1   **Title**

2   A multi-model assessment of food security implications of

3   climate change mitigation

4

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58

1 # A multi-model assessment of food security implications of
2 # climate change mitigation
3
4
5 **Abstract (approximately 150 words unreferenced)**
6 Attaining well below 2°C climate change goal affirmed by the Paris Agreement is one of the
7 societal challenges. Meanwhile, food security is another high-priority areas in the UN
8 Sustainable Development Goals that could potentially be adversely affected by stringent
9 climate mitigation. Here we show the potential negative trade-offs between food security and
10 climate mitigation using a multi-model comparison exercise. We find that carelessly designed
11 climate mitigation policies could increase the number of people at risk of hunger by 110
12 million people in 2050. Avoiding these adverse side effects would entail a cost of about
13 0.18% of global GDP in 2050. It should be noted that direct impacts of climate change on
14 yields were not assessed and that the direct benefits from mitigation in terms of avoided yield
15 losses could be significant further lessening the above cost. While results vary across models
16 and model implementations, the qualitative implications are robust and call for a careful
17 design of climate mitigation policies taking into account agriculture and land prices.
18
19
20 **Main text (<3500 words, Section headings should be used and subheadings may appear**
21 **in 'Results'. Avoid 'Introduction' as a heading. 6 display items)**
22
23   Food security is considered as one of the areas in Sustainable Development Goals
24 (SDGs), in particular SDG2 is aiming at "zero-hunger" by 2030. The global number of
25 people at risk of hunger has declined over the past decades and was estimated at 795 million[1]
26 for the year 2015, which is 184 million fewer than 1990-1992, despite a steady population
27 growth notably in low-income countries[2]. Steady income growth and a relatively stable
28 political situation helped this trend. The food security issue has been intensively investigated
29 in the context of climate change impacts over the last few decades[3, 4, 5, 6], and more recent
30 studies explored the effect of climate change mitigation effect on agricultural markets[7, 8, 9, 10,
31 11, 12]. Despite differing scenario assumptions, metrics, and quantitative outcomes, these
32 studies more or less agree that single minded mitigation policies could adversely impact food
33 security in developing countries. Although some studies propose partial solutions of how to
34 mitigate these side-effects[13, 14], most of them do not directly quantify the number of people at
35 risk of hunger. Furthermore, since the assumptions behind these studies are not harmonized,
36 the reason for the differences in the results across the studies is hard to be identified.
37   The Paris Agreement[15] defines a long-term temperature goal for international climate
38 policy: "holding the increase in the global average temperature to well below 2°C above pre-
39 industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-
40 industrial levels". Accordingly, many studies exploring the stringent climate change
41 mitigation policies required by the Paris objectives have identified a potential need for large-
42 scale land based measures like afforestation and bioenergy production, which in turn raises
43 concerns about potential implications for food security[16, 17, 18, 19, 20]. These low emissions
44 scenarios are making the connection between SDG2 and SDG13 increasingly crucial.
45   Integrated Assessment Models (IAMs) have been used for climate mitigation
46 analysis, with many climate mitigation studies conducted under Multi-model Inter-
47 comparisons Projects (MIPs) that have a major role to understand the robustness of the
48 implications and uncertainty[21]. The model behavior responding to the climate mitigation goal

49 typically finds agreement across models in some variable, such as emissions trajectories or
50 carbon budgets, while other variables vary largely across models, such as carbon prices.
51   Here we explore how food security could be affected by the climate mitigation
52 policies implemented by multi-IAMs. The primary goal of this paper is to understand the
53 relationship between food security and climate mitigation, and to identify cost estimates of
54 possible solutions to the trade-off between food security and climate mitigation, with
55 consideration of the "uncertainty" represented by an ensemble of IAMs. We consider four
56 scenarios differentiated by the stringency of mitigation levels related to the Paris Agreement:
57 no climate policy that includes currently implemented policies (Baseline), greenhouse gas
58 (GHG) emissions reductions by 2030 in line with the Nationally Determined Contributions
59 (NDC), and scenarios that limit global mean temperature in 2100 to below 2°C and 1.5°C,
60 where the emission reduction starts from 2020. Global cumulative CO_2 emissions are targeted
61 for these scenarios and more detailed assumptions of these scenarios are described in the
62 method section. To explore the uncertainty range, we employ six state-of-the-art IAMs that
63 represent energy, agriculture, land-use systems and their emissions. The six models are
64 AIM[22], IMAGE[23], MESSAGE-GLOBIOM[24], REMIND-MAgPIE[25], POLES[26] and WITCH[27].
65 The description of each model is provided in the method section. All models apply a uniform
66 carbon price, where the agricultural sector is included in the carbon pricing scheme. Besides
67 IMAGE, all models assume land use competition among food, bioenergy crops and
68 afforestation. IMAGE assumes avoided deforestation policy in competition with the food
69 system, while bio-energy does not compete with food production following a food-first
70 policy. Since REMIND-MAgPIE in turn assumes no demand-reaction to food prices shocks
71 and is therefore only included for the baseline scenarios. The representation of the interaction
72 among energy, agriculture and land use varies across IAMs, as shown in Supplementary
73 Table 1. There are three major factors by which climate change mitigation influences food
74 security: increases in land rent or production costs associated with bioenergy crops; non-CO_2
75 emissions abatement costs; and the equivalent carbon price cost of the residual non-CO_2
76 emissions that are emitted even after reduction measures are implemented, as depicted in
77 Supplementary Figure 1. The carbon price on GHG emissions from agricultural sectors is
78 assumed to be capped at $200/t$CO_2$. This avoids a situation in which further reduction in non-
79 CO_2 emissions requires a decrease in demand for agricultural products. MESSAGE, POLES,
80 and WITCH implemented this cap for all GHG emissions related to agriculture and land use
81 (e.g. forestry and land-use change)[28]. In any case, this capping of the carbon price implies
82 that at most our results can be as a lower bound of the potential impact of mitigation policies
83 on food security. Note that direct impacts of climate change on yields are not assessed in this
84 study and the direct benefits of mitigation to avoided yield losses may well be significant (see
85 more discussion in Supplementary Notes 1.3).
86   We use the number of people at risk of hunger as a primary indicator, which
87 represents the food security prevalence. Two out of six models (AIM and IMAGE) represent
88 the number of people at risk of hunger within their modeling framework, whereas the other
89 models do not. Therefore, we use a "hunger estimation tool", which has been used in
90 previous studies[29, 30, 31] for the four models that do not have a representation of the risk of
91 hunger. This tool assumes log-normal food consumption distribution function for each
92 country, which uses mean calorie consumption, minimum energy requirement and the
93 coefficient of variation (CV) of the food distribution of the dietary energy consumption
94 within countries. Each IAM provides mean calorie consumption for aggregated regions and
95 this tool downscales such geographically aggregated information on a country basis based on
96 the relative change in calorie consumption. For the possible solutions to the potential risk of
97 trade-off between food security and climate mitigation, we show the first-order cost estimates
98 using a back-of-the-envelope calculation, the details of which are explained in the results

99 section and Supporting text. Note that These represent the costs of achieving baseline levels
100 of food security rather than the costs associated with meeting the SDG2 target to eradicate
101 hunger by 2030.
102   We acknowledge that food security comprises a broad concept that includes four key
103 dimensions: food availability, stability, access, and utilisation. The metric used in this study,
104 risk of hunger, is associated with food availability[32]. In addition, complementary measures,
105 depending on how they are implemented, may influence other aspects of food security, such
106 as the rate of self-sufficiency[14]. However, these additional effects do not fall within the scope
107 of this study.
108
109 **Results**
110 *Risk of hunger projection under the Baseline scenario*
111   The population at risk of hunger in our Baseline scenario is projected to decline over
112 time and decreases by more than two thirds (to 210-250 million; 2.3-2.7% of total population)
113 in 2050 compared to the current level (795 million; 12% of total population) (Figure 1**a**). This
114 declining trend has been observed already over the past two decades. Asia is currently the
115 region that has the largest number of people at risk of hunger, with around 75% of the global
116 population at risk of hunger; however, this share declines fast during the century (Figure 1**c**
117 and Supplementary Figure 2). The other regions show a similar trend except for Africa and
118 the Middle East (dominated by Sub-Sahara). Africa and the Middle East are projected to
119 experience lower income growth and continuous population increases, which puts them under
120 the pressure of risk of food shortage. In 2050, Africa and the Middle East account for more
121 than 45% of the population at risk of hunger (median value across models, Figure 1**b**). The
122 global model uncertainty range in 2050 is large due to this region. Importantly, no model
123 achieves zero hunger (SDG2) by 2030. For the achievement of this goal, either a higher
124 income growth or notably a more equal food consumption distribution within countries is
125 needed.
126   The per-capita food consumption evolutions vary widely across models, but they tend to
127 increase steadily over time (Figure 1**d**), driven mainly by income growth (See Supplementary
128 Figure 3). This trend is the key driver of the decrease in the number of people at risk of
129 hunger. All models project a continuous increase in food consumption at the global level. In
130 developing regions, growth is stable, while in the OECD a relatively modest increase is
131 observed. IMAGE shows slightly different pathways from other models: the food
132 consumption trend also explains why IMAGE presented a slightly higher risk of hunger in the
133 second half of the century (Figure 1**ac**). The highest increase in calorie consumption can be
134 observed in the Africa and Middle East region where current food consumption level is low
135 (2330 to 2430 kcal/cap/day) and becomes 2690 to 2970 kcal/cap/day in 2050. Asia would
136 also have large food demand increase, by about 400 kcal/cap/day during the earlier part of
137 this century.
138
139
140 *Figure 1Number of the population at risk of hunger under the Baseline scenario and food consumption by 2050. Panel **a** and*
141 ***b** represents global and regional trends and panel **c** illustrates regional share of the population at risk of hunger in 2050*
142 *(model median value). Panel **d** is Food consumption under the Baseline scenario time-series data for total calorie*
143 *consumption across models. The grey lines in panels **a** and **b** are historical values. The century scale figure is presented in*
144 *Supplementary Figure 2.*
145
146 *Climate change mitigation effect on food security*
147   Climate change mitigation exclusively aimed at attaining the climate goals could
148 generate a risk of negatively impacting food security, and the response of the number of
149 people at risk of hunger to mitigation policies are remarkably amplified by the stringency of

150 mitigation policies (Figure 2): under the 2°C and 1.5°C scenarios, the risk of hunger
151 drastically changes compared to the Baseline and NDC scenarios. The population at risk of
152 hunger under the 2°C and 1.5°C scenarios in 2050 are 280-500 (median: 350; 3.8% of total
153 population) and 310-540 (median: 410; 4.5% of total population) respectively with a large
154 inter-model variation. For example, AIM shows around 290 million at risk of hunger in the
155 Baseline, while 360 and 410 million people are at risk of hunger in the 2°C and 1.5°C
156 scenarios respectively (3.1, 3.9 and 4.5% of total population respectively). MESSAGE-
157 GLOBIOM behaves similarly. WITCH and POLES are the most sensitive models to the
158 mitigation policy, where an additional 250 million people are at risk of hunger under the 2°C
159 and 1.5°C scenarios after 2030. Under both the 2°C and 1.5°C scenarios in almost all models,
160 the carbon price is reached to the carbon price cap for the agricultural sector by 2050.
161 Moreover, the large inter-model variation in carbon prices[33], generates large model
162 uncertainty and substantial overlaps in the output from the 2°C and 1.5°C scenarios (Figure
163 3**c**).
164   The spikes in the risk of hunger for the mitigation scenarios occur in 2030-2040 when
165 the carbon price required by the climate targets drastically increases. After that, the declining
166 trends similar to the Baseline trajectories are observed. Yet, the adverse side-effect of climate
167 change mitigation is large and persistent over time (Figure 3 **d**). Asia, Africa and the Middle
168 East show large side-effects. The projections by WITCH and POLES show that the adverse
169 side effect is prominent in Asia (Figure 2**c**).
170   The risk of hunger response to the mitigation policies are dependent on three factors:
171 the price elasticities of food demand, the carbon price effect on the food price, and the level
172 of the carbon price, which together push the food consumption down (Figure 4**a** and see also
173 Supplementary Figure 1 as an illustration of the logical chain of the mitigation effect on food
174 security). The price elasticity of food demand is quite heterogeneous across models (Figure
175 4**b**). REMIND-MAgPIE is the extreme case where a zero price elasticity is assumed.
176 MESSAGE-GLOBIOM, POLES, and WITCH show relatively high elasticities leading to a
177 decrease in food demand of up to 20%. The similarity across these three models is partly
178 explained due to the fact that these models use GLOBIOM based input data for their land-use
179 and agricultural representation, which is a simplified version of the full GLOBIOM
180 representation. AIM shows an intermediate food demand elasticity. Regionally, food
181 consumption in high-income countries tends to be relatively inelastic compared to that in
182 low-income countries. This is because wealthier people generally can spend money on
183 expensive food and because of a lower income-effect of the price-shock (Supplementary
184 Figure 4). The agricultural price changes are triggered by carbon prices (Figure 4**c**), which is
185 why we can see a clear correlation between food consumption reduction and carbon prices
186 (Figure 4**d**). However, carbon prices in 2050 diverge across models (Figure 3**d**). AIM,
187 WITCH, IMAGE and POLES show relatively high carbon prices compared to the other
188 models.
189   The model diversity in the hunger response can be explained by the combination of the
190 price elasticities and carbon prices, which are primary drivers of the hunger response. For
191 example, AIM, which has a modest food price elasticity, but high carbon price, shows an
192 intermediate increase in the risk of hunger (Figure 4**c**). MESSAGE-GLOBIOM's population
193 at risk of hunger is similar to AIM (Figure 2**a**), but the carbon prices is lower and the price
194 elasticities are higher than AIM (Figure 4**c**). WITCH and POLES are cases where both price
195 elasticity and carbon prices are high, and as a result, the largest negative hunger effect occurs
196 in the mitigation scenarios (Figure 4**a**).
197   The drivers of agricultural price changes differ across models, but one common
198 characteristic is the non-CO_2 emissions reduction measure and its carbon price penalty. The
199 non-CO_2 emissions can be mitigated when carbon prices are implemented in the agricultural

200   sector, but cannot be entirely removed (Figure 3**bc**). So, in addition to cost of mitigation
201   measures, the price burden of the residual emissions is passed through to the consumers. This
202   carbon price penalty effect drastically changes food price under particularly stringent
203   mitigation scenarios.
204   The other possible driver of price changes is the land use competition between food,
205   bioenergy crops and afforestation (Supplementary Figure 7 and 8). Although we cannot
206   identify numerically the magnitude of their contributions, there is a literature that finds that
207   the land rent and non-CO_2 emissions effect are of similar magnitude[7]. We can illustrate the
208   magnitude of this effect in the example from AIM (Supplementary Figure 9). The multi-
209   sector Computable General Equilibrium (CGE) model AIM incorporates other goods, service
210   prices, and wage change effects, but those factors are not large (Supplementary Figure 9).
211   AIM also identifies an income loss effect that accounts for around 20% of food demand
212   decreases.
213
214
215   *Figure 2 Number of the population at risk of hunger under the Baseline and mitigation scenarios a) time series and b) in*
216   *2050. The solid line in panel a) indicates median value across the models and the shaded area represents upper and lower*
217   *ranges of the model estimates for each scenario. c) indicates the regional risk of hunger across models and scenarios in*
218   *2050.*
219
220   *Figure 3 Global CO_2, CH_4 and N_2O emissions across scenarios (**a**, **b**, and **c**) and carbon price **d** until 2050 (full century figure*
221   *is shown in Supplementary Figure 5).*
222
223
224   *Figure 4 Food consumption, agricultural price, and carbon price relationships. Panel **a** presents food consumption*
225   *reduction rates compared to the Baseline scenarios in 2050. Panel **b**, **c**, and **d** illustrate the relationship between food*
226   *consumption reduction rates compared to the Baseline scenarios, agricultural price increase relative to the base year and*
227   *carbon prices across models and mitigation scenarios. The dots in Panel **b**, **c**, and **d** represent **each** ten year's value. Food*
228   *demand reduction is accounted for as calorie basis. The lines in panel **b** indicate 0.1 and 0.2 price elasticities of agricultural*
229   *demand.*
230
231   ***Cost estimates to avoid the adverse side effects***
232   This section examine the cost estimates that could potentially avoid the adverse side-
233   effects to food security due to climate change mitigation. We compute three cost metrics that
234   can be interpreted as : 1) an agricultural subsidy to keep the agricultural price during
235   mitigation at the same price as the Baseline scenario, 2) food-aid to supplement the reduction
236   of agricultural demand, and 3) food-aid to supplement the reduction of agricultural demand
237   "only" for those at risk of hunger. The agricultural subsidy cost is computed by the
238   agricultural price index in mitigation scenarios difference compared to baseline scenario
239   multiplied by the agricultural demand. The food-aid cost is calculated by the agricultural
240   demand decrease in the mitigation scenarios compared to the Baseline scenario multiplied by
241   its price (Supplementary Figure 10). The third metric is direct food-aid cost only for those
242   who are at risk of hunger under the climate mitigation scenario, which is shown in
243   Supplementary Figure 11. All complementary costs were derived by a back-of-the-envelope
244   calculation based on the model outputs. These are the amounts of gross subsidies or food-aid
245   payments that need to be delivered by the public sector.
246   To the price increase, the required agricultural subsidy is found to be around 0.63 (0.19
247   to 2.0) % of global GDP for 1.5°C scenario in the year 2050 (Figure 5**a**). At 2°C, the cost
248   decreases to 0.51 (0.00 to 1.3)%. REMIND-MAgPIE shows the largest cost which is
249   comparable with the mitigation policy cost (Figure 5**d**). REMIND-MAgPIE assumes a zero
250   food demand elasticity and the price change is therefore the only mechanism to adjust the

251   market. The cost computed by the other models is not as large as the mitigation policy cost.
252   WITCH has a remarkably high climate change mitigation costs and a relatively low food
253   policy costs.
254   The alternative measure to a subsidy is direct food aid to supplement the food deficit. In
255   contrast to the agricultural subsidy, food-aid is much smaller in cost and the differences
256   between 2 and 1.5°C are small in absolute term (Figure 5**be**). About 0.19 (0.00-0.46)% of
257   GDP is needed in the 1.5°C scenario in 2050 compared to 0.12 (0.00-0.39)% of GDP in the
258   2°C scenario. These results show that direct food-aid could be much cheaper than subsidizing
259   agricultural goods to reduce the price impacts. This can be explained by the price elasticity of
260   agricultural demand which is much less than -1 (around -0.2 in Figure 4**b**) and therefore
261   direct aid would be much more efficient than relying on a subsidy (as illustrated in
262   Supplementary Figure 10). Furthermore, if only people who are at risk of hunger are aided,
263   the cost is only 0.01% of GDP with an inter-model variation of 0.00-0.03%, which is even
264   smaller. However, it should also be noted that food-aid for only those at risk of hunger would
265   require a potentially sophisticated mechanism for implementation, such that the government
266   could identify who is at risk of hunger. In that sense, the food-aid cost should be interpreted
267   as a minimum cost and an additional opportunity and implementation cost would be required.
268   Moreover, the net social cost of these policy interventions is not as large as reported here,
269   with the deadweight loss illustrated in Supplementary Figure 12. To understand the order of
270   magnitude of differences between welfare changes and these policy costs, we ran an
271   additional scenario in AIM to obtain the point marked deadweight loss in Supplementary
272   Figure 12. Consequently, the welfare changes in 1.5 and 2 °C scenarios were 20% and 4% of
273   the food-aid respectively or 3.1% and 0.5% of the food subsidy respectively, which are
274   roughly 0.04% and 0.006% of GDP.
275   To explore the robustness of this finding to the key mode assumptions, we carried out a
276   sensitivity analysis by changing the food demand parametrization of each model including
277   food price and income elasticities (see Supplementary Notes). The people at risk of hunger
278   and food policy costs show similar trends to the original default scenarios (as is shown in
279   Supplementary Figure 13), which indicates that our qualitative findings are robust to the food
280   demand related parameters.
281
282
283   *Figure 5 Complementary food policy cost compared to the mitigation cost. Panel **a** and **d** show an additional agricultural*
284   *subsidy in the mitigation scenarios. The 2050 plots are highlighted by big markers. Panels **b** and **e** illustrate food-aid which*
285   *is derived from the agricultural demand decrease in the mitigation scenarios compared to the baseline scenario multiplied*
286   *by the agricultural price. Panel **c** and **f** illustrate the cost of food aid targeted at the population at risk of hunger. The x-axis*
287   *in panels **d, e,** and **f** are the policy cost variable, which depends on the model (GDP loss is used for AIM, MESSAGE-*
288   *GLOBIOM, REMIND-MAgPIE and WITCH. The area under MAC curve is used for IMAGE and POLES). The solid line*
289   *indicates a 45° line where the food policy cost is equal to the mitigation cost. The dashed lines have 0.1 and 0.2 gradients.*

290
291   **Discussion and conclusion**
292   We find that climate mitigation could potentially have adverse side-effects on food security.
293   The magnitude of this adverse side-effect is amplified by the stringency of the mitigation
294   level. These phenomena are robustly observed by multiple IAMs. Moreover, we identified
295   the cost of alternative illustrative complementary policy that simultaneously meet the climate
296   goal and, at the same time, ensuring food security. Such policy, in the form of a subsidy or
297   food-aid program in addition to the climate change mitigation effort by developed countries,
298   would target the decrease in the number of people at risk of hunger in developing regions.
299   When it comes to the relationship of multi-SDG concerning with climate change
300   mitigation, goals related to air pollution[34] and energy security[35] seem to have a synergy
301   effects with climate mitigation. The reduction of fossil fuel consumption to mitigate climate

302 change also lowers air pollution[36, 37]. Shifting from fossil fuels to renewable energy decreases
303 the reliance on oil and gas imports, which also benefits energy security[35, 37]. However, food
304 security, similarly to energy access[38], would have trade-off relationship.
305   There can be several discussion points with respect to the interpretation of the results.

1) Currently, the total (not only food) Official Development Assistance (ODA) is 0.32% of Gross National Income from the developed world[39]. This amount is in the order of magnitude of what would be necessary as food aid subsidy to alleviate the implications of a climate policy. However, one should keep in mind that the subsidy would come on top of current ODA. Notably, ear-marking parts of the carbon tax revenues could provide a measure to raise the required public funds.

2) An increase in food prices may, in some instances, translate into higher wages for low-income households or farmers[40]. However, when increases in food prices are caused by a carbon tax[10], the increased production costs are due to carbon pricing and land rent, and income from increased spending tends not to be distributed to low-income farmers[41]. Additionally, Sub-Saharan countries, which have large populations at risk of hunger, rely heavily on food imports, particularly of staple foods[43, 44]. These populations would suffer if food prices increase.

3) In some simulations, we imposed a price cap on GHG emissions from the agricultural sector. We then explored the sensitivity of our results to changes in price caps. The population at risk of hunger is sensitive to GHG pricing during the implementation of mitigation policies (Supplementary Figure 15). The cost of reducing the adverse effects of mitigation policies on food security was also sensitive to the price cap assumptions (Supplementary Figure 16).

4) Agricultural prices increase not only because of emissions pricing, but also because of other factors such as bioenergy expansion. These other factors play important roles and should be considered when designing policies. It is possible to achieve the 1.5°C goal even under scenarios that are less dependent on reducing bioenergy use[42, 43]. These alternative measures can complement the use of emission price caps to alleviate risks to food security stemming from climate change mitigation action. However, alternative measures that rely on societal changes, such as switching diets and using advanced technologies, have their own challenges. Therefore, a suite of complementary measures needs to be applied to completely alleviate the side effects of climate change mitigation. If the agricultural sector were exempted from carbon pricing, greater and more costly reductions in CO_2 emissions will be needed to achieve climate goals.

5) The cost estimates for avoiding the trade-offs between climate change mitigation and food security in this study were not based on a comprehensive assessment of policy options, but rather on simple global carbon-pricing schemes. Food security is a multi-faceted concept that cannot be adequately represented by a single indicator. Local circumstances and other societal aspects should also be considered when designing climate policies. Nevertheless, our modelling analysis provides first-order cost estimates of reducing risks to food security from climate change mitigation policies, and furthers understanding of the uncertainties surrounding such estimates[44]. In that sense, our modeling exercise contributes to show the first order policy cost and an understanding of the magnitude of the surrounding uncertainty, and to better understand the relationship between climate change and one of the other societal challenges (in this case food security), which is also highlighted in IPCC special report on 1.5°C[44].

6) Previous studies have revealed that different climate change mitigation policies can lead to varying effects on the consumption of agricultural goods and land use. For example, if carbon pricing is only applied to fossil fuels and not emissions from land-use changes, natural forests would be replaced by short-rotation plantations or large fields of bioenergy crops[45]. The carbon

352 price applied to agricultural non-CO_2 emissions can change food consumption amounts[46]; thus,
353 how mitigation policies are implemented in the agricultural sector can impact food security.
354
355 There are some caveats and limitations of this study. The model uncertainty shown in
356 this article sheds light on the drivers of uncertainty in the assessment of the population at risk
357 of hunger. This uncertainty is generated by two main factors: carbon prices and food demand
358 price elasticity. There have been some studies of agricultural economic MIPs to see the
359 uncertainty among the models[47, 48, 49, 50]. Notably, it might be necessary to focus more
360 attention on the price and income elasticities of food demand since this study is the first study
361 focusing on the multi-model agricultural outcomes with the extremely high carbon prices. In
362 the analysis, we did not include the effect of climate change impacts, but they should be
363 explored with the consideration of extreme events. We believe that this study would be a
364 milestone for further studies (Supplementary Note 4)
365
366
367

368 **Method**
369 **Overall methodology**
370   We use six IAMs which sufficiently represent energy, emissions, land use and
371 agriculture to assess the interaction between climate mitigation and food security. Note that to
372 investigate the agriculture and food security implications associated with climate change
373 mitigation targets, we need models that are somehow consistently able to capture the
374 interaction of energy, agriculture and land-use markets, which means the IAMs used in this
375 study are suitable for our purposes. Importantly, each model has its own strengths and
376 weaknesses, although the agricultural representations in some models are not very detailed.
377 However, the hunger estimation tool bridges this gap, which enables us to deal with the
378 model uncertainty and derive robust conclusions. Four representative scenarios are examined
379 which differentiate the stringency of climate mitigation. As a metric of food security, a
380 number of people at risk of hunger is implemented, which is calculated either within IAMs
381 (AIM and IMAGE) or a hunger estimation tool. Here we describe 1) a brief model overview
382 for each IAM (a summary is in Supporting Information Supplementary Table 2 and model
383 scope is in Supplementary Table 3), 2) scenario definition, and 3) hunger tool description.
384   The relationship between model inputs and outputs is illustrated in Supplementary
385 Figure 1 (similar to Hall et al.[51] for global circulation models). Model structures and
386 assumptions strongly influence predictions of increases and decreases in non-CO_2 emissions
387 associated with bioenergy use Supplementary Figure 1. The amount of bioenergy depends on
388 the energy system, particularly those in which technological costs (e.g. cost of biomass-
389 power generation) and model types (e.g. linear least-cost optimisation, non-linear substitution
390 functions)[52] are the main factors. The emission of non-CO_2 gases depends on the marginal
391 abatement cost curves used in each IAM[28, 46]. Finally, food demand responses to price
392 changes are determined by price elasticity (Figure 4).
393
394 **Model description**
395 **AIM/CGE[22]** is a one-year-step recursive-type dynamic general equilibrium model that covers
396 all regions of the world. The AIM/CGE model includes 17 regions and 42 industrial
397 classifications. For appropriate assessment of bioenergy and land use competition,
398 agricultural sectors are also highly disaggregated[53]. Details of the model structure and
399 mathematical formulae are described by Fujimori, Masui [54]. The production sectors are
400 assumed to maximize profits under multi-nested constant elasticity substitution (CES)
401 functions and each input price. Energy transformation sectors input energy and value-added
402 are fixed coefficients of output. They are treated in this manner to deal with energy
403 conversion efficiency appropriately in the energy transformation sectors. Power generation
404 values from several energy sources are combined with a Logit function. This functional form
405 was used to ensure energy balance because the CES function does not guarantee an energy
406 balance. Household expenditures on each commodity are described by a linear expenditure
407 system function. The parameters adopted in the linear expenditure system function are
408 recursively updated by income elasticity assumptions[29]. Land use is determined by Logit
409 selection[55]. In addition to energy-related CO_2, CO_2 from other sources, CH_4, N_2O, and
410 fluorinated gases (F-gases) are treated as GHGs in the model. Energy-related emissions are
411 associated with fossil fuel feedstock use. The non-energy-related CO_2 emissions consist of
412 land use change and industrial processes. Land use change emissions are derived from the
413 forest area change relative to the previous year multiplied by the carbon stock density, which
414 is differentiated by AEZs (Global Agro-Ecological Zones). Non-energy-related emissions
415 other than land use change emissions are assumed to be in proportion to the level of each
416 activity (such as output). CH_4 has a range of sources, mainly the rice production, livestock,
417 fossil fuel mining, and waste management sectors. N_2O is emitted as a result of fertilizer

418 application and livestock manure management and by the chemical industry. F-gases are
419 emitted mainly from refrigerants used in air conditioners and cooling devices in the industry.
420 Air pollutant gases (BC, CO, NH_3, NMVOC, NO_X, OC, SO_2) are also associated with fuel
421 combustion and activity levels. Emissions factors change over time with the implementation
422 of air pollutant removal technologies and relevant legislation.
423
424 **IMAGE 3.0** is a comprehensive integrated assessment framework, modelling interacting
425 human and natural systems[56]. The framework comprises a number of sub-models describing
426 land use, agricultural economy, the energy system, natural vegetation, hydrology, and the
427 climate system. The sub-models operate at different spatial resolutions. The socio-economic
428 components work at the level of 26 regions while the environmental components work at the
429 grid level to take into account heterogeneities in environmental circumstances. Interaction
430 between the models takes place through upscaling and downscaling algorithms.
431 Land use and crop production are spatially explicitly modelled on a 5 minute grid in the
432 IMAGE-LandManagement model using an empirical land-use allocation algorithm.
433 Livestock systems are modelled on 26 regions for intensive and extensive systems. Data on
434 demand for agricultural production and intensification/extensification of the agricultural
435 sector is provided by the agricultural economy model MAGNET: a multi-regional, multi-
436 sectoral, applied general equilibrium model [57] based on neo-classical microeconomic theory
437 which is an extension of the standard GTAP model. The core of MAGNET is an input–output
438 model, which links industries in value added chains from primary goods to final goods and
439 services for consumption. Input and output prices are endogenously determined by the
440 markets to achieve supply and demand equilibrium. The agricultural sector is represented in
441 high detail compared to standard CGE models. Developments in productivity are driven by a
442 combination of assumptions on autonomous technological change provided by IMAGE-
443 LandManagement and by economic processes as modelled by MAGNET (i.e. substitution
444 between production factors). Land is modelled as an explicit production factor described by a
445 land supply curve, constructed with land availability data provided by IMAGE-
446 LandManagement.
447 The energy system is modelled for 12 primary energy carriers by the energy simulation
448 model TIMER. The TIMER model determines demand for bioenergy production which is
449 implemented in IMAGE-LandManagement following a food-first policy preventing
450 competition with food production. The dynamic global vegetation model LPJmL is
451 dynamically coupled to IMAGE-LandManagement to model the carbon and hydrological
452 cycles and provides spatial explicit information on potential crop yields. An implementation
453 of the simple climate model MAGICC is used to calculate climate change based on GHG
454 emissions calculated by IMAGE-LandManagement and TIMER.
455 Climate change mitigation policy is modelled by the FAIR-SimCAP model which uses
456 carbon prices and marginal abatement cost curves (MACs) representing costs of mitigation
457 actions to determine a cost optimal emission pathway. Technical mitigation of non-CO_2 GHG
458 emissions from agricultural is based on Lucas et al[58]. The residual emissions are taxed in
459 MAGNET. The costs of technical mitigation are also implemented as part of the tax. Avoided
460 deforestation policy (e.g. REDD) is calibrated to the carbon tax of FAIR-SimCAP and
461 implemented in MAGNET through reduced land availability.
462
463
464 **MESSAGEix-GLOBIOM** integrates the energy engineering model MESSAGE with the
465 land-use model GLOBIOM via soft-linkage into a global integrated assessment modeling
466 framework[24].

467 MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental
468 Impact) is a linear programming (LP) energy engineering model with global coverage. As a
469 systems engineering optimization model, MESSAGE is primarily used for medium- to long-
470 term energy system planning, energy policy analysis, and scenario development. The model
471 provides a framework for representing an energy system with all its interdependencies from
472 resource extraction, imports and exports, conversion, transport, and distribution, to the
473 provision of energy end-use services such as light, space conditioning, industrial production
474 processes, and transportation. To assess economic implications and to capture economic
475 feedbacks of climate and energy policies, MESSAGE is linked to the aggregated macro-
476 economic model MACRO[59].
477 Land-use dynamics are modelled with the GLOBIOM (GLobal BIOsphere Management)
478 model, which is a partial-equilibrium model[12]. GLOBIOM represents the competition
479 between different land-use based activities. It includes a detailed representation of the
480 agricultural, forestry and bio-energy sector, which allows for the inclusion of detailed grid-
481 cell information on biophysical constraints and technological costs, as well as a rich set of
482 environmental parameters, incl. comprehensive AFOLU (agriculture, forestry and other land
483 use) GHG emission accounts and irrigation water use. For spatially explicit projections of the
484 change in afforestation, deforestation, forest management, and their related CO_2 emissions,
485 GLOBIOM is coupled with the G4M (Global FORest Model) model[60]. As outputs, G4M
486 provides estimates of forest area change, carbon uptake and release by forests, and supply of
487 biomass for bioenergy and timber.
488 MESSAGE-GLOBIOM covers all greenhouse gas (GHG)-emitting sectors, including energy,
489 industrial processes as well as agriculture and forestry. The emissions of the full basket of
490 greenhouse gases including CO_2, CH4, N2O and F-gases (CF4, C2F6, HFC125, HFC134a,
491 HFC143a, HFC227ea, HFC245ca and SF6) as well as other radiatively active substances,
492 such as NOx, volatile organic compounds (VOCs), CO, SO_2, and BC/OC is represented in the
493 model. MESSAGE-GLOBIOM is used in conjunction with MAGICC (Model for Greenhouse
494 gas Induced Climate Change) version 6.8 (Ref.[61]) for calculating atmospheric concentrations,
495 radiative forcing, and annual-mean global surface air temperature increase.
496
497 The **POLES** (Prospective Outlook on Long-term Energy System) model is a global partial
498 equilibrium simulation model of the energy sector with an annual step, covering 38 regions
499 world-wide (G20, OECD, principal energy consumers) plus the EU. The model covers 15
500 fuel supply branches, 30 technologies in power production, 6 in transformation, 15 final
501 demand sectors and corresponding greenhouse gas emissions. GDP is an exogenous input of
502 the model, while endogenous resource prices, endogenous global technological progress in
503 electricity generation technologies and price induced lagged adjustments of energy supply
504 and demand are important features of the model. Mitigation policies are implemented by
505 introducing carbon prices up to the level where emission reduction targets are met: carbon
506 prices affect the average energy prices, inducing energy efficiency responses on the demand
507 side, and the relative prices of different fuels and technologies, leading to adjustments on
508 both the demand side (e.g. fuel switch) and the supply side (e.g. investments in renewables).
509 Non-CO_2 emissions in energy and industry are endogenously modelled with potentials
510 derived from literature (marginal abatement cost curves). Projections for agriculture,
511 LULUCF emissions and food indicators are derived from the GLOBIOM model (dynamic
512 look-up of emissions depending on climate policy and biomass-energy use), calibrated on
513 historical emissions and food demand (from UNFCCC, EDGAR and FAO). A full
514 documentation of POLES is available at http://ec.europa.eu/jrc/poles and report[62].
515

516 **REMIND-MAgPIE** models the global energy-economy-climate system for 11 world regions
517 and for the time horizon until 2100. For the present study, REMIND in its version 1.7 was
518 used. REMIND represents five individual countries and six aggregated regions formed by the
519 remaining countries. For each region, intertemporal welfare is optimized based on a Ramsey-
520 type macro-economic growth model. The model explicitly represents trade in final goods,
521 primary energy carriers, and in the case of climate policy, emission allowances and computes
522 simultaneous and intertemporal market equilibria based on an iterative procedure. Macro-
523 economic production factors are capital, labor, and final energy. REMIND uses economic
524 output for investments in the macro-economic capital stock as well as consumption, trade,
525 and energy system expenditures.
526 MAgPIE (Model of Agricultural Production and Its Impacts on the Environment) [17, 63] is a
527 global partial equilibrium agro−economic model that operates on a spatially explicit scale,
528 where local biophysical conditions (crop yield, water availability, and terrestrial carbon
529 content) influence decision making for optimal agricultural production patterns. The
530 objective function is the costs of global agricultural supply, which are minimized such that
531 the demand for agricultural products is fulfilled. Agricultural demand is aggregated at the
532 level of ten MAgPIE defined geo-economic regions. Food demand is exogenously calculated,
533 based on an econometric regression model that projects per capita caloric consumption on a
534 national level, considering historical patterns and socio−economic assumption of future
535 growth in population and income[64]. The demand implementation accounts for the long-term
536 income effect on agricultural consumption, but the model is limited with respect to
537 representing short-term demand adjustments to changes in prices. Material demand is
538 assumed to be proportional to total food demand. Agricultural demand in addition comprises
539 demand for animal feed (feed crops, fodder, grazed biomass) calculated based on feed
540 baskets content. Regional agricultural supply is endogenously determined based on costs of
541 production and spatially explicit agricultural productivity levels. The costs account for input
542 factors of production, transport, and investment costs for conversion of other land types into
543 arable land, irrigation infrastructure, and yield-increasing technological progress [65](Input of
544 local biophysical conditions (land, water, terrestrial carbon) and crop yields is provided on
545 the gridded resolution ($0.5° \times 0.5°$ geographic longitude−latitude) from the global crop model
546 LPJmL (Lund−Potsdam−Jena model with managed Land). MAgPIE estimates flows of CO_2,
547 CH_4, and nitrogen (N) related emissions[66]. CO_2 emissions are computed from land-use
548 change dynamics, i.e. from conversion of different biomes into agricultural land and
549 consequent loss of terrestrial carbon stocks. Land conversion into cropland can occur from
550 pasture, forest (pristine and unmanaged), and other natural vegetation (e.g., savannahs,
551 shrublands) land pools. The reduction of GHGs is incentivized by an imposed price (tax). In
552 the case of CO_2 emissions, the price serves as an incentive to restrain land-use conversion and
553 consequent carbon release. Reduction of CH_4 and N emissions is possible by applying
554 technical mitigation at additional cost, also triggered by an emission price.
555
556 **WITCH-GLOBIOM** (World Induced Technical Change Hybrid) is an integrated assessment
557 model designed to assess climate change mitigation and adaptation policies. It is developed
558 and maintained at the Fondazione Eni Enrico Mattei and the Centro Euro-Mediterraneo sui
559 Cambiamenti Climatici. WITCH-GLOBIOM is of a global dynamic model that integrates
560 into a unified framework the most important drivers of climate change. An inter-temporal
561 optimal growth model captures the long-term economic growth dynamics. A compact
562 representation of the energy sector is fully integrated (hard linked) with the rest of the
563 economy so that energy investments and resources are chosen optimally, together with the
564 other macroeconomic variables.

565 WITCH-GLOBIOM represents the world in a set of a varying number of macro regions – for
566 the present study, the version with thirteen representative native regions has been used; for
567 each, it generates the optimal mitigation strategy for the long-term (from 2005 to 2100) as a
568 response to external constraints on emissions. A modelling mechanism aggregates the
569 national policies on emission reduction or the energy mix into the WITCH regions. Finally, a
570 distinguishing feature of WITCH is the endogenous representation of R&D diffusion and
571 innovation processes that allows a description of how R&D investments in energy efficiency
572 and carbon-free technologies integrate the mitigation options currently available. Non-CO_2
573 emissions in energy and industry are endogenously modelled with potentials derived from
574 literature (marginal abatement cost curves). Projections for agriculture, LULUCF emissions
575 and food indicators are derived from the GLOBIOM model (dynamic look-up of emissions
576 depending on climate policy and biomass-energy use), calibrated on historical emissions and
577 food demand (from UNFCCC, FAO and EDGAR).
578 For this study, WITCH 2016 has been used; key publications describing the model are
579 Refs.[27, 67], and a full documentation is available at http://doc.witchmodel.org/.
580
581 **Scenario definition**
582   We employed four scenarios in this study as listed below:
583 (1) Baseline
584   It does not include climate policy but currently planned non-climate policy such as
585   energy policies.
586 (2) NDC
587   Currently planned policies + NDCs are reflected. Thus, the emissions meet the NDC
588   targets for 2025 and 2030. After 2030, the same emissions reduction effort by 2030 is
589   assumed.
590 (3) 2°C
591   Currently planned policies + Cost effective mitigation pathway with global
592   cumulative CO_2 emissions constraint as 1000 $GtCO_2$ from 2011 to 2100 is adopted.
593   This level of mitigation efforts likely (>66% change) enables the global mean
594   temperature staying below 2 °C. The emission reduction starts from 2020.
595 (4) 1.5°C
596   Currently planned policies + Cost effective mitigation pathway with global
597   cumulative CO_2 emissions constraint as 400$GtCO_2$ from 2011 to 2100 is adopted.
598   This level of mitigation efforts enables the global mean temperature staying below
599   2 °C by roughly 50%. The emission reduction starts from 2020.
600
601 **The estimation method of number of people at risk of hunger**
602   In principle, the risk of hunger can be calculated by referring to the mean calorie
603 consumption, which is the same approach as in AIM and IMAGE. Moreover, GLOBIOM
604 recently released a publication quantifying the number of people at risk of hunger[13], with its
605 emulator now used by three IAMs (MESSAGE-GLOBIOM, POLES and WITCH-
606 GLOBIOM). MAgPIE is also well known among the agricultural economic models that have
607 been applied in this research field. Therefore, the combination of the IAMs and the hunger
608 estimation tool were sufficient for our purposes, i.e. to represent agricultural and land use
609 changes.
610   The narrow definition of undernourishment or hunger is a state of energy (calorie)
611 deprivation lasting over one year; this does not include the short-lived effects of temporary
612 crises [68, 69]. Furthermore, this does not include inadequate intake of other essential nutrients
613 [68]. The population at risk of hunger is a proportion of the total population and is calculated
614 using Eq. 1.

615 $$Risk_t = POP_t \cdot PoU_t \qquad\qquad\qquad\text{(Eq. 1)}$$

where,

t : year

616 $Risk_t$: population at risk of hunger in year t [person]

POP_t : population in year t [person]

PoU_t : proportion of the population at risk of hunger in year t [−]

617

618   According to the Food and Agriculture Organization (FAO) methodology [70], the proportion
619 of the population at risk of hunger is defined using Eqs. 2 to 4. With the FAO methodology,
620 the proportion is calculated using three parameters: the mean food calorie consumption per
621 person per day (*cal*), the mean minimum dietary energy requirement (*M*), and the coefficient
622 of variation of the food distribution of the dietary energy consumption in a country (*CV*). The
623 food distribution within a country is assumed to follow a log normal distribution. The
624 proportion of the population under the mean minimum dietary energy requirement (*M*) is
625 defined as the proportion of the population at risk of hunger. The log normal distribution has
626 two parameters, the mean μ_t and the variance σ_t, as in Eq. 2. The parameters μ_t and σ_t can be
627 represented using the mean food calorie consumption per person per day (*cal*) and the
628 coefficient of variation of the domestic distribution of dietary energy consumption (*CV*) as
629 Eqs. 3 and 4.
630   Each IAM reports the mean food calorie consumption per person per day (*cal*). We
631 standardize the base year calorie consumption to what FAO reports and take the change ratio
632 of each year to the base year for IAMs. We then compute the standardized calorie
633 consumption to make a consistent number for those at risk of hunger. In this process, since
634 the IAM's are regionally aggregated values, they are downscaled to the individual country
635 level by taking the base year value reported FAO and future change ratio from IAMs. The *CV*
636 is an indicator of food security observed in a household survey conducted by the FAO. It
637 ranges from 0 to 1. FAO country data for CV are weighted on the basis of population data in
638 the base year and aggregated to regional classification to obtain the CV of aggregated
639 regions. The CV is changed over time with the consideration of income growth dynamics as
640 presented in Hasegawa et al.[29]. Note that there is an assumption that the future CV changes of
641 each region are based on the current regional values.
642

643 $$PoU_t = \Phi\left(\frac{\log M_t - \mu(cal_t, \sigma_t)}{\sigma_t} \right) \qquad\qquad\text{(Eq. 2)}$$

644 $$\mu(cal_t, \sigma_t) = \log_e cal_t - \frac{\sigma_t^2}{2} \qquad\qquad\qquad\text{(Eq. 3)}$$

645 $$\sigma_t = \left[\log_e\left(CV^2 + 1 \right) \right]^{0.5} \qquad\qquad\text{(Eq. 4)}$$

where,

M_t : mean minimum dietary energy requirement in year t

646 CV_t : coefficient of variation of the inter-national distribution of dietary energy consumption in year t

Φ : standard normal cumulative distribution

cal_t : mean food calorie intake per person per day in year t

647

648   The mean minimum dietary energy requirement (*M*) is calculated for each year and
649 country by using the mean minimum dietary energy requirement in the base year at the
650 country level [71, 72, 73] and an adjustment coefficient for the minimum energy requirements per

651 person in different age and sex groups [72] and the population of each age and sex group in
652 each year [73], as in Eqs. 5 and 6.

653
$$M_t = Mbase \cdot \frac{MER_t}{MERbase}$$
(Eq. 5)

654
$$MER_t = \frac{\sum_{i,j} RMER_{i,j} \cdot Pclass_{i,j,t}}{\sum_{i,j} Pclass_{i,j,t}}$$
(Eq. 6)

655 *where*,
656 *i*: age group;
657 *j*: sex;
658 *Mbase*: mean minimum dietary energy requirement per person in the base year;
659 *MER$_t$*: Mean adjustment coefficient of minimum energy requirements per person in year *t*;
660 *MER$_{base}$*: Mean adjustment coefficient of the minimum energy requirements per person in the
661 base year;
662 *RMER$_{i,j}$*: Adjustment coefficient for the minimum energy requirements per person of age *i*
663 and sex *j*;
664 *Pclass$_{i,j,t}$*: population of age *i* and sex *j* in year *t*.
665
666 **Data Availability**
667
668 Scenario data is accessible online via the CDLINKS Database portal
669 https://db1.ene.iiasa.ac.at/CDLINKSDB.
670 The data which is derived from the original scenario database shown as figures but not in the
671 above database is available upon requests.
672
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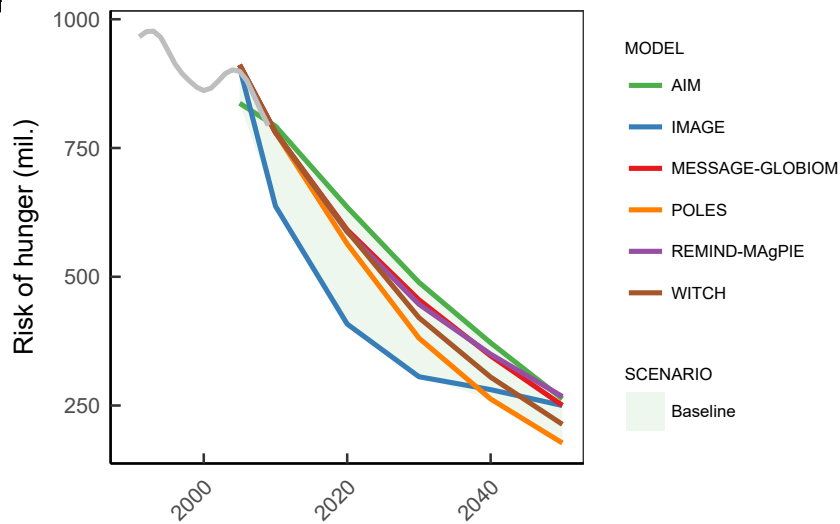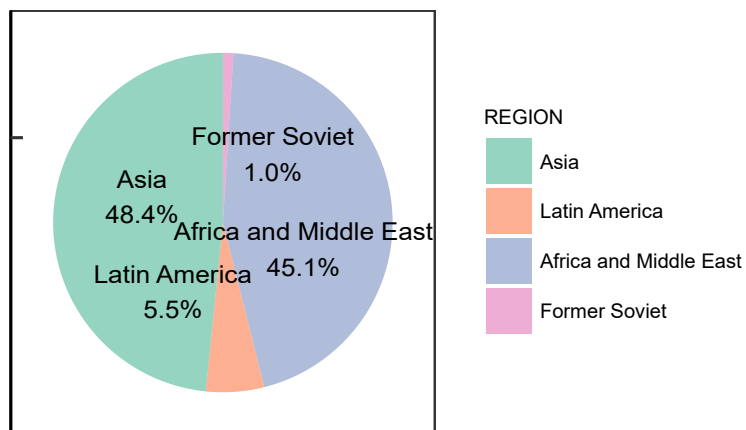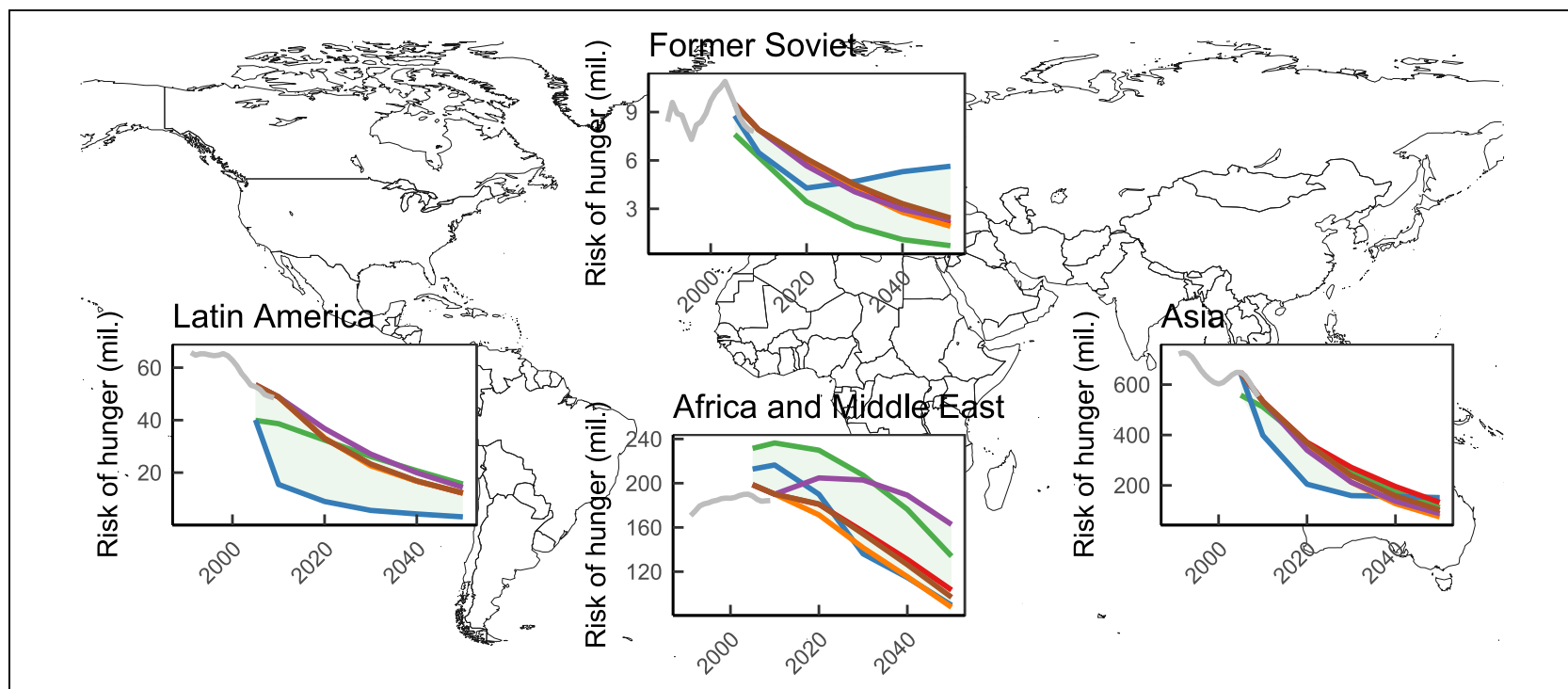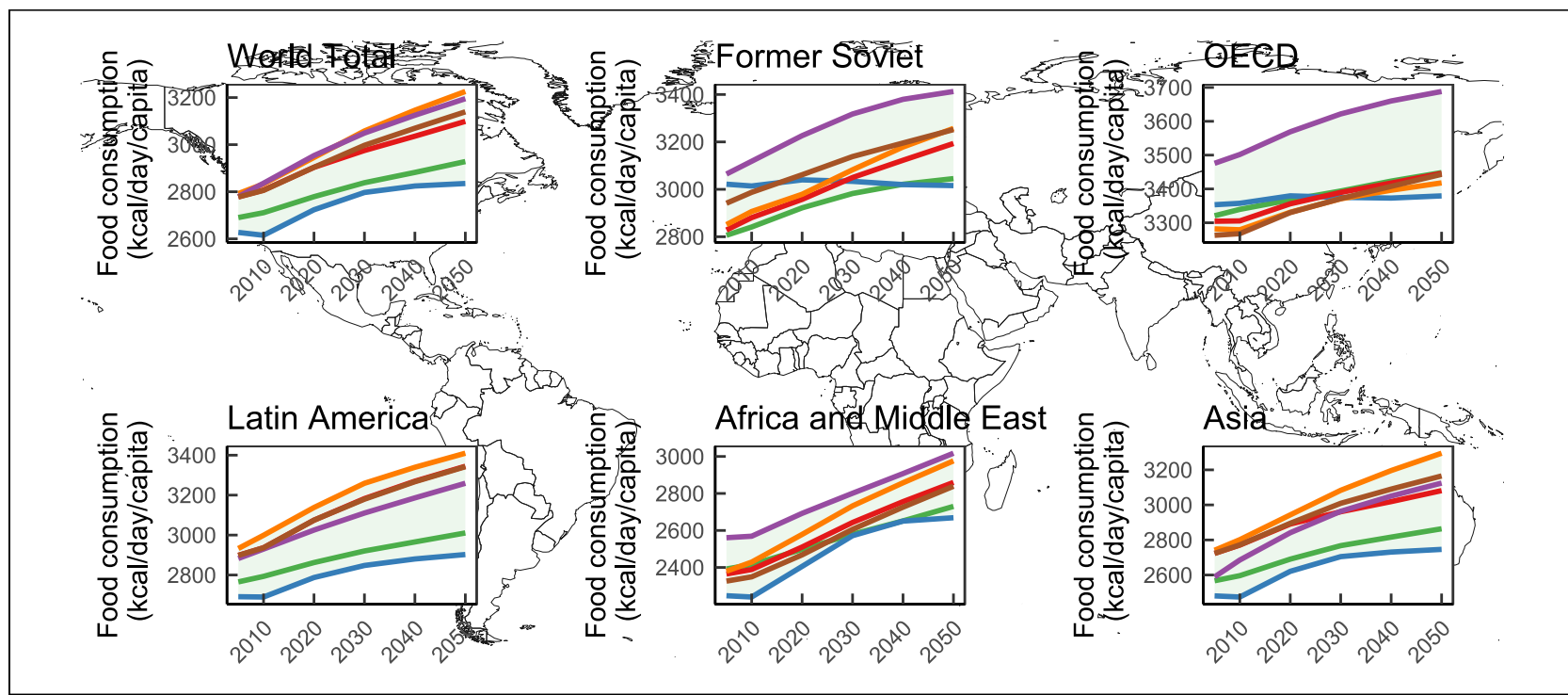
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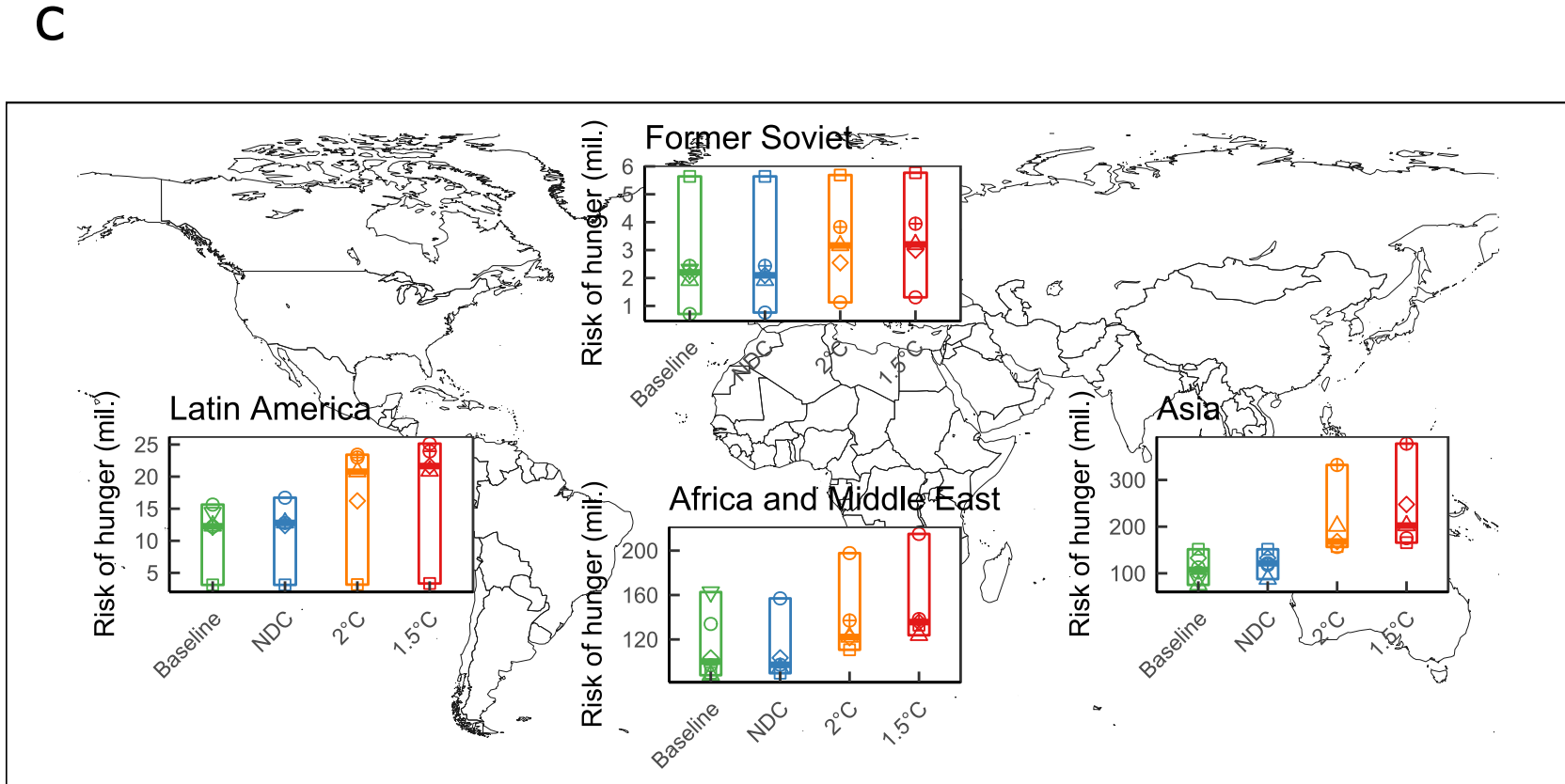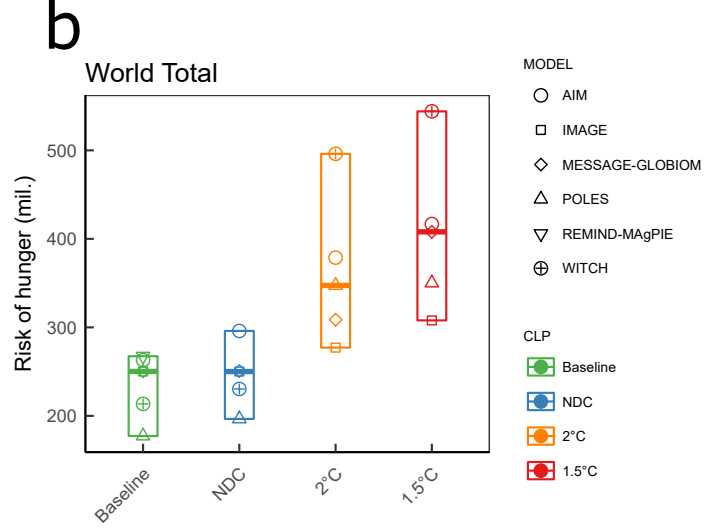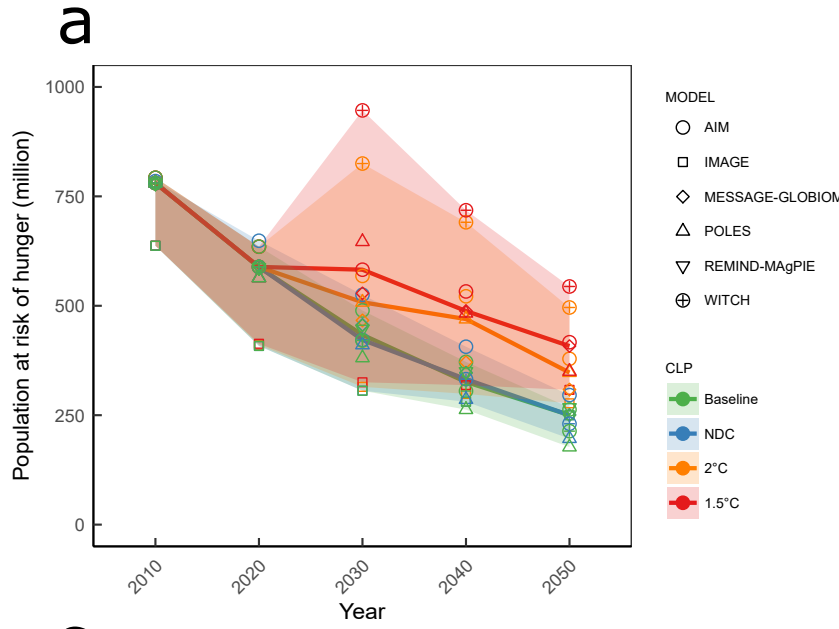764 *Global Environmental Change 2017, **42**(Supplement C): 251-267.*

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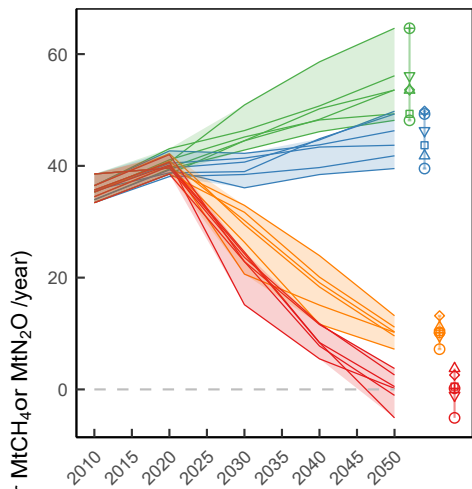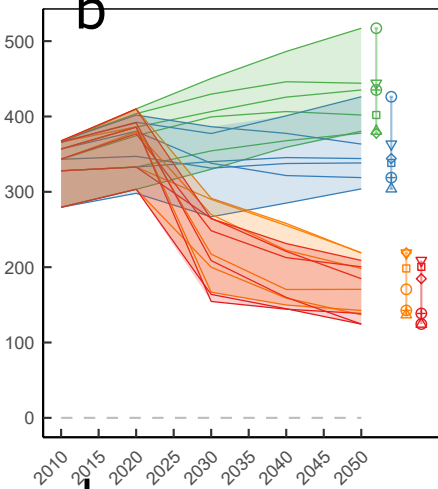809   *34(4): 444-460.*

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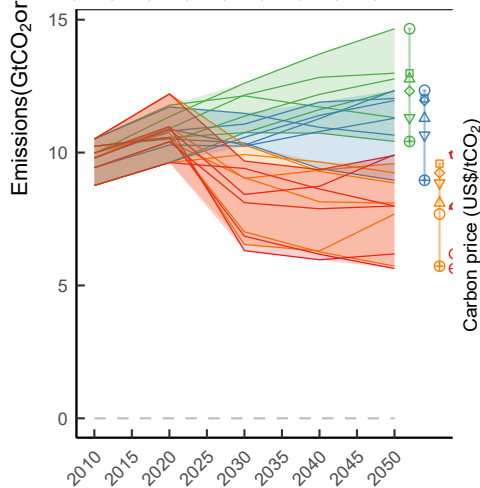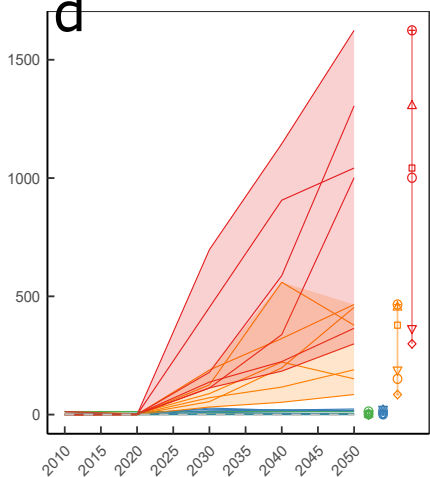
a

b

Former Soviet
1.0%

Asia
48.4%

Latin America
5.5%

Africa and Middle East
45.1%
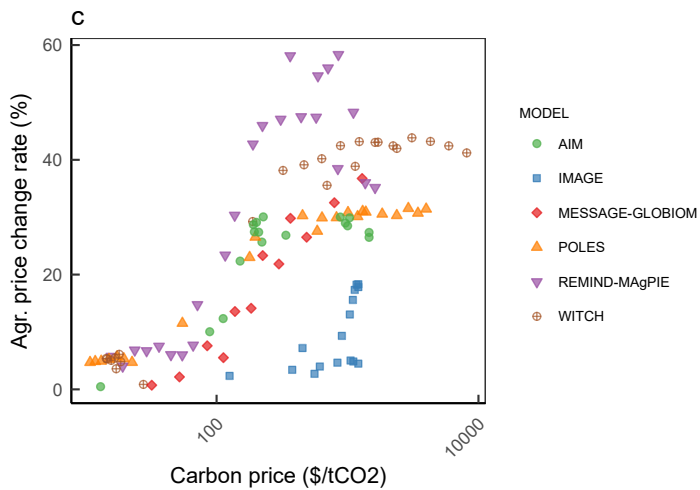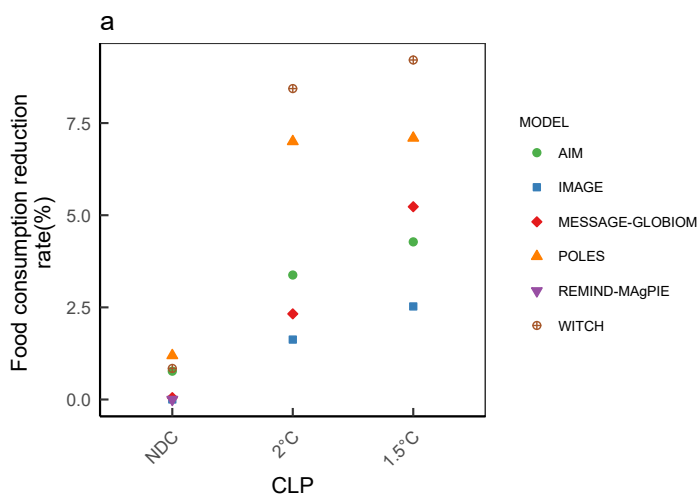
MODEL
- AIM
- IMAGE
- MESSAGE-GLOBIOM
- POLES
- REMIND-MAgPIE
- WITCH

SCENARIO
- Baseline

REGION
- Asia
- Latin America
- Africa and Middle East
- Former Soviet

c

Former Soviet

Latin America

Africa and Middle East

Asia

d

World Total

Former Soviet

OECD

Latin America

Africa and Middle East

Asia
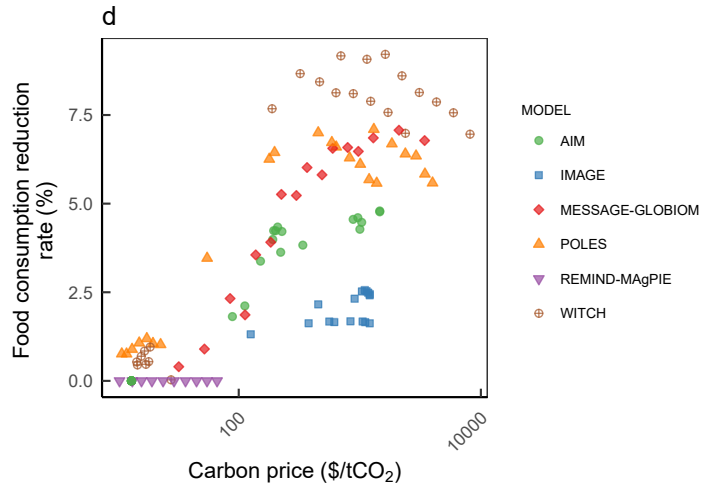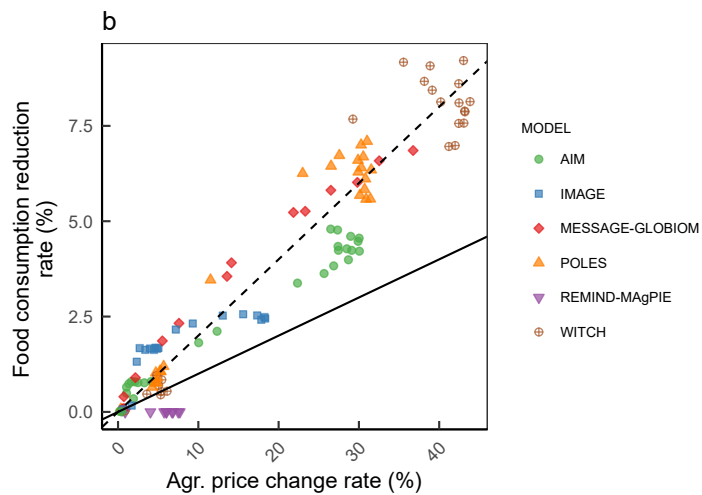
a Food Subsidy   **b Food Aid**   **c Food deficit**
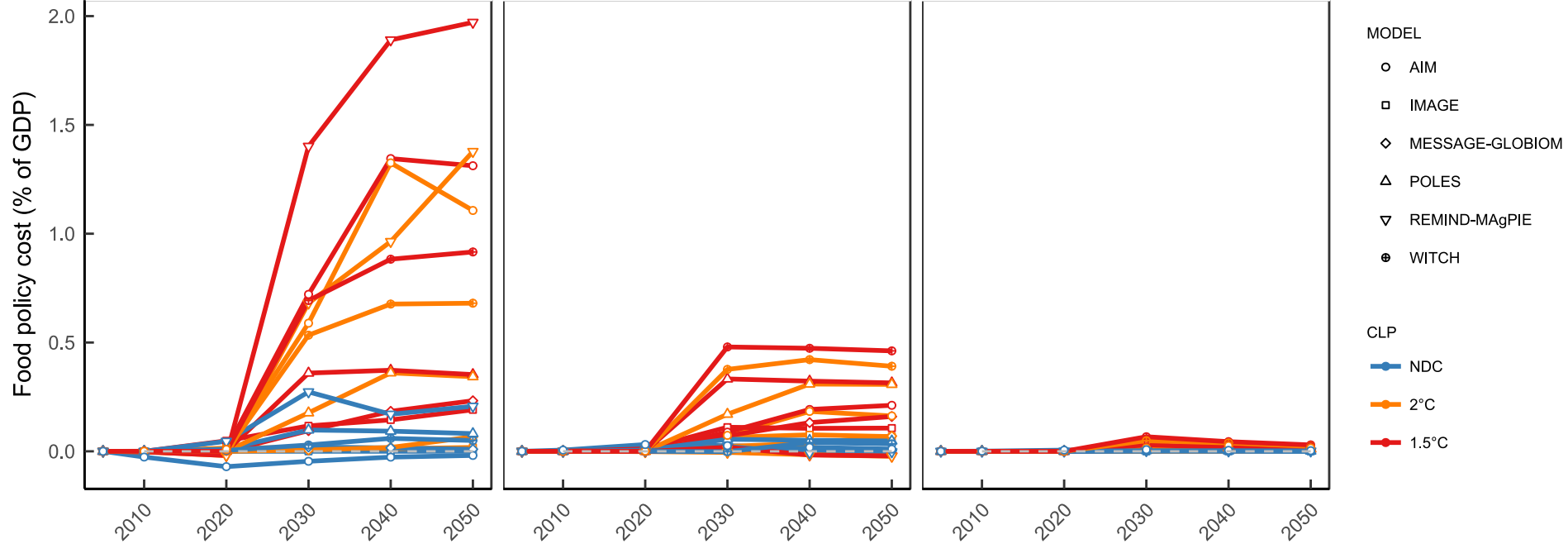
d Food Subsidy   **e Food Aid**   **f Food deficit**

MODEL
○ AIM
□ IMAGE
◇ MESSAGE-GLOBIOM
△ POLES
▽ REMIND-MAgPIE
⊕ WITCH

CLP
— NDC
— 2°C
— 1.5°C

Food policy cost (% of GDP)

Mitigation policy cost (% of GDP)