Title

A multi-model assessment of food security implications of climate change mitigation

Authors

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Author Contributions

SFu, VK, and KR designed the research; SFu carried out analysis of the modelling results, created figures and wrote the first draft of the paper; TH and OY carried out hunger estimation tool simulation; SFu and HT provided AIM data; JD, JL, HvM and DvV provided IMAGE data; OF, SFr and PH provided MESSAGE-GLOBIOM data; JD and AS provided POLES data; BLB, FH and AP provided REMIND-MAgPIE data; VB, LD and JE provided WITCH data; JC edited English expression; all authors contributed to the discussion and interpretation of the results.

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Abstract (approximately 150 words unreferenced)
Attaining well below 2°C climate change goal affirmed by the Paris Agreement is one of the societal challenges. Meanwhile, food security is another high-priority areas in the UN Sustainable Development Goals that could potentially be adversely affected by stringent climate mitigation. Here we show the potential negative trade-offs between food security and climate mitigation using a multi-model comparison exercise. We find that carelessly designed climate mitigation policies could increase the number of people at risk of hunger by 110 million people in 2050. Avoiding these adverse side effects would entail a cost of about 0.18% of global GDP in 2050. It should be noted that direct impacts of climate change on yields were not assessed and that the direct benefits from mitigation in terms of avoided yield losses could be significant further lessening the above cost. While results vary across models and model implementations, the qualitative implications are robust and call for a careful design of climate mitigation policies taking into account agriculture and land prices.

Main text (<3500 words, Section headings should be used and subheadings may appear in 'Results'. Avoid 'Introduction' as a heading. 6 display items)

Food security is considered as one of the areas in Sustainable Development Goals (SDGs), in particular SDG2 is aiming at "zero-hunger" by 2030. The global number of people at risk of hunger has declined over the past decades and was estimated at 795 million[1] for the year 2015, which is 184 million fewer than 1990-1992, despite a steady population growth notably in low-income countries[2]. Steady income growth and a relatively stable political situation helped this trend. The food security issue has been intensively investigated in the context of climate change impacts over the last few decades[3, 4, 5, 6], and more recent studies explored the effect of climate change mitigation effect on agricultural markets[7, 8, 9, 10, 11, 12]. Despite differing scenario assumptions, metrics, and quantitative outcomes, these studies more or less agree that single minded mitigation policies could adversely impact food security in developing countries. Although some studies propose partial solutions of how to mitigate these side-effects[13, 14], most of them do not directly quantify the number of people at risk of hunger. Furthermore, since the assumptions behind these studies are not harmonized, the reason for the differences in the results across the studies is hard to be identified.

The Paris Agreement[15] defines a long-term temperature goal for international climate policy: "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels". Accordingly, many studies exploring the stringent climate change mitigation policies required by the Paris objectives have identified a potential need for large-scale land based measures like afforestation and bioenergy production, which in turn raises concerns about potential implications for food security[16, 17, 18, 19, 20]. These low emissions scenarios are making the connection between SDG2 and SDG13 increasingly crucial.

Integrated Assessment Models (IAMs) have been used for climate mitigation analysis, with many climate mitigation studies conducted under Multi-model Inter-comparisons Projects (MIPs) that have a major role to understand the robustness of the implications and uncertainty[21]. The model behavior responding to the climate mitigation goal typically finds agreement across models in some variable, such as emissions trajectories or carbon budgets, while other variables vary largely across models, such as carbon prices.

Here we explore how food security could be affected by the climate mitigation policies implemented by multi-IAMs. The primary goal of this paper is to understand the relationship between food security and climate mitigation, and to identify cost estimates of possible solutions to the trade-off between food security and climate mitigation, with consideration of the "uncertainty" represented by an ensemble of IAMs. We consider four scenarios differentiated by the stringency of mitigation levels related to the Paris Agreement: no climate policy that includes currently implemented policies (Baseline), greenhouse gas (GHG) emissions reductions by 2030 in line with the Nationally Determined Contributions (NDC), and scenarios that limit global mean temperature in 2100 to below 2°C and 1.5°C, where the emission reduction starts from 2020. Global cumulative CO_2 emissions are targeted for these scenarios and more detailed assumptions of these scenarios are described in the method section. To explore the uncertainty range, we employ six state-of-the-art IAMs that represent energy, agriculture, land-use systems and their emissions. The six models are AIM[22], IMAGE[23], MESSAGE-GLOBIOM[24], REMIND-MAgPIE[25], POLES[26] and WITCH[27]. The description of each model is provided in the method section. All models apply a uniform carbon price, where the agricultural sector is included in the carbon pricing scheme. Besides IMAGE, all models assume land use competition among food, bioenergy crops and afforestation. IMAGE assumes avoided deforestation policy in competition with the food system, while bio-energy does not compete with food production following a food-first policy. Since REMIND-MAgPIE in turn assumes no demand-reaction to food prices shocks and is therefore only included for the baseline scenarios. The representation of the interaction among energy, agriculture and land use varies across IAMs, as shown in Supplementary Table 1. There are three major factors by which climate change mitigation influences food security: increases in land rent or production costs associated with bioenergy crops; non-CO_2 emissions abatement costs; and the equivalent carbon price cost of the residual non-CO_2 emissions that are emitted even after reduction measures are implemented, as depicted in Supplementary Figure 1. The carbon price on GHG emissions from agricultural sectors is assumed to be capped at \$200/tCO_2. This avoids a situation in which further reduction in non-CO_2 emissions requires a decrease in demand for agricultural products. MESSAGE, POLES, and WITCH implemented this cap for all GHG emissions related to agriculture and land use (e.g. forestry and land-use change)[28]. In any case, this capping of the carbon price implies that at most our results can be as a lower bound of the potential impact of mitigation policies on food security. Note that direct impacts of climate change on yields are not assessed in this study and the direct benefits of mitigation to avoided yield losses may well be significant (see more discussion in Supplementary Notes 1.3).

We use the number of people at risk of hunger as a primary indicator, which represents the food security prevalence. Two out of six models (AIM and IMAGE) represent the number of people at risk of hunger within their modeling framework, whereas the other models do not. Therefore, we use a "hunger estimation tool", which has been used in previous studies[29, 30, 31] for the four models that do not have a representation of the risk of hunger. This tool assumes log-normal food consumption distribution function for each country, which uses mean calorie consumption, minimum energy requirement and the coefficient of variation (CV) of the food distribution of the dietary energy consumption within countries. Each IAM provides mean calorie consumption for aggregated regions and this tool downscales such geographically aggregated information on a country basis based on the relative change in calorie consumption. For the possible solutions to the potential risk of trade-off between food security and climate mitigation, we show the first-order cost estimates using a back-of-the-envelope calculation, the details of which are explained in the results section and Supporting text. Note that These represent the costs of achieving baseline levels of food security rather than the costs associated with meeting the SDG2 target to eradicate hunger by 2030.

We acknowledge that food security comprises a broad concept that includes four key dimensions: food availability, stability, access, and utilisation. The metric used in this study, risk of hunger, is associated with food availability[32]. In addition, complementary measures, depending on how they are implemented, may influence other aspects of food security, such as the rate of self-sufficiency[14]. However, these additional effects do not fall within the scope of this study.

Results

Risk of hunger projection under the Baseline scenario

The population at risk of hunger in our Baseline scenario is projected to decline over time and decreases by more than two thirds (to 210-250 million; 2.3-2.7% of total population) in 2050 compared to the current level (795 million; 12% of total population) (Figure 1**a**). This declining trend has been observed already over the past two decades. Asia is currently the region that has the largest number of people at risk of hunger, with around 75% of the global population at risk of hunger; however, this share declines fast during the century (Figure 1**c** and Supplementary Figure 2). The other regions show a similar trend except for Africa and the Middle East (dominated by Sub-Sahara). Africa and the Middle East are projected to experience lower income growth and continuous population increases, which puts them under the pressure of risk of food shortage. In 2050, Africa and the Middle East account for more than 45% of the population at risk of hunger (median value across models, Figure 1**b**). The global model uncertainty range in 2050 is large due to this region. Importantly, no model achieves zero hunger (SDG2) by 2030. For the achievement of this goal, either a higher income growth or notably a more equal food consumption distribution within countries is needed.

The per-capita food consumption evolutions vary widely across models, but they tend to increase steadily over time (Figure 1**d**), driven mainly by income growth (See Supplementary Figure 3). This trend is the key driver of the decrease in the number of people at risk of hunger. All models project a continuous increase in food consumption at the global level. In developing regions, growth is stable, while in the OECD a relatively modest increase is observed. IMAGE shows slightly different pathways from other models: the food consumption trend also explains why IMAGE presented a slightly higher risk of hunger in the second half of the century (Figure 1**ac**). The highest increase in calorie consumption can be observed in the Africa and Middle East region where current food consumption level is low (2330 to 2430 kcal/cap/day) and becomes 2690 to 2970 kcal/cap/day in 2050. Asia would also have large food demand increase, by about 400 kcal/cap/day during the earlier part of this century.

Figure 1Number of the population at risk of hunger under the Baseline scenario and food consumption by 2050. Panel **a** *and* **b** *represents global and regional trends and panel* **c** *illustrates regional share of the population at risk of hunger in 2050 (model median value). Panel* **d** *is Food consumption under the Baseline scenario time-series data for total calorie consumption across models. The grey lines in panels* **a** *and* **b** *are historical values. The century scale figure is presented in Supplementary Figure 2.*

Climate change mitigation effect on food security

Climate change mitigation exclusively aimed at attaining the climate goals could generate a risk of negatively impacting food security, and the response of the number of people at risk of hunger to mitigation policies are remarkably amplified by the stringency of mitigation policies (Figure 2): under the 2°C and 1.5°C scenarios, the risk of hunger drastically changes compared to the Baseline and NDC scenarios. The population at risk of hunger under the 2°C and 1.5°C scenarios in 2050 are 280-500 (median: 350; 3.8% of total population) and 310-540 (median: 410; 4.5% of total population) respectively with a large inter-model variation. For example, AIM shows around 290 million at risk of hunger in the Baseline, while 360 and 410 million people are at risk of hunger in the 2°C and 1.5°C scenarios respectively (3.1, 3.9 and 4.5% of total population respectively). MESSAGE-GLOBIOM behaves similarly. WITCH and POLES are the most sensitive models to the mitigation policy, where an additional 250 million people are at risk of hunger under the 2°C and 1.5°C scenarios after 2030. Under both the 2°C and 1.5°C scenarios in almost all models, the carbon price is reached to the carbon price cap for the agricultural sector by 2050. Moreover, the large inter-model variation in carbon prices[33], generates large model uncertainty and substantial overlaps in the output from the 2°C and 1.5°C scenarios (Figure 3**c**).

The spikes in the risk of hunger for the mitigation scenarios occur in 2030-2040 when the carbon price required by the climate targets drastically increases. After that, the declining trends similar to the Baseline trajectories are observed. Yet, the adverse side-effect of climate change mitigation is large and persistent over time (Figure 3 **d**). Asia, Africa and the Middle East show large side-effects. The projections by WITCH and POLES show that the adverse side effect is prominent in Asia (Figure 2**c**).

The risk of hunger response to the mitigation policies are dependent on three factors: the price elasticities of food demand, the carbon price effect on the food price, and the level of the carbon price, which together push the food consumption down (Figure 4**a** and see also Supplementary Figure 1 as an illustration of the logical chain of the mitigation effect on food security). The price elasticity of food demand is quite heterogeneous across models (Figure 4**b**). REMIND-MAgPIE is the extreme case where a zero price elasticity is assumed. MESSAGE-GLOBIOM, POLES, and WITCH show relatively high elasticities leading to a decrease in food demand of up to 20%. The similarity across these three models is partly explained due to the fact that these models use GLOBIOM based input data for their land-use and agricultural representation, which is a simplified version of the full GLOBIOM representation. AIM shows an intermediate food demand elasticity. Regionally, food consumption in high-income countries tends to be relatively inelastic compared to that in low-income countries. This is because wealthier people generally can spend money on expensive food and because of a lower income-effect of the price-shock (Supplementary Figure 4). The agricultural price changes are triggered by carbon prices (Figure 4**c**), which is why we can see a clear correlation between food consumption reduction and carbon prices (Figure 4**d**). However, carbon prices in 2050 diverge across models (Figure 3**d**). AIM, WITCH, IMAGE and POLES show relatively high carbon prices compared to the other models.

The model diversity in the hunger response can be explained by the combination of the price elasticities and carbon prices, which are primary drivers of the hunger response. For example, AIM, which has a modest food price elasticity, but high carbon price, shows an intermediate increase in the risk of hunger (Figure 4**c**). MESSAGE-GLOBIOM's population at risk of hunger is similar to AIM (Figure 2**a**), but the carbon prices is lower and the price elasticities are higher than AIM (Figure 4**c**). WITCH and POLES are cases where both price elasticity and carbon prices are high, and as a result, the largest negative hunger effect occurs in the mitigation scenarios (Figure 4**a**).

The drivers of agricultural price changes differ across models, but one common characteristic is the non-CO_2 emissions reduction measure and its carbon price penalty. The non-CO_2 emissions can be mitigated when carbon prices are implemented in the agricultural sector, but cannot be entirely removed (Figure 3**bc**). So, in addition to cost of mitigation measures, the price burden of the residual emissions is passed through to the consumers. This carbon price penalty effect drastically changes food price under particularly stringent mitigation scenarios.

The other possible driver of price changes is the land use competition between food, bioenergy crops and afforestation (Supplementary Figure 7 and 8). Although we cannot identify numerically the magnitude of their contributions, there is a literature that finds that the land rent and non-CO_2 emissions effect are of similar magnitude[7]. We can illustrate the magnitude of this effect in the example from AIM (Supplementary Figure 9). The multi-sector Computable General Equilibrium (CGE) model AIM incorporates other goods, service prices, and wage change effects, but those factors are not large (Supplementary Figure 9). AIM also identifies an income loss effect that accounts for around 20% of food demand decreases.

Figure 2 Number of the population at risk of hunger under the Baseline and mitigation scenarios a) time series and b) in 2050. The solid line in panel a) indicates median value across the models and the shaded area represents upper and lower ranges of the model estimates for each scenario. c) indicates the regional risk of hunger across models and scenarios in 2050.

*Figure 3 Global CO_2,$CH_4$and N_2Oemissions across scenarios (***a**, **b**, *and* **c***) and carbon price* **d** *until 2050 (full century figure is shown in Supplementary Figure 5).*

Figure 4 Food consumption, agricultural price, and carbon price relationships. Panel **a** *presents food consumption reduction rates compared to the Baseline scenarios in 2050. Panel* **b**, **c**, *and* **d** *illustrate the relationship between food consumption reduction rates compared to the Baseline scenarios, agricultural price increase relative to the base year and carbon prices across models and mitigation scenarios. The dots in Panel* **b**, **c**, *and* **d** *represent* ***each*** *ten year's value. Food demand reduction is accounted for as calorie basis. The lines in panel* **b** *indicate 0.1 and 0.2 price elasticities of agricultural demand.*

Cost estimates to avoid the adverse side effects

This section examine the cost estimates that could potentially avoid the adverse side-effects to food security due to climate change mitigation. We compute three cost metrics that can be interpreted as : 1) an agricultural subsidy to keep the agricultural price during mitigation at the same price as the Baseline scenario, 2) food-aid to supplement the reduction of agricultural demand, and 3) food-aid to supplement the reduction of agricultural demand "only" for those at risk of hunger. The agricultural subsidy cost is computed by the agricultural price index in mitigation scenarios difference compared to baseline scenario multiplied by the agricultural demand. The food-aid cost is calculated by the agricultural demand decrease in the mitigation scenarios compared to the Baseline scenario multiplied by its price (Supplementary Figure 10). The third metric is direct food-aid cost only for those who are at risk of hunger under the climate mitigation scenario, which is shown in Supplementary Figure 11. All complementary costs were derived by a back-of-the-envelope calculation based on the model outputs. These are the amounts of gross subsidies or food-aid payments that need to be delivered by the public sector.

To the price increase, the required agricultural subsidy is found to be around 0.63 (0.19 to 2.0) % of global GDP for 1.5°C scenario in the year 2050 (Figure 5**a**). At 2°C, the cost decreases to 0.51 (0.00 to 1.3)%. REMIND-MAgPIE shows the largest cost which is comparable with the mitigation policy cost (Figure 5**d**). REMIND-MAgPIE assumes a zero food demand elasticity and the price change is therefore the only mechanism to adjust the market. The cost computed by the other models is not as large as the mitigation policy cost. WITCH has a remarkably high climate change mitigation costs and a relatively low food policy costs.

The alternative measure to a subsidy is direct food aid to supplement the food deficit. In contrast to the agricultural subsidy, food-aid is much smaller in cost and the differences between 2 and 1.5°C are small in absolute term (Figure 5**be**). About 0.19 (0.00-0.46)% of GDP is needed in the 1.5°C scenario in 2050 compared to 0.12 (0.00-0.39)% of GDP in the 2°C scenario. These results show that direct food-aid could be much cheaper than subsidizing agricultural goods to reduce the price impacts. This can be explained by the price elasticity of agricultural demand which is much less than -1 (around -0.2 in Figure 4**b**) and therefore direct aid would be much more efficient than relying on a subsidy (as illustrated in Supplementary Figure 10). Furthermore, if only people who are at risk of hunger are aided, the cost is only 0.01% of GDP with an inter-model variation of 0.00-0.03%, which is even smaller. However, it should also be noted that food-aid for only those at risk of hunger would require a potentially sophisticated mechanism for implementation, such that the government could identify who is at risk of hunger. In that sense, the food-aid cost should be interpreted as a minimum cost and an additional opportunity and implementation cost would be required. Moreover, the net social cost of these policy interventions is not as large as reported here, with the deadweight loss illustrated in Supplementary Figure 12. To understand the order of magnitude of differences between welfare changes and these policy costs, we ran an additional scenario in AIM to obtain the point marked deadweight loss in Supplementary Figure 12. Consequently, the welfare changes in 1.5 and 2 °C scenarios were 20% and 4% of the food-aid respectively or 3.1% and 0.5% of the food subsidy respectively, which are roughly 0.04% and 0.006% of GDP.

To explore the robustness of this finding to the key mode assumptions, we carried out a sensitivity analysis by changing the food demand parametrization of each model including food price and income elasticities (see Supplementary Notes). The people at risk of hunger and food policy costs show similar trends to the original default scenarios (as is shown in Supplementary Figure 13), which indicates that our qualitative findings are robust to the food demand related parameters.

Figure 5 Complementary food policy cost compared to the mitigation cost. Panel **a** *and* **d** *show an additional agricultural subsidy in the mitigation scenarios. The 2050 plots are highlighted by big markers. Panels* **b** *and* **e** *illustrate food-aid which is derived from the agricultural demand decrease in the mitigation scenarios compared to the baseline scenario multiplied 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 in panels* **d, e,** *and* **f** *are the policy cost variable, which depends on the model (GDP loss is used for AIM, MESSAGE-GLOBIOM, REMIND-MAgPIE and WITCH. The area under MAC curve is used for IMAGE and POLES). The solid line 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.*

Discussion and conclusion

We find that climate mitigation could potentially have adverse side-effects on food security. The magnitude of this adverse side-effect is amplified by the stringency of the mitigation level. These phenomena are robustly observed by multiple IAMs. Moreover, we identified the cost of alternative illustrative complementary policy that simultaneously meet the climate goal and, at the same time, ensuring food security. Such policy, in the form of a subsidy or food-aid program in addition to the climate change mitigation effort by developed countries, would target the decrease in the number of people at risk of hunger in developing regions.

When it comes to the relationship of multi-SDG concerning with climate change mitigation, goals related to air pollution[34] and energy security[35] seem to have a synergy effects with climate mitigation. The reduction of fossil fuel consumption to mitigate climate change also lowers air pollution[36, 37]. Shifting from fossil fuels to renewable energy decreases the reliance on oil and gas imports, which also benefits energy security[35, 37]. However, food security, similarly to energy access[38], would have trade-off relationship.

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

price applied to agricultural non-CO_2 emissions can change food consumption amounts[46]; thus, how mitigation policies are implemented in the agricultural sector can impact food security.

There are some caveats and limitations of this study. The model uncertainty shown in this article sheds light on the drivers of uncertainty in the assessment of the population at risk of hunger. This uncertainty is generated by two main factors: carbon prices and food demand price elasticity. There have been some studies of agricultural economic MIPs to see the uncertainty among the models[47, 48, 49, 50]. Notably, it might be necessary to focus more attention on the price and income elasticities of food demand since this study is the first study focusing on the multi-model agricultural outcomes with the extremely high carbon prices. In the analysis, we did not include the effect of climate change impacts, but they should be explored with the consideration of extreme events. We believe that this study would be a milestone for further studies (Supplementary Note 4)

Method

Overall methodology

We use six IAMs which sufficiently represent energy, emissions, land use and agriculture to assess the interaction between climate mitigation and food security. Note that to investigate the agriculture and food security implications associated with climate change mitigation targets, we need models that are somehow consistently able to capture the interaction of energy, agriculture and land-use markets, which means the IAMs used in this study are suitable for our purposes. Importantly, each model has its own strengths and weaknesses, although the agricultural representations in some models are not very detailed. However, the hunger estimation tool bridges this gap, which enables us to deal with the model uncertainty and derive robust conclusions. Four representative scenarios are examined which differentiate the stringency of climate mitigation. As a metric of food security, a number of people at risk of hunger is implemented, which is calculated either within IAMs (AIM and IMAGE) or a hunger estimation tool. Here we describe 1) a brief model overview for each IAM (a summary is in Supporting Information Supplementary Table 2 and model scope is in Supplementary Table 3), 2) scenario definition, and 3) hunger tool description.

The relationship between model inputs and outputs is illustrated in Supplementary Figure 1 (similar to Hall et al.[51] for global circulation models). Model structures and assumptions strongly influence predictions of increases and decreases in non-CO_2 emissions associated with bioenergy use Supplementary Figure 1. The amount of bioenergy depends on the energy system, particularly those in which technological costs (e.g. cost of biomass-power generation) and model types (e.g. linear least-cost optimisation, non-linear substitution functions)[52] are the main factors. The emission of non-CO_2 gases depends on the marginal abatement cost curves used in each IAM[28, 46]. Finally, food demand responses to price changes are determined by price elasticity (Figure 4).

Model description

AIM/CGE[22] is a one-year-step recursive-type dynamic general equilibrium model that covers all regions of the world. The AIM/CGE model includes 17 regions and 42 industrial classifications. For appropriate assessment of bioenergy and land use competition, agricultural sectors are also highly disaggregated[53]. Details of the model structure and mathematical formulae are described by Fujimori, Masui [54]. The production sectors are assumed to maximize profits under multi-nested constant elasticity substitution (CES) functions and each input price. Energy transformation sectors input energy and value-added are fixed coefficients of output. They are treated in this manner to deal with energy conversion efficiency appropriately in the energy transformation sectors. Power generation values from several energy sources are combined with a Logit function. This functional form was used to ensure energy balance because the CES function does not guarantee an energy balance. Household expenditures on each commodity are described by a linear expenditure system function. The parameters adopted in the linear expenditure system function are recursively updated by income elasticity assumptions[29]. Land use is determined by Logit selection[55]. In addition to energy-related CO_2, CO_2 from other sources, CH_4, N_2O, and fluorinated gases (F-gases) are treated as GHGs in the model. Energy-related emissions are associated with fossil fuel feedstock use. The non-energy-related CO_2 emissions consist of land use change and industrial processes. Land use change emissions are derived from the forest area change relative to the previous year multiplied by the carbon stock density, which is differentiated by AEZs (Global Agro-Ecological Zones). Non-energy-related emissions other than land use change emissions are assumed to be in proportion to the level of each activity (such as output). CH_4 has a range of sources, mainly the rice production, livestock, fossil fuel mining, and waste management sectors. N_2O is emitted as a result of fertilizer application and livestock manure management and by the chemical industry. F-gases are emitted mainly from refrigerants used in air conditioners and cooling devices in the industry. Air pollutant gases (BC, CO, NH_3, NMVOC, NO_X, OC, SO_2) are also associated with fuel combustion and activity levels. Emissions factors change over time with the implementation of air pollutant removal technologies and relevant legislation.

IMAGE 3.0 is a comprehensive integrated assessment framework, modelling interacting human and natural systems[56]. The framework comprises a number of sub-models describing land use, agricultural economy, the energy system, natural vegetation, hydrology, and the climate system. The sub-models operate at different spatial resolutions. The socio-economic components work at the level of 26 regions while the environmental components work at the grid level to take into account heterogeneities in environmental circumstances. Interaction between the models takes place through upscaling and downscaling algorithms.
Land use and crop production are spatially explicitly modelled on a 5 minute grid in the IMAGE-LandManagement model using an empirical land-use allocation algorithm. Livestock systems are modelled on 26 regions for intensive and extensive systems. Data on demand for agricultural production and intensification/extensification of the agricultural sector is provided by the agricultural economy model MAGNET: a multi-regional, multi-sectoral, applied general equilibrium model [57] based on neo-classical microeconomic theory which is an extension of the standard GTAP model. The core of MAGNET is an input–output model, which links industries in value added chains from primary goods to final goods and services for consumption. Input and output prices are endogenously determined by the markets to achieve supply and demand equilibrium. The agricultural sector is represented in high detail compared to standard CGE models. Developments in productivity are driven by a combination of assumptions on autonomous technological change provided by IMAGE-LandManagement and by economic processes as modelled by MAGNET (i.e. substitution between production factors). Land is modelled as an explicit production factor described by a land supply curve, constructed with land availability data provided by IMAGE-LandManagement.
The energy system is modelled for 12 primary energy carriers by the energy simulation model TIMER. The TIMER model determines demand for bioenergy production which is implemented in IMAGE-LandManagement following a food-first policy preventing competition with food production. The dynamic global vegetation model LPJmL is dynamically coupled to IMAGE-LandManagement to model the carbon and hydrological cycles and provides spatial explicit information on potential crop yields. An implementation of the simple climate model MAGICC is used to calculate climate change based on GHG emissions calculated by IMAGE-LandManagement and TIMER.
Climate change mitigation policy is modelled by the FAIR-SimCAP model which uses carbon prices and marginal abatement cost curves (MACs) representing costs of mitigation actions to determine a cost optimal emission pathway. Technical mitigation of non-CO_2 GHG emissions from agricultural is based on Lucas et al[58]. The residual emissions are taxed in MAGNET. The costs of technical mitigation are also implemented as part of the tax. Avoided deforestation policy (e.g. REDD) is calibrated to the carbon tax of FAIR-SimCAP and implemented in MAGNET through reduced land availability.

MESSAGEix-GLOBIOM integrates the energy engineering model MESSAGE with the land-use model GLOBIOM via soft-linkage into a global integrated assessment modeling framework[24].

MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) is a linear programming (LP) energy engineering model with global coverage. As a systems engineering optimization model, MESSAGE is primarily used for medium- to long-term energy system planning, energy policy analysis, and scenario development. The model provides a framework for representing an energy system with all its interdependencies from resource extraction, imports and exports, conversion, transport, and distribution, to the provision of energy end-use services such as light, space conditioning, industrial production processes, and transportation. To assess economic implications and to capture economic feedbacks of climate and energy policies, MESSAGE is linked to the aggregated macro-economic model MACRO[59].
Land-use dynamics are modelled with the GLOBIOM (GLobal BIOsphere Management) model, which is a partial-equilibrium model[12]. GLOBIOM represents the competition between different land-use based activities. It includes a detailed representation of the agricultural, forestry and bio-energy sector, which allows for the inclusion of detailed grid-cell information on biophysical constraints and technological costs, as well as a rich set of environmental parameters, incl. comprehensive AFOLU (agriculture, forestry and other land use) GHG emission accounts and irrigation water use. For spatially explicit projections of the change in afforestation, deforestation, forest management, and their related CO_2 emissions, GLOBIOM is coupled with the G4M (Global FORest Model) model[60]. As outputs, G4M provides estimates of forest area change, carbon uptake and release by forests, and supply of biomass for bioenergy and timber.
MESSAGE-GLOBIOM covers all greenhouse gas (GHG)-emitting sectors, including energy, industrial processes as well as agriculture and forestry. The emissions of the full basket of greenhouse gases including CO_2, CH4, N2O and F-gases (CF4, C2F6, HFC125, HFC134a, HFC143a, HFC227ea, HFC245ca and SF6) as well as other radiatively active substances, such as NOx, volatile organic compounds (VOCs), CO, SO_2, and BC/OC is represented in the model. MESSAGE-GLOBIOM is used in conjunction with MAGICC (Model for Greenhouse gas Induced Climate Change) version 6.8 (Ref.[61]) for calculating atmospheric concentrations, radiative forcing, and annual-mean global surface air temperature increase.

The **POLES** (Prospective Outlook on Long-term Energy System) model is a global partial equilibrium simulation model of the energy sector with an annual step, covering 38 regions world-wide (G20, OECD, principal energy consumers) plus the EU. The model covers 15 fuel supply branches, 30 technologies in power production, 6 in transformation, 15 final demand sectors and corresponding greenhouse gas emissions. GDP is an exogenous input of the model, while endogenous resource prices, endogenous global technological progress in electricity generation technologies and price induced lagged adjustments of energy supply and demand are important features of the model. Mitigation policies are implemented by introducing carbon prices up to the level where emission reduction targets are met: carbon prices affect the average energy prices, inducing energy efficiency responses on the demand side, and the relative prices of different fuels and technologies, leading to adjustments on both the demand side (e.g. fuel switch) and the supply side (e.g. investments in renewables). Non-CO_2 emissions in energy and industry are endogenously modelled with potentials derived from literature (marginal abatement cost curves). Projections for agriculture, LULUCF emissions and food indicators are derived from the GLOBIOM model (dynamic look-up of emissions depending on climate policy and biomass-energy use), calibrated on historical emissions and food demand (from UNFCCC, EDGAR and FAO). A full documentation of POLES is available at http://ec.europa.eu/jrc/poles and report[62].

REMIND-MAgPIE models the global energy-economy-climate system for 11 world regions and for the time horizon until 2100. For the present study, REMIND in its version 1.7 was used. REMIND represents five individual countries and six aggregated regions formed by the remaining countries. For each region, intertemporal welfare is optimized based on a Ramsey-type macro-economic growth model. The model explicitly represents trade in final goods, primary energy carriers, and in the case of climate policy, emission allowances and computes simultaneous and intertemporal market equilibria based on an iterative procedure. Macro-economic production factors are capital, labor, and final energy. REMIND uses economic output for investments in the macro-economic capital stock as well as consumption, trade, and energy system expenditures.

MAgPIE (Model of Agricultural Production and Its Impacts on the Environment) [17, 63] is a global partial equilibrium agro−economic model that operates on a spatially explicit scale, where local biophysical conditions (crop yield, water availability, and terrestrial carbon content) influence decision making for optimal agricultural production patterns. The objective function is the costs of global agricultural supply, which are minimized such that the demand for agricultural products is fulfilled. Agricultural demand is aggregated at the level of ten MAgPIE defined geo-economic regions. Food demand is exogenously calculated, based on an econometric regression model that projects per capita caloric consumption on a national level, considering historical patterns and socio−economic assumption of future growth in population and income[64]. The demand implementation accounts for the long-term income effect on agricultural consumption, but the model is limited with respect to representing short-term demand adjustments to changes in prices. Material demand is assumed to be proportional to total food demand. Agricultural demand in addition comprises demand for animal feed (feed crops, fodder, grazed biomass) calculated based on feed baskets content. Regional agricultural supply is endogenously determined based on costs of production and spatially explicit agricultural productivity levels. The costs account for input factors of production, transport, and investment costs for conversion of other land types into arable land, irrigation infrastructure, and yield-increasing technological progress [65](Input of local biophysical conditions (land, water, terrestrial carbon) and crop yields is provided on the gridded resolution (0.5° × 0.5° geographic longitude−latitude) from the global crop model LPJmL (Lund−Potsdam−Jena model with managed Land). MAgPIE estimates flows of CO_2, CH_4, and nitrogen (N) related emissions[66]. CO_2 emissions are computed from land-use change dynamics, i.e. from conversion of different biomes into agricultural land and consequent loss of terrestrial carbon stocks. Land conversion into cropland can occur from pasture, forest (pristine and unmanaged), and other natural vegetation (e.g., savannahs, shrublands) land pools. The reduction of GHGs is incentivized by an imposed price (tax). In the case of CO_2 emissions, the price serves as an incentive to restrain land-use conversion and consequent carbon release. Reduction of CH_4 and N emissions is possible by applying technical mitigation at additional cost, also triggered by an emission price.

WITCH-GLOBIOM (World Induced Technical Change Hybrid) is an integrated assessment model designed to assess climate change mitigation and adaptation policies. It is developed and maintained at the Fondazione Eni Enrico Mattei and the Centro Euro-Mediterraneo sui Cambiamenti Climatici. WITCH-GLOBIOM is of a global dynamic model that integrates into a unified framework the most important drivers of climate change. An inter-temporal optimal growth model captures the long-term economic growth dynamics. A compact representation of the energy sector is fully integrated (hard linked) with the rest of the economy so that energy investments and resources are chosen optimally, together with the other macroeconomic variables.

WITCH-GLOBIOM represents the world in a set of a varying number of macro regions – for the present study, the version with thirteen representative native regions has been used; for each, it generates the optimal mitigation strategy for the long-term (from 2005 to 2100) as a response to external constraints on emissions. A modelling mechanism aggregates the national policies on emission reduction or the energy mix into the WITCH regions. Finally, a distinguishing feature of WITCH is the endogenous representation of R&D diffusion and innovation processes that allows a description of how R&D investments in energy efficiency and carbon-free technologies integrate the mitigation options currently available. Non-CO_2 emissions in energy and industry are endogenously modelled with potentials derived from literature (marginal abatement cost curves). Projections for agriculture, LULUCF emissions and food indicators are derived from the GLOBIOM model (dynamic look-up of emissions depending on climate policy and biomass-energy use), calibrated on historical emissions and food demand (from UNFCCC, FAO and EDGAR).
For this study, WITCH 2016 has been used; key publications describing the model are Refs.[27, 67], and a full documentation is available at http://doc.witchmodel.org/.

Scenario definition

We employed four scenarios in this study as listed below:

(1) Baseline

It does not include climate policy but currently planned non-climate policy such as energy policies.

(2) NDC

Currently planned policies + NDCs are reflected. Thus, the emissions meet the NDC targets for 2025 and 2030. After 2030, the same emissions reduction effort by 2030 is assumed.

(3) 2°C

Currently planned policies + Cost effective mitigation pathway with global cumulative CO_2 emissions constraint as 1000 $GtCO_2$ from 2011 to 2100 is adopted. This level of mitigation efforts likely (>66% change) enables the global mean temperature staying below 2 °C. The emission reduction starts from 2020.

(4) 1.5°C

Currently planned policies + Cost effective mitigation pathway with global cumulative CO_2 emissions constraint as 400$GtCO_2$ from 2011 to 2100 is adopted. This level of mitigation efforts enables the global mean temperature staying below 2 °C by roughly 50%. The emission reduction starts from 2020.

The estimation method of number of people at risk of hunger

In principle, the risk of hunger can be calculated by referring to the mean calorie consumption, which is the same approach as in AIM and IMAGE. Moreover, GLOBIOM recently released a publication quantifying the number of people at risk of hunger[13], with its emulator now used by three IAMs (MESSAGE-GLOBIOM, POLES and WITCH-GLOBIOM). MAgPIE is also well known among the agricultural economic models that have been applied in this research field. Therefore, the combination of the IAMs and the hunger estimation tool were sufficient for our purposes, i.e. to represent agricultural and land use changes.

The narrow definition of undernourishment or hunger is a state of energy (calorie) deprivation lasting over one year; this does not include the short-lived effects of temporary crises [68, 69]. Furthermore, this does not include inadequate intake of other essential nutrients [68]. The population at risk of hunger is a proportion of the total population and is calculated using Eq. 1.

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

where,

t : year

$Risk_t$: 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 [−]

According to the Food and Agriculture Organization (FAO) methodology [70], the proportion of the population at risk of hunger is defined using Eqs. 2 to 4. With the FAO methodology, the proportion is calculated using three parameters: the mean food calorie consumption per person per day (*cal*), the mean minimum dietary energy requirement (*M*), and the coefficient of variation of the food distribution of the dietary energy consumption in a country (*CV*). The food distribution within a country is assumed to follow a log normal distribution. The proportion of the population under the mean minimum dietary energy requirement (*M*) is defined as the proportion of the population at risk of hunger. The log normal distribution has two parameters, the mean μ_t and the variance σ_t, as in Eq. 2. The parameters $\mu_{t,}$ and σ_t can be represented using the mean food calorie consumption per person per day (*cal*) and the coefficient of variation of the domestic distribution of dietary energy consumption (*CV*) as Eqs. 3 and 4.

Each IAM reports the mean food calorie consumption per person per day (*cal*). We standardize the base year calorie consumption to what FAO reports and take the change ratio of each year to the base year for IAMs. We then compute the standardized calorie consumption to make a consistent number for those at risk of hunger. In this process, since the IAM's are regionally aggregated values, they are downscaled to the individual country level by taking the base year value reported FAO and future change ratio from IAMs. The *CV* is an indicator of food security observed in a household survey conducted by the FAO. It ranges from 0 to 1. FAO country data for CV are weighted on the basis of population data in the base year and aggregated to regional classification to obtain the CV of aggregated regions. The CV is changed over time with the consideration of income growth dynamics as presented in Hasegawa et al.[29]. Note that there is an assumption that the future CV changes of each region are based on the current regional values.

$$PoU_t = \Phi\left(\left. \log M_t - \mu(cal_t, \sigma_t) \middle/ \sigma_t \right. \right) \quad \text{(Eq. 2)}$$

$$\mu(cal_t, \sigma_t) = \log_e cal_t - \sigma_t^2 / 2 \quad \text{(Eq. 3)}$$

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

where,

M_t : mean minimum dietary energy requirement in year t

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

The mean minimum dietary energy requirement (*M*) is calculated for each year and country by using the mean minimum dietary energy requirement in the base year at the country level [71, 72, 73] and an adjustment coefficient for the minimum energy requirements per person in different age and sex groups [72] and the population of each age and sex group in each year [73], as in Eqs. 5 and 6.

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

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

where,
i: age group;
j: sex;
Mbase: mean minimum dietary energy requirement per person in the base year;
MER_t: Mean adjustment coefficient of minimum energy requirements per person in year *t*;
MER_{base}: Mean adjustment coefficient of the minimum energy requirements per person in the base year;
$RMER_{i,j}$: Adjustment coefficient for the minimum energy requirements per person of age *i* and sex *j*;
$Pclass_{i.j,t}$: population of age *i* and sex *j* in year *t.*

Data Availability

Scenario data is accessible online via the CDLINKS Database portal https://db1.ene.iiasa.ac.at/CDLINKSDB.
The data which is derived from the original scenario database shown as figures but not in the above database is available upon requests.

References

1. *Food and Agriculture Organization of the United Nations, (FAO). FAOSTAT. 2016 [cited 2016 9.02]Available from: http://faostat.fao.org/*

2. *FAO I, WFP. The state of food insecurity in the world 2015—Meeting the 2015 international hunger targets: taking stock of uneven progress. FAO, Rome, 56p 2015.*

3. *Parry ML, Rosenzweig C, Iglesias A, Livermore M, Fischer G. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change 2004,* ***14****(1)****:*** *53-67.*

4. *Nelson GC, Rosegrant MW, Amanda P, Gray I, Ingersoll C, Robertson R, et al. Food security, farming, and climate change to 2050, Scenarios, results, policy options. IFPRI, Washington, D. C., USA.; 2010.*

5. *Rosenzweig C, Parry ML. Potential impact of climate change on world food supply. Nature 1994,* ***367****(6459)****:*** *6.*

6. *Hasegawa T, Fujimori S, Shin Y, Takahashi K, Masui T, Tanaka A. Climate Change Impact and Adaptation Assessment on Food Consumption Utilizing a New Scenario Framework. Environmental science & technology 2014,* ***48****(1)****:*** *438-445.*

7. *Hasegawa T, Fujimori S, Shin Y, Tanaka A, Takahashi K, Masui T. Consequence of Climate Mitigation on the Risk of Hunger. Environmental science & technology 2015,* ***49****(12)****:*** *7245-7253.*

8. *Obersteiner M, Walsh B, Frank S, Havlík P, Cantele M, Liu J, et al. Assessing the land resource–food price nexus of the Sustainable Development Goals. Science Advances 2016,* ***2****(9).*

9. *Lotze-Campen H, von Lampe M, Kyle P, Fujimori S, Havlik P, van Meijl H, et al. Impacts of increased bioenergy demand on global food markets: an AgMIP economic model intercomparison. Agricultural Economics 2014,* ***45****(1)****:*** *103-116.*

10. *Stevanović M, Popp A, Bodirsky BL, Humpenöder F, Müller C, Weindl I, et al. Mitigation Strategies for Greenhouse Gas Emissions from Agriculture and Land-Use Change: Consequences for Food Prices. Environmental science & technology 2017,* ***51****(1)****:*** *365-374.*

11. *Springmann M, Mason-D/'Croz D, Robinson S, Wiebe K, Godfray HCJ, Rayner M, et al. Mitigation potential and global health impacts from emissions pricing of food commodities. Nature Clim Change 2017,* ***7****(1)****:*** *69-74.*

12. *Havlík P, Valin H, Herrero M, Obersteiner M, Schmid E, Rufino MC, et al. Climate change mitigation through livestock system transitions. Proceedings of the National Academy of Sciences 2014,* ***111****(10)****:*** *3709-3714.*

13. *Stefan F, Petr H, Jean-François S, Antoine L, Hugo V, Eva W, et al. Reducing greenhouse gas emissions in agriculture without compromising food security? Environmental Research Letters 2017,* ***12****(10)***:** *105004.*

14. *Fujimori S, Hasegawa T, Rogelj J, Su X, Havlik P, Krey V, et al. Inclusive climate change mitigation and food security policy under 1.5 °C climate goal. Environmental Research Letters 2018,* ***13****(7)***:** *074033.*

15. *United Nations Framework Convention on Climate Change, (UNFCCC). Adoption of the Paris Agreement. Proposal by the President (1/CP21). 2015 [cited 2016 02, Feb.]Available from:* http://unfccc.int/resource/docs/2015/cop21/eng/10a01.pdf

16. *Fujimori S, Su X, Liu J-Y, Hasegawa T, Takahashi K, Masui T, et al. Implication of Paris Agreement in the context of long-term climate mitigation goals. SpringerPlus 2016,* ***5****(1)***:** *1-11.*

17. *Popp A, Humpenoder F, Weindl I, Bodirsky BL, Bonsch M, Lotze-Campen H, et al. Land-use protection for climate change mitigation. Nature Clim Change 2014,* ***4****(12)***:** *1095-1098.*

18. *Rose SK, Kriegler E, Bibas R, Calvin K, Popp A, van Vuuren DP, et al. Bioenergy in energy transformation and climate management. Climatic Change 2014,* ***123****(3)***:** *477-493.*

19. *Fuss S, Canadell JG, Peters GP, Tavoni M, Andrew RM, Ciais P, et al. Betting on negative emissions. Nature Clim Change 2014,* ***4****(10)***:** *850-853.*

20. *Reilly J, Melillo J, Cai Y, Kicklighter D, Gurgel A, Paltsev S, et al. Using Land To Mitigate Climate Change: Hitting the Target, Recognizing the Trade-offs. Environmental science & technology 2012,* ***46****(11)***:** *5672-5679.*

21. *Kriegler E, Riahi K, Bauer N, Schwanitz VJ, Petermann N, Bosetti V, et al. Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy. Technological Forecasting and Social Change 2014.*

22. *Fujimori S, Hasegawa T, Masui T, Takahashi K, Herran DS, Dai H, et al. SSP3: AIM implementation of Shared Socioeconomic Pathways. Global Environmental Change 2017,* ***42:*** *268-283.*

23. *van Vuuren DP, Stehfest E, Gernaat DEHJ, Doelman JC, van den Berg M, Harmsen M, et al. Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. Global Environmental Change 2017,* ***42****(Supplement C)***:** *237-250.*

24. *Fricko O, Havlik P, Rogelj J, Klimont Z, Gusti M, Johnson N, et al. The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change 2017,* ***42****(Supplement C)***:** *251-267.*

25. *Kriegler E, Bauer N, Popp A, Humpenöder F, Leimbach M, Strefler J, et al. Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change 2017,* ***42****(Supplement C)****:*** *297-315.*

26. *JRC. POLES: Global Energy Model. 2016 [cited 2017 10, 10]Available from: http://ec.europa.eu/jrc/poles*

27. *Emmerling J, Drouet L, Reis LA, Bevione M, Berger L, Bosetti V, et al. The WITCH 2016 Model-Documentation and Implementation of the Shared Socioeconomic Pathways. 2016.*

28. *Gernaat DEHJ, Calvin K, Lucas PL, Luderer G, Otto SAC, Rao S, et al. Understanding the contribution of non-carbon dioxide gases in deep mitigation scenarios. Global Environmental Change 2015,* ***33****(0)****:*** *142-153.*

29. *Hasegawa T, Fujimori S, Takahashi K, Masui T. Scenarios for the risk of hunger in the twenty-first century using Shared Socioeconomic Pathways. Environmental Research Letters 2015,* ***10****(1)****:*** *014010.*

30. *Hasegawa T, Fujimori S, Takahashi K, Yokohata T, Masui T. Economic implications of climate change impacts on human health through undernourishment. Climatic Change 2016,* ***136:*** *1-14.*

31. *Hasegawa T, Fujimori S, Havlík P, Valin H, Bodirsky BL, Doelman JC, et al. Risk of increased food insecurity under stringent global climate change mitigation policy. Nature Climate Change 2018,* ***8****(8)****:*** *699-703.*

32. *Schmidhuber J, Tubiello FN. Global food security under climate change. Proceedings of the National Academy of Sciences 2007,* ***104****(50)****:*** *19703-19708.*

33. *Rogelj J, Shindell D, Jiang K, Fifita S, Forster P, Ginzburg V, et al. Mitigation pathways compatible with 1.5°C in the context of sustainable development. Special Report on the impacts of global warming of 1.5 °C. Intergovernmental Panel on Climate Change: Geneva, 2018.*

34. *McCollum DL, Krey V, Riahi K. An integrated approach to energy sustainability. Nature Climate Change 2011,* ***1****(9)****:*** *428-429.*

35. *Jewell J, Vinichenko V, McCollum D, Bauer N, Riahi K, Aboumahboub T, et al. Comparison and interactions between the long-term pursuit of energy independence and climate policies. Nature Energy 2016,* ***1:*** *16073.*

36. *van Vuuren DP, Cofala J, Eerens HE, Oostenrijk R, Heyes C, Klimont Z, et al. Exploring the ancillary benefits of the Kyoto Protocol for air pollution in Europe. Energy Policy 2006,* ***34****(4)****:*** *444-460.*

37. *McCollum DL, Krey V, Riahi K, Kolp P, Grubler A, Makowski M, et al. Climate policies can help resolve energy security and air pollution challenges. Climatic Change 2013,* ***119****(2)****:*** *479-494.*

38. *Cameron C, Pachauri S, Rao N, McCollum D, Rogelj J, Riahi K. Policy trade-offs between climate mitigation and clean cook-stove access in South Asia. Nature Energy 2016,* ***1:*** *e15010.*

39. *OECD. OECD Data. Net ODA (Official Development Assistance) 2017 [cited 2017 May]Available from: https://data.oecd.org/oda/net-oda.htm*

40. *Hertel TW, Burke MB, Lobell DB. The poverty implications of climate-induced crop yield changes by 2030. Global Environmental Change 2010,* ***20****(4)****:*** *577-585.*

41. *Zekarias H, Thomas H, Alla G. Climate change mitigation policies and poverty in developing countries. Environmental Research Letters 2013,* ***8****(3)****:*** *035009.*

42. *Grubler A, Wilson C, Bento N, Boza-Kiss B, Krey V, McCollum DL, et al. A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. Nature Energy 2018,* ***3****(6)****:*** *515-527.*

43. *van Vuuren DP, Stehfest E, Gernaat DEHJ, van den Berg M, Bijl DL, de Boer HS, et al. Alternative pathways to the 1.5 °C target reduce the need for negative emission technologies. Nature Climate Change 2018,* ***8****(5)****:*** *391-397.*

44. *Roy J, Tschakert P, Waisman H, Halim SA, Antwi-Agyei P, Dasgupta P, et al. Sustainable Development, Poverty Eradication and Reducing Inequalities. Global Warming of 1.5° c. IPCC: Intergovernmental Panel on Climate Change, 2018.*

45. *Wise M, Calvin K, Thomson A, Clarke L, Bond-Lamberty B, Sands R, et al. Implications of limiting CO2 concentrations for land use and energy. Science 2009,* ***324****(5931)****:*** *1183-1186.*

46. *Frank S, Havlík P, Stehfest E, van Meijl H, Witzke P, Pérez-Domínguez I, et al. Agricultural non-CO2 emission reduction potential in the context of the 1.5 °C target. Nature Climate Change 2019,* ***9****(1)****:*** *66-72.*

47. *von Lampe M, Willenbockel D, Ahammad H, Blanc E, Cai Y, Calvin K, et al. Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison. Agricultural Economics 2014,* ***45****(1)****:*** *3-20.*

48. *Nelson GC, Valin H, Sands RD, Havlík P, Ahammad H, Deryng D, et al. Climate change effects on agriculture: Economic responses to biophysical shocks. Proceedings of the National Academy of Sciences 2014,* ***111****(9)****:*** *3274-3279.*

49. *Keith W, Hermann L-C, Ronald S, Andrzej T, Dominique van der M, Anne B, et al. Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios. Environmental Research Letters 2015,* ***10****(8)****:*** *085010.*

50. *Valin H, Sands RD, van der Mensbrugghe D, Nelson GC, Ahammad H, Blanc E, et al. The future of food demand: understanding differences in global economic models. Agricultural Economics 2014,* ***45****(1)****:*** *51-67.*

51. *Hall A. Projecting regional change. Science 2014,* ***346****(6216)****:*** *1461-1462.*

52. *Krey V, Guo F, Kolp P, Zhou W, Schaeffer R, Awasthy A, et al. Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models. Energy 2018.*

53. *Fujimori S, Hasegawa T, Masui T, Takahashi K. Land use representation in a global CGE model for long-term simulation: CET vs. logit functions. Food Security 2014,* ***6****(5)****:*** *685-699.*

54. *Fujimori S, Masui T, Matsuoka Y. AIM/CGE [basic] manual: Center for Social and Environmental Systems Research, National Institute Environmental Studies; 2012. Report No.: 2012-01.*

55. *Fujimori S, Hasegawa T, Masui T, Takahashi K. Land use representation in a global CGE model for long-term simulation: CET vs. logit functions. Food Secur 2014,* ***6****.*

56. *Stehfest E, van Vuuren D, Bouwman L, Kram T. Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications. Netherlands Environmental Assessment Agency (PBL), 2014.*

57. *Woltjer GB, Kuiper MH. The MAGNET model: Module description. Wageningen: LEI Wageningen UR; 2014.*

58. *Lucas PL, van Vuuren DP, Olivier JGJ, den Elzen MGJ. Long-term reduction potential of non-CO2 greenhouse gases. Environmental Science & Policy 2007,* ***10****(2)****:*** *85-103.*

59. *Messner S, Schrattenholzer L. MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy 2000,* ***25****(3)****:*** *267-282.*

60. *Kindermann GE, Obersteiner M, Rametsteiner E, McCallum I. Predicting the deforestation-trend under different carbon-prices. Carbon Balance and management 2006,* ***1****(1)****:*** *15.*

61. *Meinshausen M, Raper SCB, Wigley TML. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. Atmos Chem Phys 2011,* ***11****(4)****:*** *1417-1456.*

62. *Keramidas K, Kitous A, Després J, Schmitz A. POLES-JRC model documentation: JRC; 2017.*

63. *Lotze-Campen H, Müller C, Bondeau A, Rost S, Popp A, Lucht W. Global food demand, productivity growth, and the scarcity of land and water resources: a spatially explicit mathematical programming approach. Agricultural Economics 2008.*

64. *Bonsch M, Humpenöder F, Popp A, Bodirsky B, Dietrich JP, Rolinski S, et al. Trade-offs between land and water requirements for large-scale bioenergy production. GCB Bioenergy 2016,* ***8****(1)***:*** *11-24.*

65. *Dietrich JP, Schmitz C, Lotze-Campen H, Popp A, Müller C. Forecasting technological change in agriculture—An endogenous implementation in a global land use model. Technological Forecasting and Social Change 2014,* ***81:*** *236-249.*

66. *Bodirsky BL, Popp A, Weindl I, Dietrich JP, Rolinski S, Scheiffele L, et al. N₂O emissions from the global agricultural nitrogen cycle – current state and future scenarios. Biogeosciences 2012,* ***9****(10)***:*** *4169-4197.*

67. *Bosetti V, Carraro C, Galeotti M, Massetti E, Tavoni M. WITCH-A world induced technical change hybrid model. 2006.*

68. *FAO. The State of Food Insecurity in the World 2012 Economic growth is necessary but not sufficient to accelerate reduction of hunger and malnutrition: Rome, Italy, 2012.*

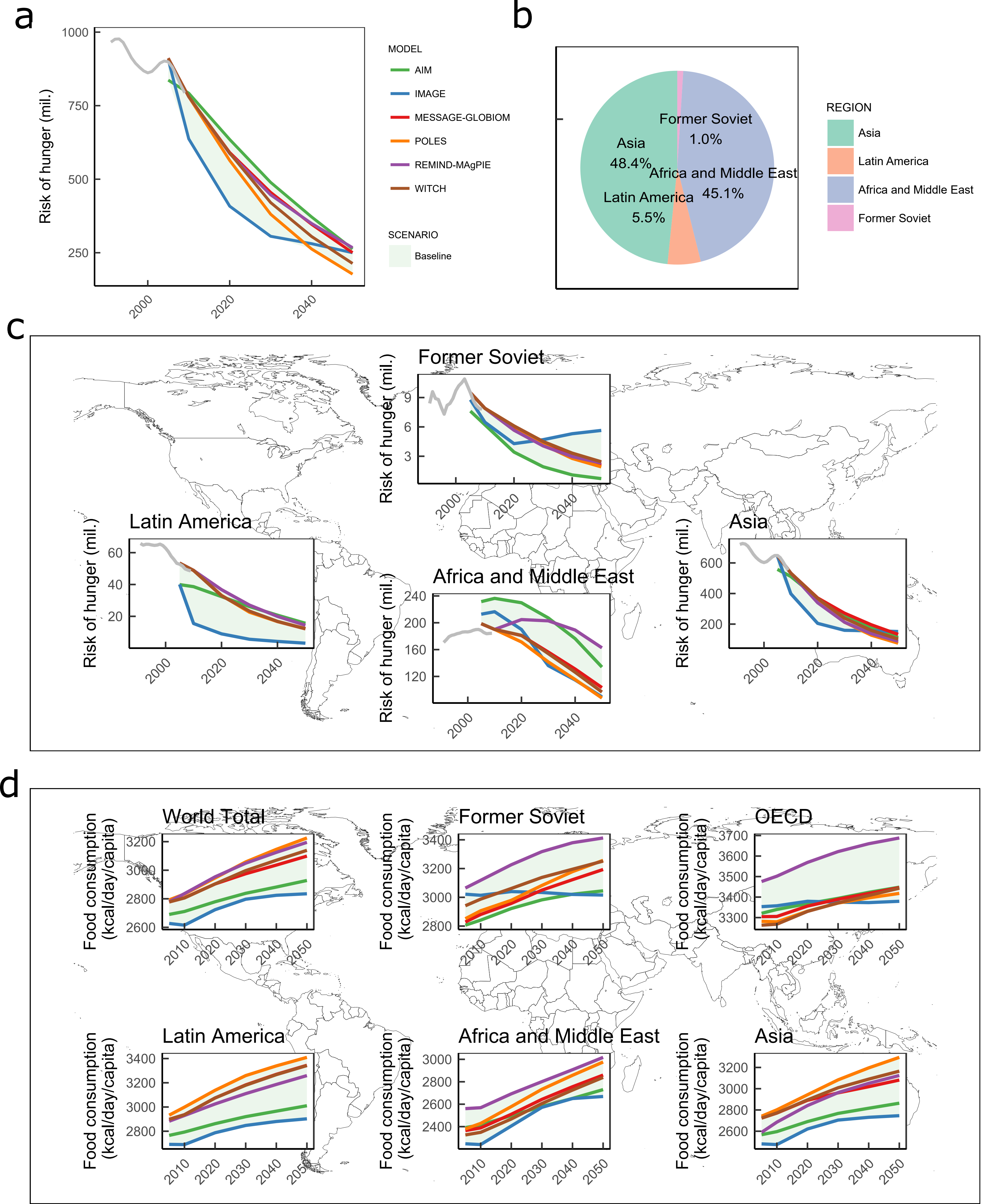
69. *EC-JRC/PBL. Emission Database for Global Atmospheric Research (EDGAR), release version 4.2. 2012 [cited]Available from: http://edgar.jrc.ec.europa.eu*

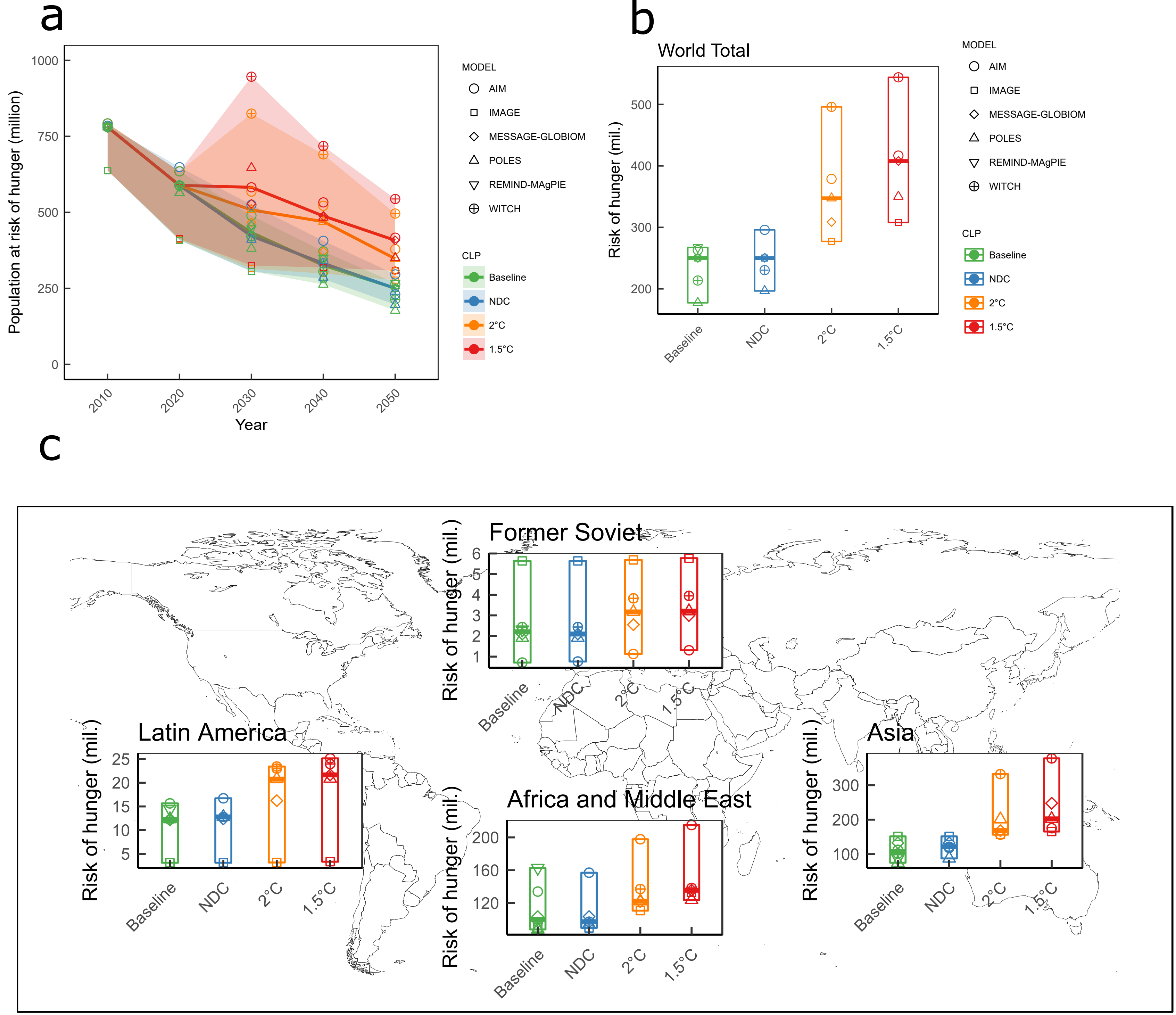
70. *FAO. FAO Methodology for the measurement of food deprivation: updating the minimum dietary energy requirements. Rome: FAO; 2008.*

71. *FAO. Food security indicators. In: FAO, editor. Rome, Italy; 2013.*

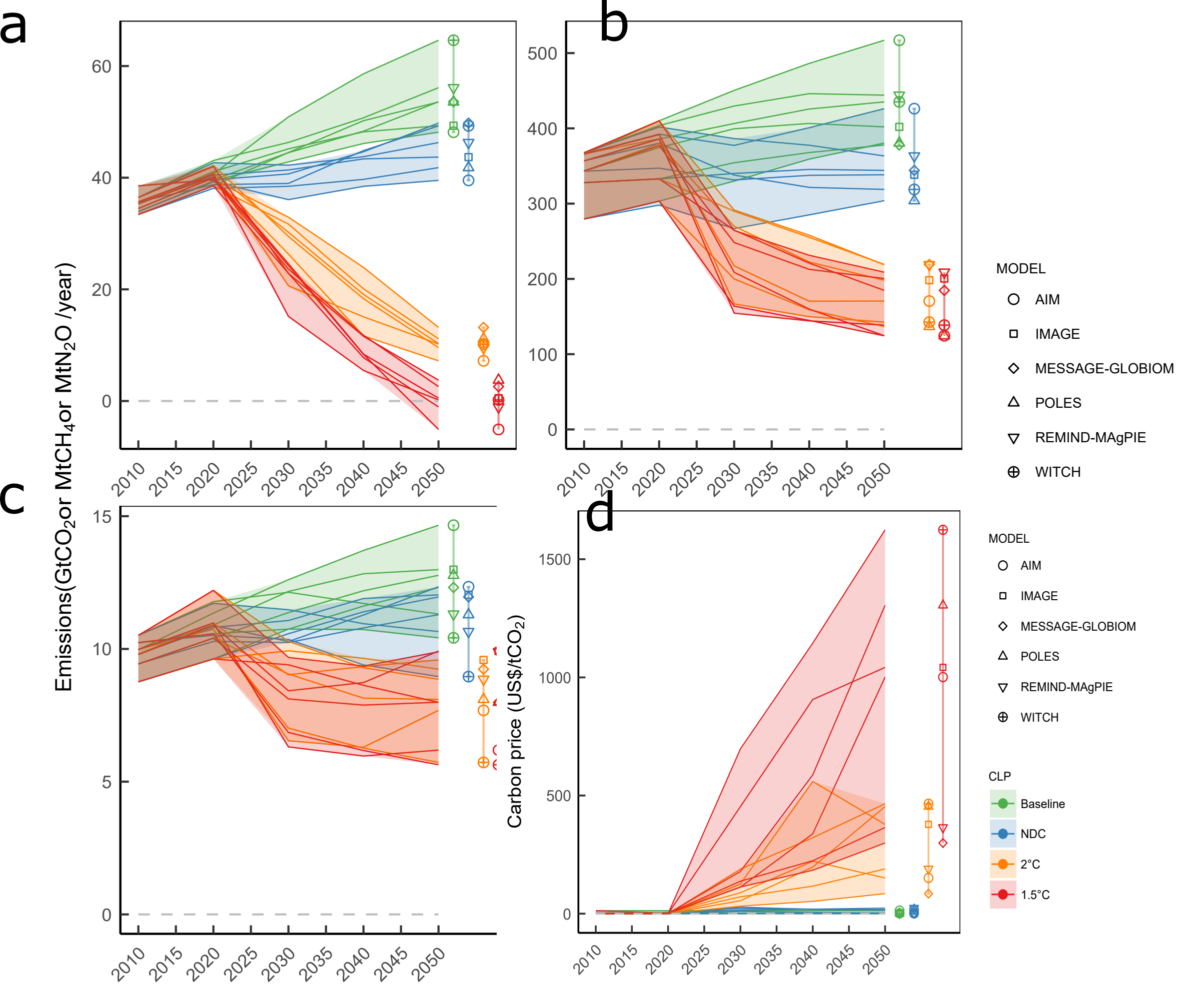
72. *FAO/WHO. Energy and protein requirements. Geneva, Switzerland: FAO/WHO; 1973.*

73. *IIASA. Shared Socioeconomic Pathways (SSP) Database Version 0.9.3.; 2012.*

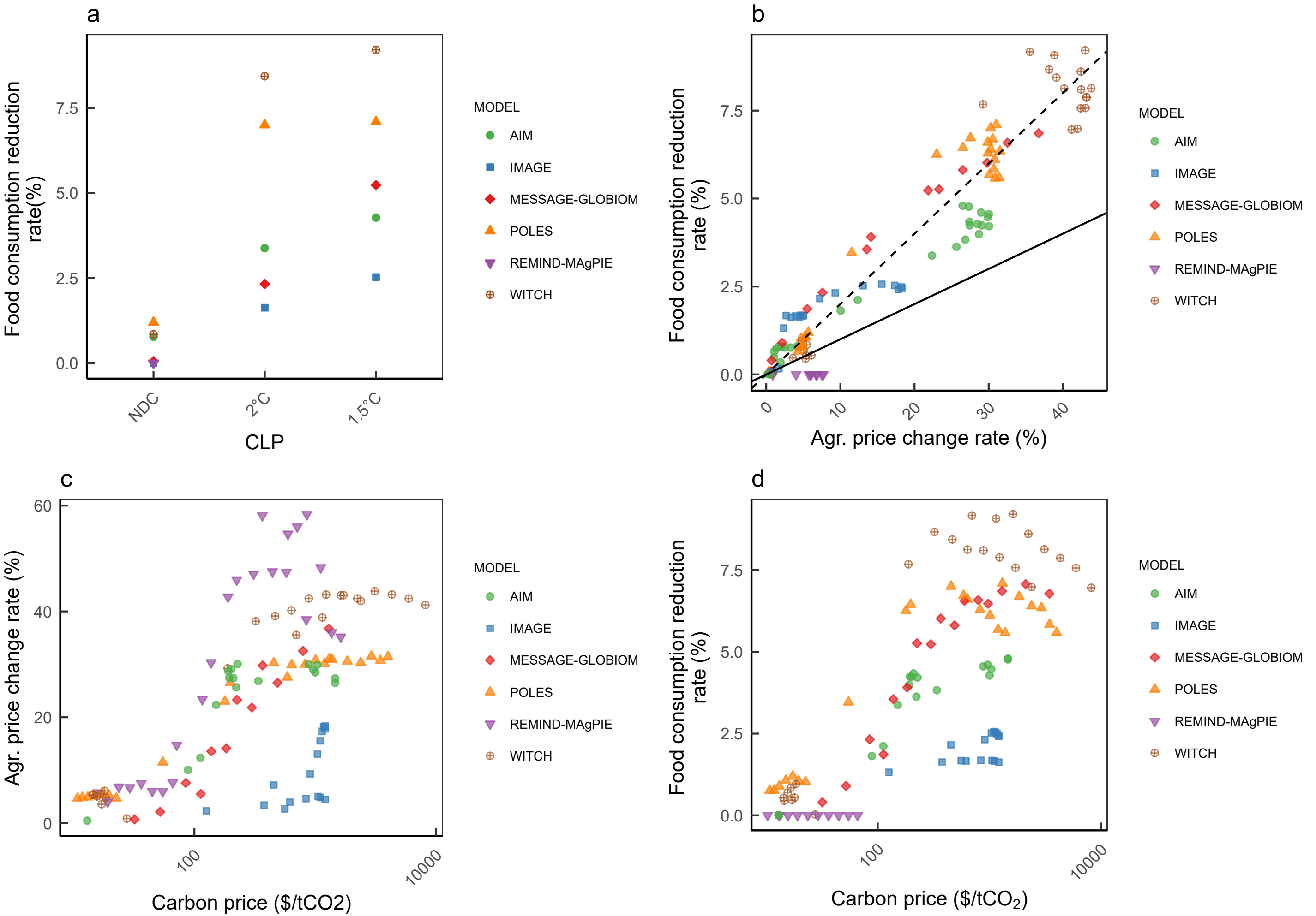

a
Risk of hunger (mil.)
1000
750
500
250
2000
2020
2040
MODEL
AIM
IMAGE
MESSAGE-GLOBIOM
POLES
REMIND-MAgPIE
WITCH
SCENARIO
Baseline
b
Asia 48.4%
Former Soviet 1.0%
Africa and Middle East 45.1%
Latin America 5.5%
REGION
Asia
Latin America
Africa and Middle East
Former Soviet
c
Former Soviet
Latin America
Africa and Middle East
Asia
Risk of hunger (mil.)
d
World Total
Former Soviet
OECD
Latin America
Africa and Middle East
Asia
Food consumption (kcal/day/capita)
2010
2020
2030
2040
2050



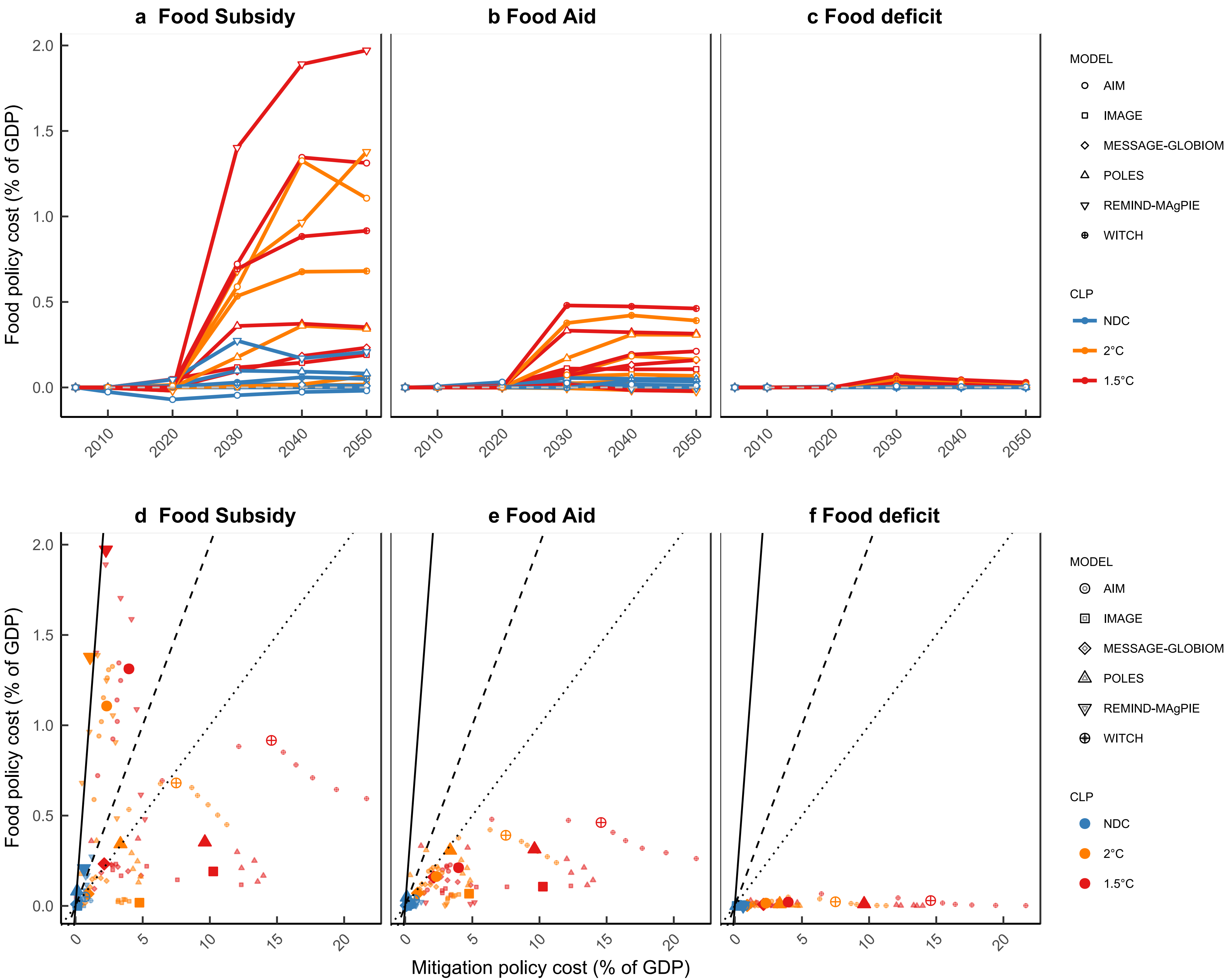
a
Population at risk of hunger (million)
Year
MODEL
AIM
IMAGE
MESSAGE-GLOBIOM
POLES
REMIND-MAgPIE
WITCH
CLP
Baseline
NDC
2°C
1.5°C
b
World Total
Risk of hunger (mil.)
c
Former Soviet
Latin America
Africa and Middle East
Asia



a
b
c
d
Emissions(GtCO$_2$or MtCH$_4$or MtN$_2$O /year)
Carbon price (US$/tCO$_2$)
2010
2015
2020
2025
2030
2035
2040
2045
2050
MODEL
AIM
IMAGE
MESSAGE-GLOBIOM
POLES
REMIND-MAgPIE
WITCH
CLP
Baseline
NDC
2°C
1.5°C



a
Food consumption reduction rate(%)
7.5
5.0
2.5
0.0
NDC
2°C
1.5°C
CLP
MODEL
AIM
IMAGE
MESSAGE-GLOBIOM
POLES
REMIND-MAgPIE
WITCH
b
Food consumption reduction rate (%)
Agr. price change rate (%)
0
10
20
30
40
c
Agr. price change rate (%)
60
40
20
0
100
10000
Carbon price ($/tCO2)
d
Food consumption reduction rate (%)
Carbon price ($/tCO$_2$)


a Food Subsidy
b Food Aid
c Food deficit
Food policy cost (% of GDP)
2.0
1.5
1.0
0.5
0.0
2010
2020
2030
2040
2050
MODEL
AIM
IMAGE
MESSAGE-GLOBIOM
POLES
REMIND-MAgPIE
WITCH
CLP
NDC
2°C
1.5°C
d Food Subsidy
e Food Aid
f Food deficit
0
5
10
15
20
Mitigation policy cost (% of GDP)