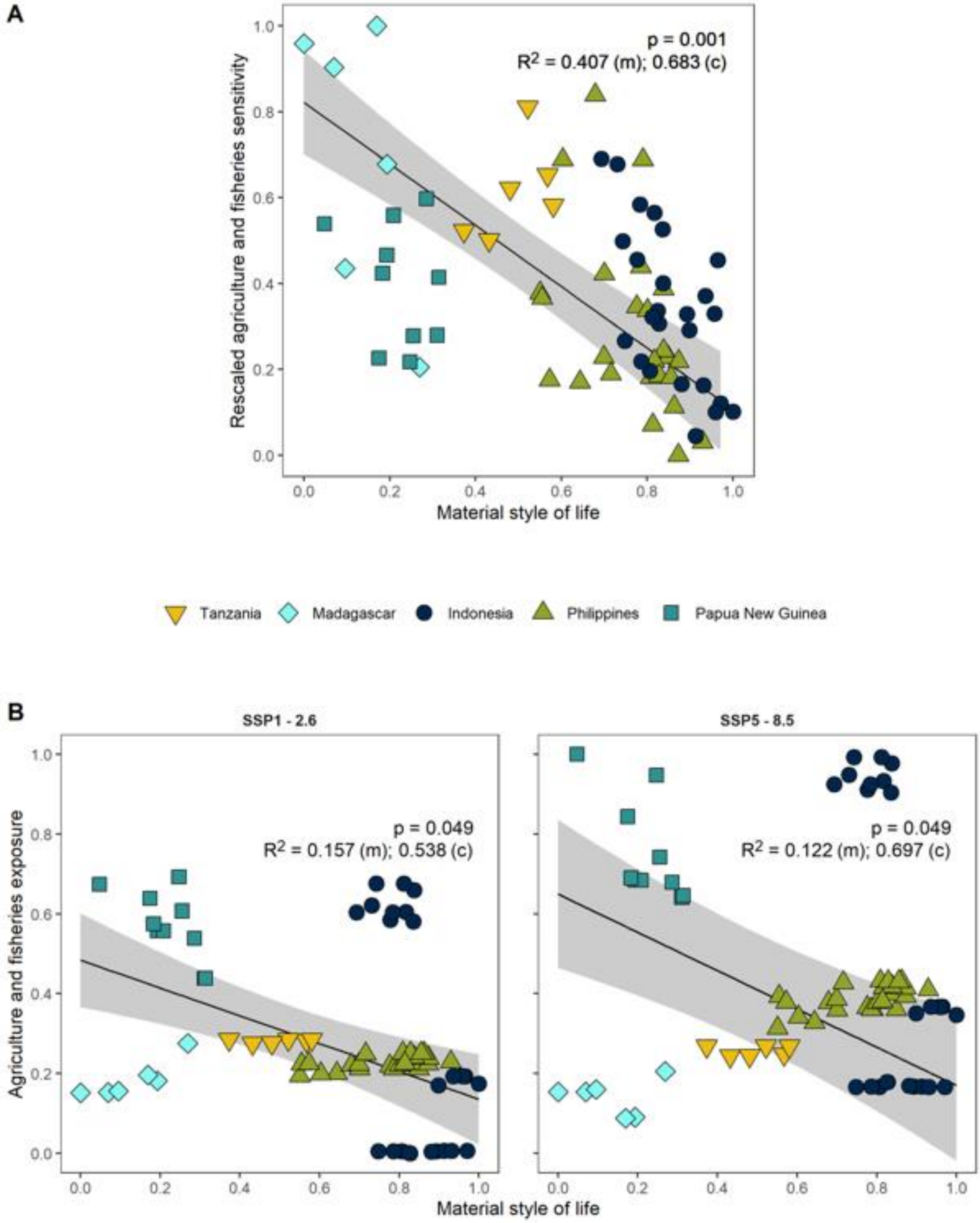

Fig S4. Relationships between MSL and (A) Ag-Fish sensitivity, (B) Ag-Fish exposure under SSP1-2.6 and (C) SSP5-8.5. **(m)=marginal R^2, (c)=conditional R^2**

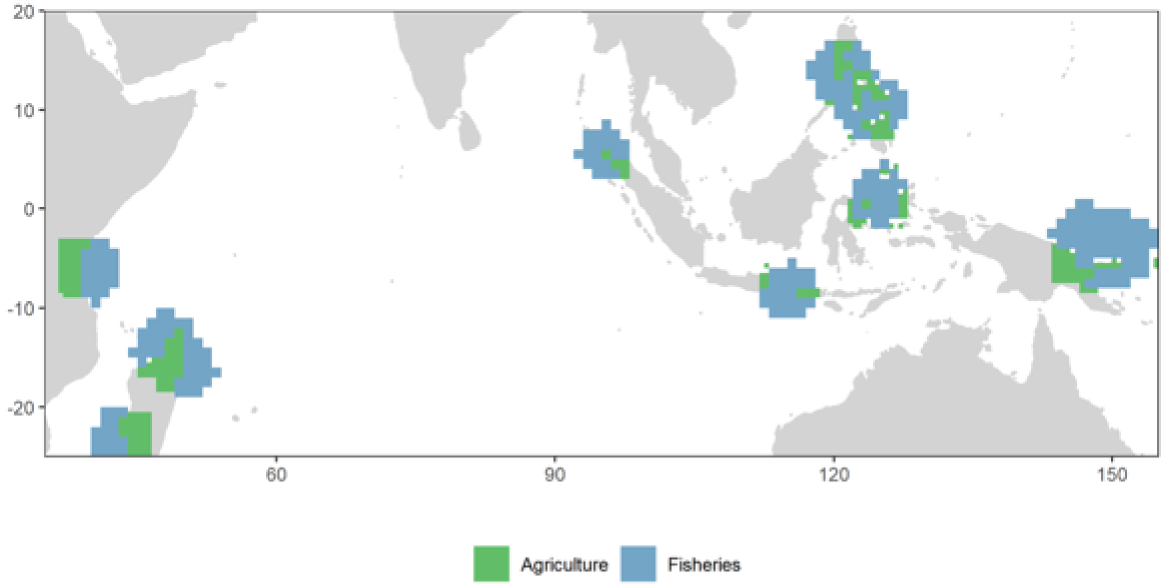

Fig. S5. The cells used in determining fisheries and agriculture exposure.

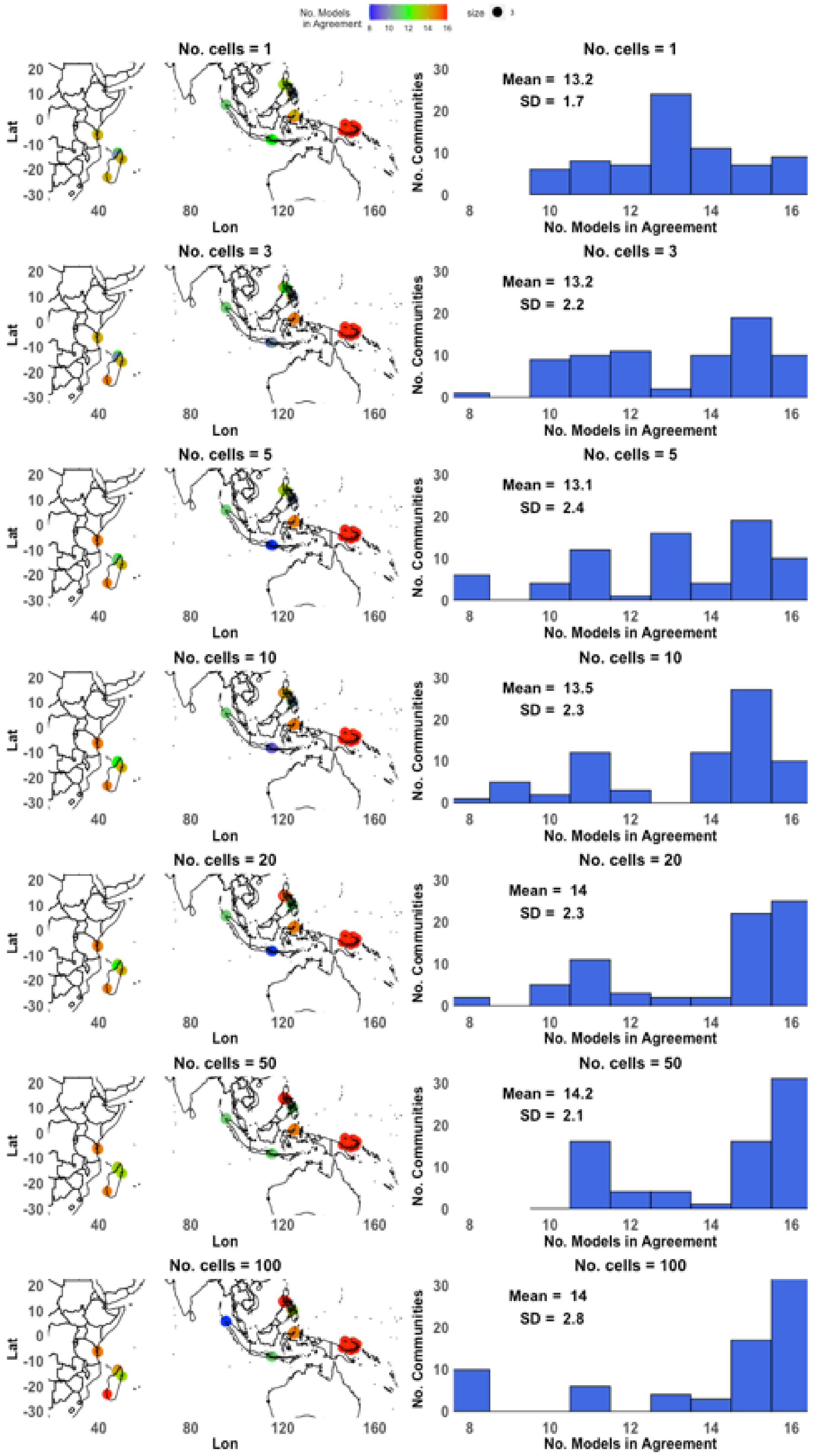

Figure S6. Trade-off between model agreement and number of cells used for fisheries SSP1-2.6. A model run agreement of 50%, the lowest possible value, indicates that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree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

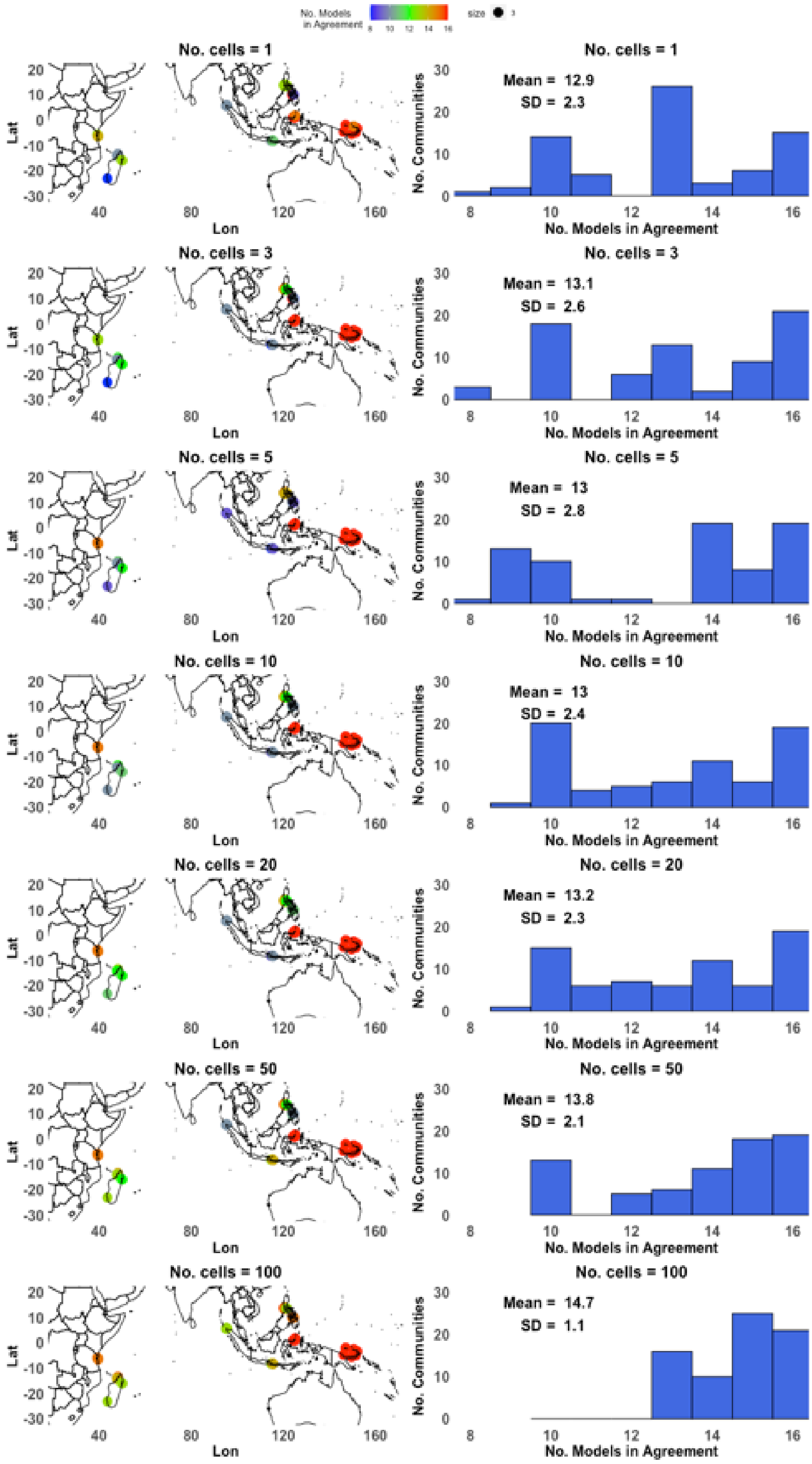

Fig S7. Trade-off between model agreement and number of cells used for fisheries SSP5-8.5. A model run agreement of 50%, the lowest possible value, indicates that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree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

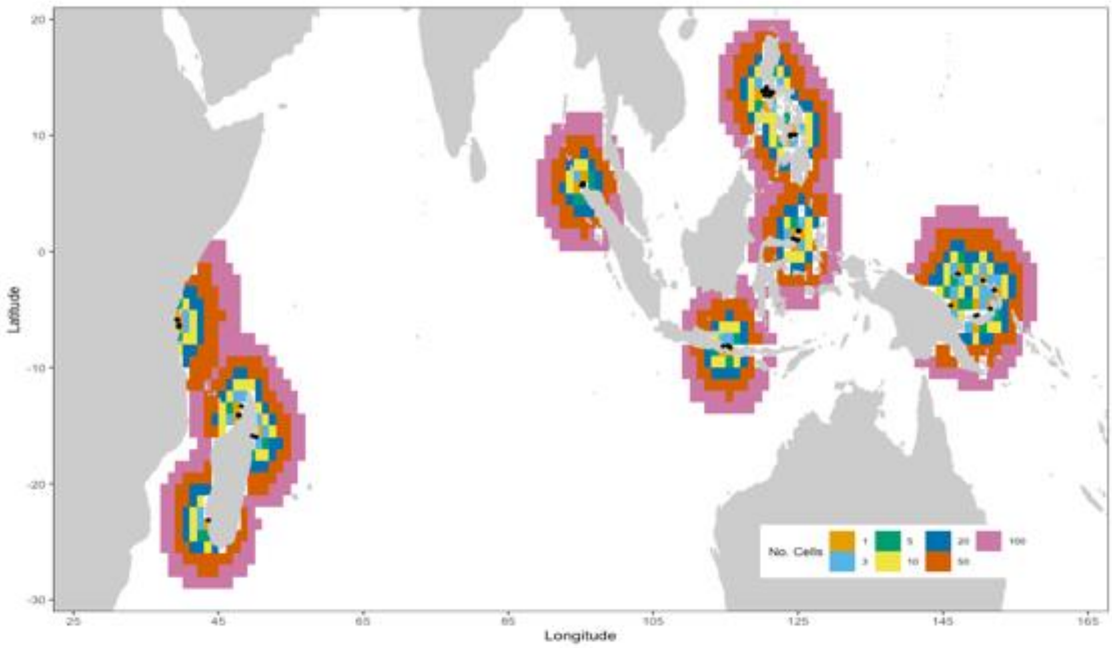

Figure S8. Spatial extent covered by using different numbers of grid cells to determine fisheries exposure. Black dots are coastal study sites associated with each?

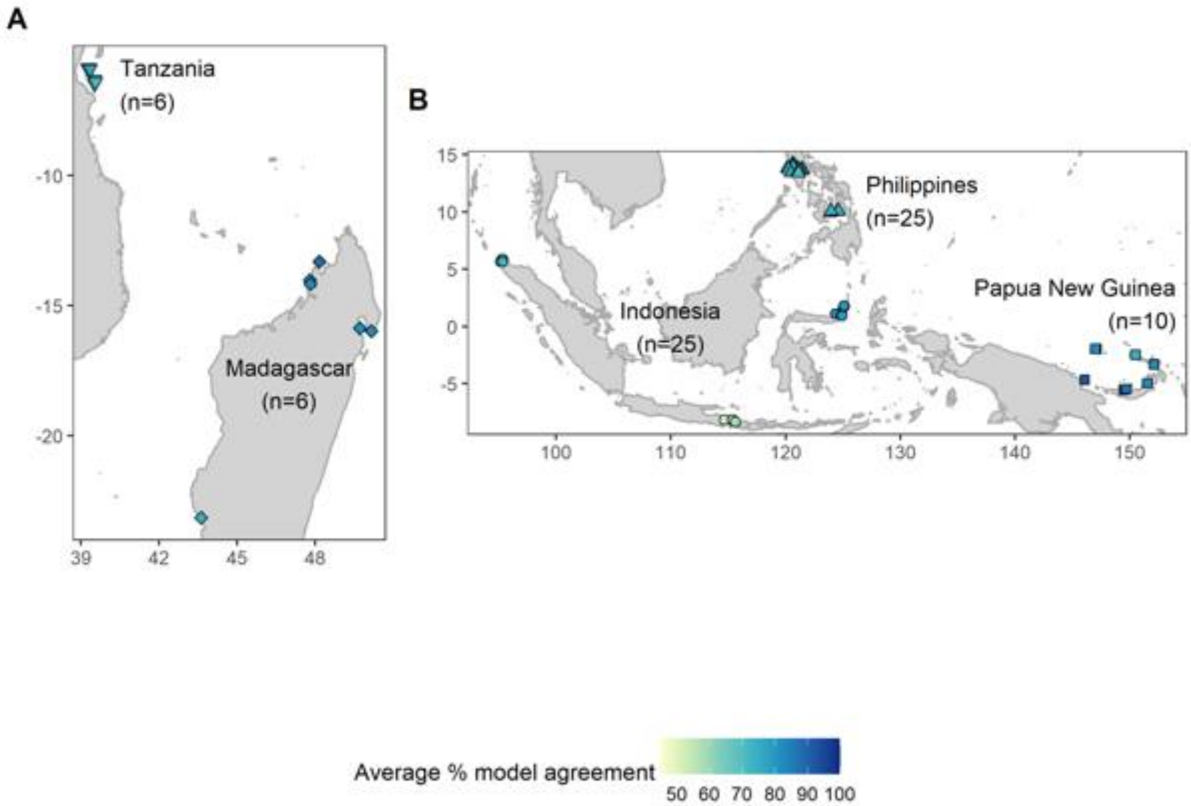

Fig. S9. Inset map of study sites and average agriculture-fisheries model run agreement at each site. A model run agreement of 50% means that half of model runs indicate one direction of change, and half the opposite; conversely, a value of 100% indicates that all model runs agree on the direction of change.

Table S1. Sample size and proportion of social surveys

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