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

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Holding the global increase in temperature caused by climate change well below 2 °C above pre-industrial levels, the goal affirmed by the Paris Agreement, is a major societal challenge. Meanwhile, food security is a high-priority area in the UN Sustainable Development Goals, which 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 160 million in 2050. Avoiding these adverse side effects would entail a cost of about 0.18% of global gross domestic product 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 substantial, further reducing the above cost. Although results vary across models and model implementations, the qualitative implications are robust and call for careful design of climate mitigation policies taking into account agriculture and land prices.

Food security is considered as a key target in the UN Sustainable Development Goals (SDGs); in particular, SDG2 is aiming for 'zero hunger' by 2030. The number of people at risk of hunger has declined globally over the past few decades. The number was estimated at 795 million[1] for 2015, 184 million fewer than in 1990–1992, despite a steady population growth over this period[2]. Steady income growth and a relatively stable political situation have contributed to this trend. The issue of food security has been studied in the context of climate change impacts associated with agricultural yield changes over the last few decades[3–6], and more recent studies have explored the effects of climate change mitigation on agricultural markets[7–12]. Although scenario assumptions, the considered metrics and quantitative outcomes in these studies differ, the studies agree that mitigation policies that do not consider side effects on agricultural markets could adversely impact food security, particularly in low-income countries. Whereas some studies propose partial solutions of how to mitigate these side effects[13,14], most do not directly quantify the number of people at risk of hunger. Furthermore, since the assumptions behind these studies are not harmonized, it is difficult to identify the reasons for the differences in the results across the studies.

The Paris Agreement[15] defines a long-term temperature goal for international climate policy as "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, studies investigating the climate change mitigation required by the Paris objectives have identified a potential need for land-based measures such as afforestation and large-scale bioenergy production, which could raise concerns about implications for food security[16–20]. These low-emissions scenarios are making the connection between SDG2 and SDG13 (combating climate change) increasingly crucial.

Integrated assessment models (IAMs) have been used for climate mitigation analysis, with many climate mitigation studies being conducted under multi-model intercomparisons projects, which have a major role in understanding the robustness of the implications and uncertainty[21]. The model behaviour in response to the climate mitigation goal typically finds agreement across models in some variable, such as emissions trajectories or carbon budgets, whereas other variables, such as carbon prices, vary widely across models.

Here we investigate how food security could be affected by the climate mitigation policies implemented by six IAMs. The primary goal is to understand the relationship between food security and climate mitigation, and to estimate costs 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 considered four scenarios differentiated by the stringency of mitigation levels related to the Paris Agreement: no climate policy which includes currently implemented policies (baseline); greenhouse gas

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(GHG) emissions reductions by 2030 in line with the nationally determined contributions (NDCs); and scenarios that limit global mean temperature in 2100 to below 2 °C and 1.5 °C, respectively, in which 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 Methods. To explore the uncertainty range, we employed six state-of-the-art IAMs representing 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]. A description of each model is provided in Methods. All the models apply a uniform carbon price, with the agricultural sector included in the carbon-pricing scheme. Except for IMAGE, all the models assume land-use competition among food, bioenergy crops and afforestation. IMAGE assumes that deforestation policy is not in competition with the food system, and that bioenergy does not compete with food production, following a food-first policy. REMIND–MAgPIE assumes no demand reaction to food price 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 shown in Supplementary Fig. 1. The carbon price of GHG emissions from agricultural sectors is assumed to be capped at US$200 per 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 implement this cap for all GHG emissions related to agriculture and land use (for example, forestry and land-use change)[28]. This capping of the carbon price implies that, at best, our results can provide a lower boundary 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 substantial (discussed further in Supplementary Notes 1.3).

We use the number of people at risk of hunger as a primary indicator representing food security. Two out of six models (AIM and IMAGE) represent the number of people at risk of hunger within their modelling framework, whereas the other models do not. Therefore, we use a 'hunger estimation tool', as used in previous studies[29–31] for the four models that do not have a representation of the risk of hunger. This tool assumes a log-normal food consumption distribution function for each country, which uses mean calorie consumption, minimum energy requirement and the coefficient of variation of the food distribution of 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 and Supplementary Information . Note that these estimates 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 is a broad concept that includes four key dimensions: food availability, stability, access and utilization. Risk of hunger, the metric used in this study, 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 decrease by more than two-thirds (to 180–270 million; 1.9–2.9% of total population) by 2050 compared with the current level (795 million; 12% of total population) (Fig. 1a). This declining trend has already been observed over the past two decades. Asia is currently the region with the largest number of people at risk of hunger, with around 75% of the total population at risk of hunger; however, this share declines rapidly between the present day and 2050 (Fig. 1c and Supplementary Fig. 2). The other regions show a similar trend, except for Africa and the Middle East (dominated by sub-Sahara), which are projected to experience lower income growth and continuous population increases, putting 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, Fig. 1b). The global model uncertainty range in 2050 is largely due to this region. Of note, no model achieves zero hunger (SDG2) by 2030. For this goal to be achieved, either higher income growth or more equal food consumption distribution within countries is needed.

The evolution of per capita food consumption varies widely across models, but food consumption tends to increase steadily over time (Fig. 1d), driven mainly by income growth (see Supplementary Fig. 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, whereas in the Organisation for Economic Co-operation and Development (OECD), a relatively modest increase is observed. IMAGE shows slightly different pathways than the other models: the food consumption trend also explains why IMAGE presents a slightly higher risk of hunger in the second half of the century (Fig. 1a,c). The highest increase in calorie consumption was observed in the Africa and Middle East region, where current food consumption level is low (2,330 to 2,430 kcal per capita per day) and becomes 2,690 to 2,970 kcal per capita per day in 2050. Asia also shows a large food demand increase of about 400 kcal per capita per day during the earlier part of this century by 2050.

Climate change mitigation effect on food security. Climate change mitigation exclusively aimed at attaining the climate goals could risk negatively impacting food security, and the response of the number of people at risk of hunger to mitigation policies may be amplified by the stringency of mitigation policies (Fig. 2). Under the 2 °C and 1.5 °C scenarios, the risk of hunger changes drastically compared with the baseline and NDC scenarios. The population at risk of hunger under the 2 °C and 1.5 °C scenarios in 2050 numbers 280–500 million (median: 350 million; 3.8% of total population) and 310–540 million (median: 410 million; 4.5% of total population), respectively. In the latter case, an additional population of 160 million relative to the baseline scenario (1.7% of total population) would be at risk of hunger. However, there is a large intermodel variation. For example, AIM shows around 290 million at risk of hunger in the baseline scenario, whereas 360 million 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—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 reaches the carbon price cap for the agricultural sector by 2050. Moreover, the large intermodel

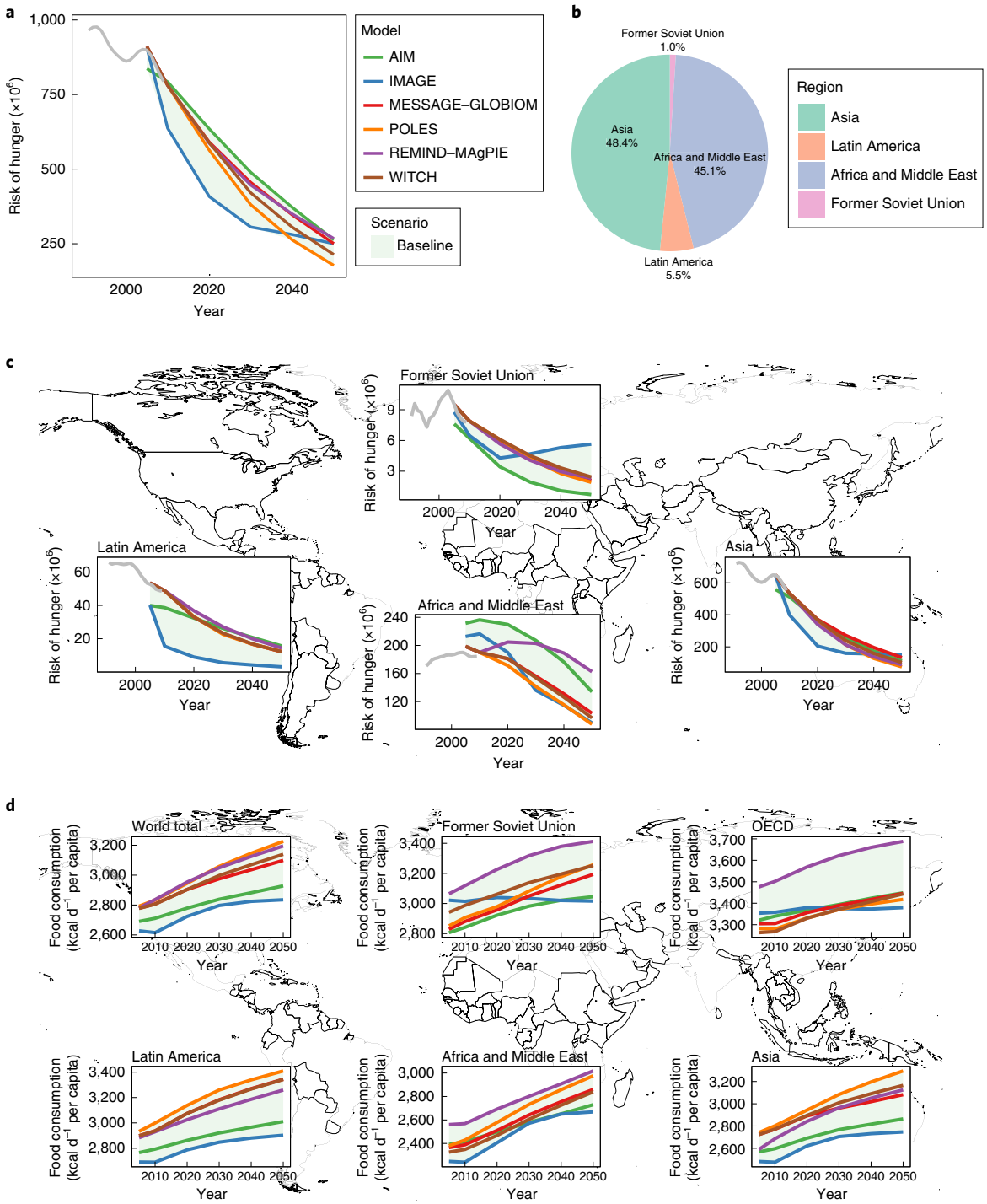

Fig. 1 | Population at risk of hunger under the baseline scenario and food consumption. a–c, Global (**a**) and regional (**b**) trends and regional share of the population at risk of hunger (model median value) (**c**). **d**, Food consumption under the baseline scenario time-series data for total calorie consumption across models. The grey lines in **a** and **c** show historical values. The century-scale figure is presented in Supplementary Fig. 2.

variation in carbon prices[33] generates large model uncertainty and substantial overlaps in the output from the 2 °C and 1.5 °C scenarios (Fig. 3c).

Spikes in the risk of hunger for the mitigation scenarios occur in 2030–2040 when the carbon price required by the climate targets increases sharply. After this period, declining trends similar to the baseline trajectories are observed. Nevertheless, the adverse side effect of climate change mitigation is large and persistent over time (Fig. 3d). 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 (Fig. 2c).

The risk-of-hunger response to the mitigation policies is 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 food consumption down (Fig. 4a and Supplementary Fig. 1, which illustrates the logical chain of the mitigation effect on food security). The price elasticity of food demand is quite heterogeneous across models (Fig. 4b).

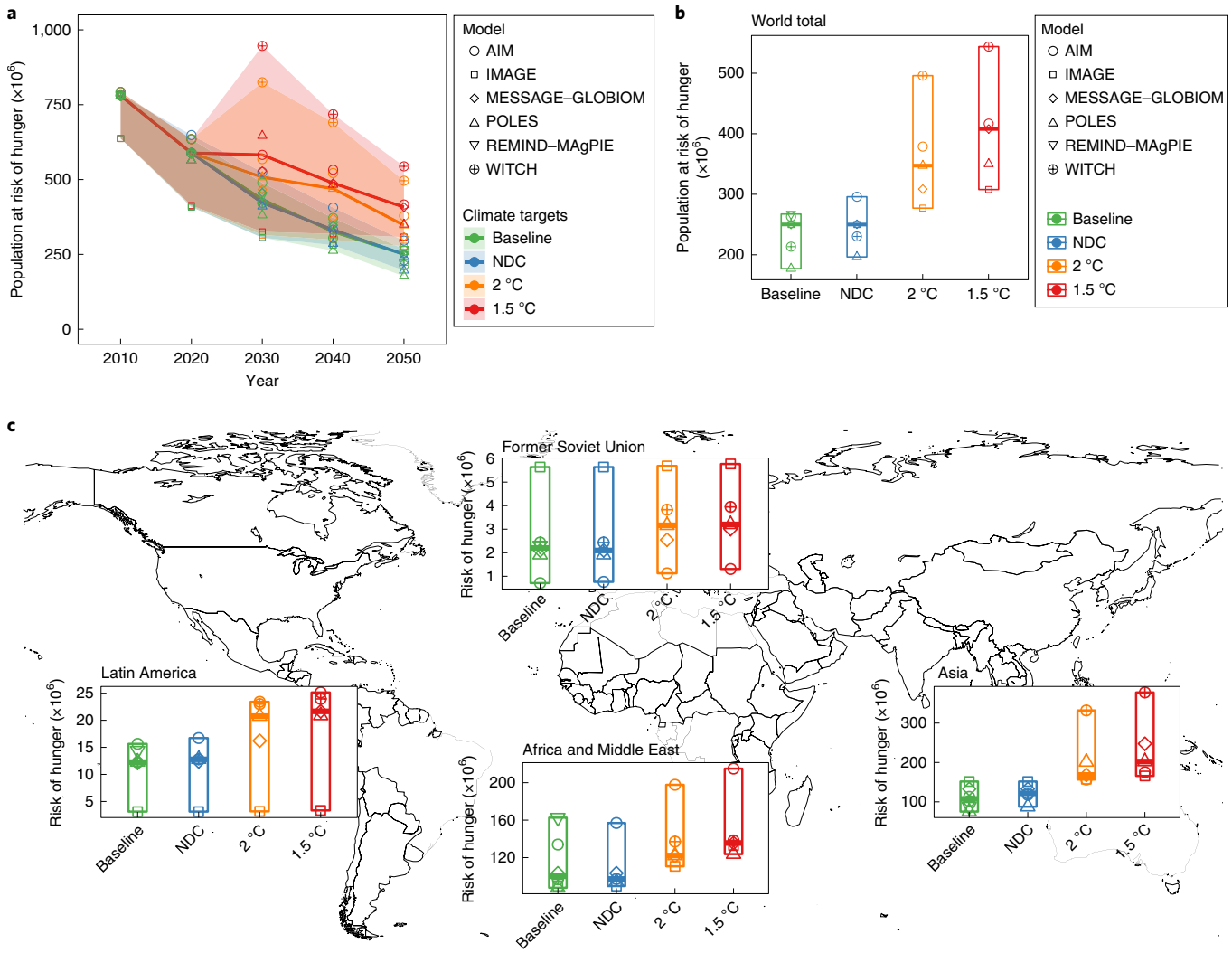

Fig. 2 | The population at risk of hunger under the baseline and mitigation scenarios. a, Population at risk of hunger. The solid line indicates median value across the models and the shaded area represents upper and lower ranges of the model estimates for each scenario. **b**, Population at risk of hunger in 2050 under the various scenarios. **c**, The regional risk of hunger across models and scenarios in 2050.

REMIND–MAgPIE is the extreme case where 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 by 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 with that in low-income countries. This is because wealthier people can generally spend money on expensive food due to low price elasticities (Supplementary Fig. 4). Agricultural price changes are triggered by carbon prices (Fig. 4c), which is why there is a clear correlation between food consumption reduction and carbon prices (Fig. 4d). However, carbon prices in 2050 diverge across the models (Fig. 3d). AIM, WITCH, IMAGE and POLES show relatively high carbon prices compared with 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 (Fig. 4c). MESSAGE–GLOBIOM shows a similar population at risk of hunger that is similar to that of AIM (Fig. 2a), but the carbon prices are lower and the price elasticities are higher than in AIM (Fig. 4c). WITCH and POLES are cases in which both price elasticity and carbon prices are high, and as a result, the largest negative hunger effect occurs in the mitigation scenarios (Fig. 4a).

The drivers of agricultural price changes differ across models, but one common characteristic is non-CO_2 emissions reduction measures and their carbon price penalty. Non-CO_2 emissions can be mitigated when carbon prices are implemented in the agricultural sector, but cannot be entirely removed (Fig. 3b). Therefore, as well as the cost of mitigation measures, the price burden of the residual emissions is passed on 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 Figs. 7 and 8). Although we cannot quantify their contributions, the land-rent and non-CO_2 emissions effect have previously been found to be of similar magnitude[7]. We can illustrate the magnitude of this effect in the example from AIM (Supplementary Fig. 9). The multi-sector computable general equilibrium (CGE) model AIM incorporates other goods, service prices and

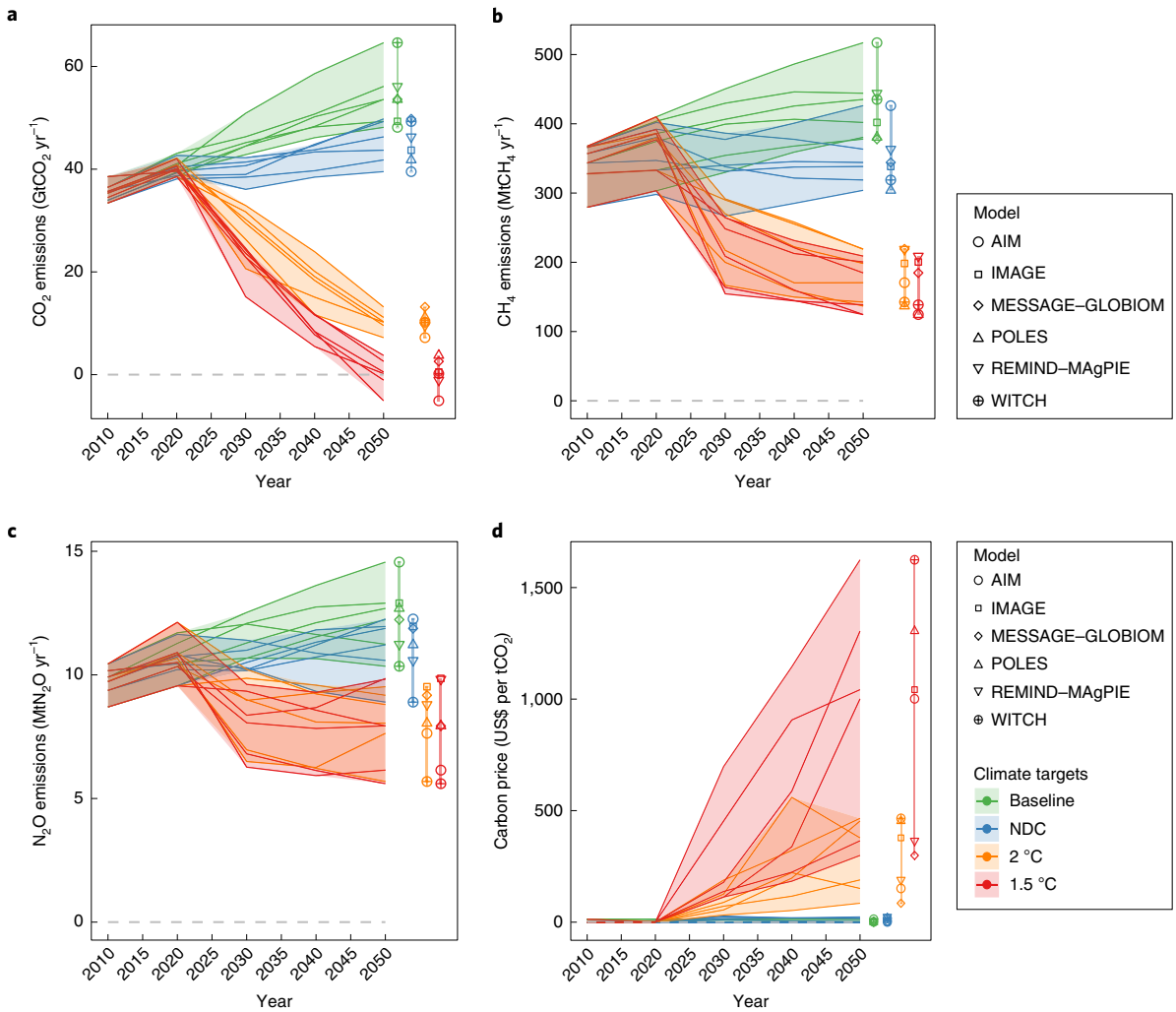

Fig. 3 | Emissions and carbon prices. a–d, Global CO_2 (**a**), CH_4 (**b**) and N_2O (**c**) emissions across scenarios and carbon price (**d**) until 2050 (a full-century figure is shown in Supplementary Fig. 5) according to the models.

wage-change effects, but these factors are not large (Supplementary Fig. 9). AIM also identifies an income-loss effect that accounts for around 20% of food demand decreases.

Cost estimates to avoid adverse side effects. This section examines the cost estimates that could potentially avoid the adverse side effects on 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 difference in agricultural price index in mitigation scenarios compared with the baseline scenario, multiplied by the agricultural demand. The food-aid cost is calculated by the decrease in agricultural demand in the mitigation scenarios compared with the baseline scenario, multiplied by food price (Supplementary Fig. 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 Fig. 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.

For the price increase, the required agricultural subsidy was found to be around 0.63% (model uncertainty: 0.19–2.0%) of global gross domestic product (GDP) for the scenario with a 1.5 °C global temperature increase by 2050 (Fig. 5a). With a 2 °C increase, the cost decreases to 0.51% (0.00 to 1.3%). REMIND–MAgPIE results in the highest cost, comparable with the mitigation policy cost (Fig. 5d). REMIND–MAgPIE assumes zero elasticity in food demand, and price change is therefore the only mechanism by which the market can be adjusted. The cost computed by the other models is not as large as the mitigation policy cost. WITCH estimates a remarkably high climate change mitigation cost 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 agricultural subsidy, food aid has a much lower cost and the differences between the 2 °C and 1.5 °C scenarios are small in absolute terms (Fig. 5b). About 0.19% (0.00–0.46%) of GDP is needed in the 1.5 °C scenario in 2050, compared with 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 price impacts. This can be explained by the price elasticity of agricultural demand, which is much less than −1 (around −0.2 in Fig. 4b), and thus direct aid would be much more efficient than relying on a subsidy (as shown in Supplementary Fig. 10). Furthermore, if only people who are at

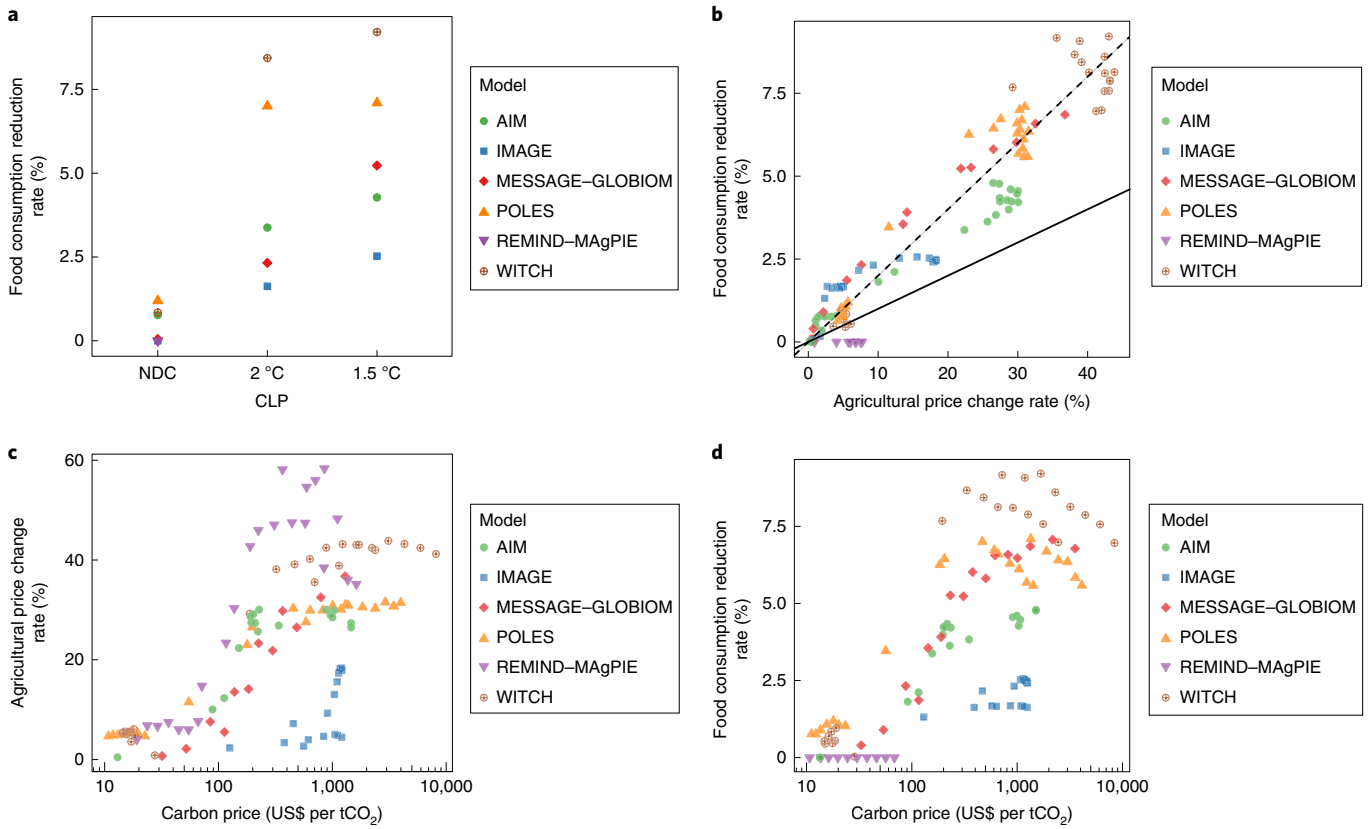

Fig. 4 | Food consumption, agricultural price and carbon price relationships. a, Food consumption reduction rates compared with the baseline scenarios in 2050. **b**–**d**, The relationship between food consumption reduction rates compared with the baseline scenario (**b**), agricultural price increase relative to the base year (**c**) and carbon prices across models and mitigation scenarios (**d**). The dots in **b**, **c** and **d** each represent a ten-year value. Food demand reduction is accounted for on a calorie basis. The lines in **b** indicate price elasticities of agricultural demand of 0.1 and 0.2.

risk of hunger are given aid, the cost is only 0.01% of GDP, with a small intermodel variation of 0.00–0.03%. However, it should also be noted that providing aid exclusively to those at risk of hunger would require a potentially sophisticated mechanism for implementation, so that the government could identify those who are at risk of hunger. Therefore, 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 Fig. 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, as shown in Supplementary Fig. 12. Consequently, the welfare changes in the 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 shown in Supplementary Fig. 13), indicating that our qualitative findings are robust to the food-demand-related parameters.

Discussion and conclusion

Our results indicate that climate mitigation could have potentially adverse side effects on food security. The magnitude of these adverse side effects is amplified with increasing stringency of the mitigation level. These phenomena are robustly observed by multiple IAMs. Moreover, we identified the cost of alternative illustrative complementary policies that simultaneously meet the climate goal and ensure food security. Such policies, in the form of a subsidy or food-aid programme, in addition to the climate change mitigation effort by developed countries, would target a decrease in the number of people at risk of hunger in developing regions.

In relation to climate change mitigation, SDG goals related to air pollution[34] and energy security[35] seem to have synergistic 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 a trade-off relationship with climate change mitigation if the mitigation policy were designed without considering food security.

There are several potential discussion points with respect to the interpretation of the results.

(1) Currently, the total (not only food) Official Development Assistance (ODA) from the developed world is 0.32% of gross national income[39]. This amount is of the same order of magnitude that would be necessary as food-aid subsidy to alleviate the implications of a climate change mitigation policy. However, this subsidy would be in addition to current ODA. Notably, earmarking a proportion of carbon tax revenues is a potential measure to raise the required public funds.
(2) An increase in food prices may, in some instances, translate to higher wages for low-income households or farmers[40].

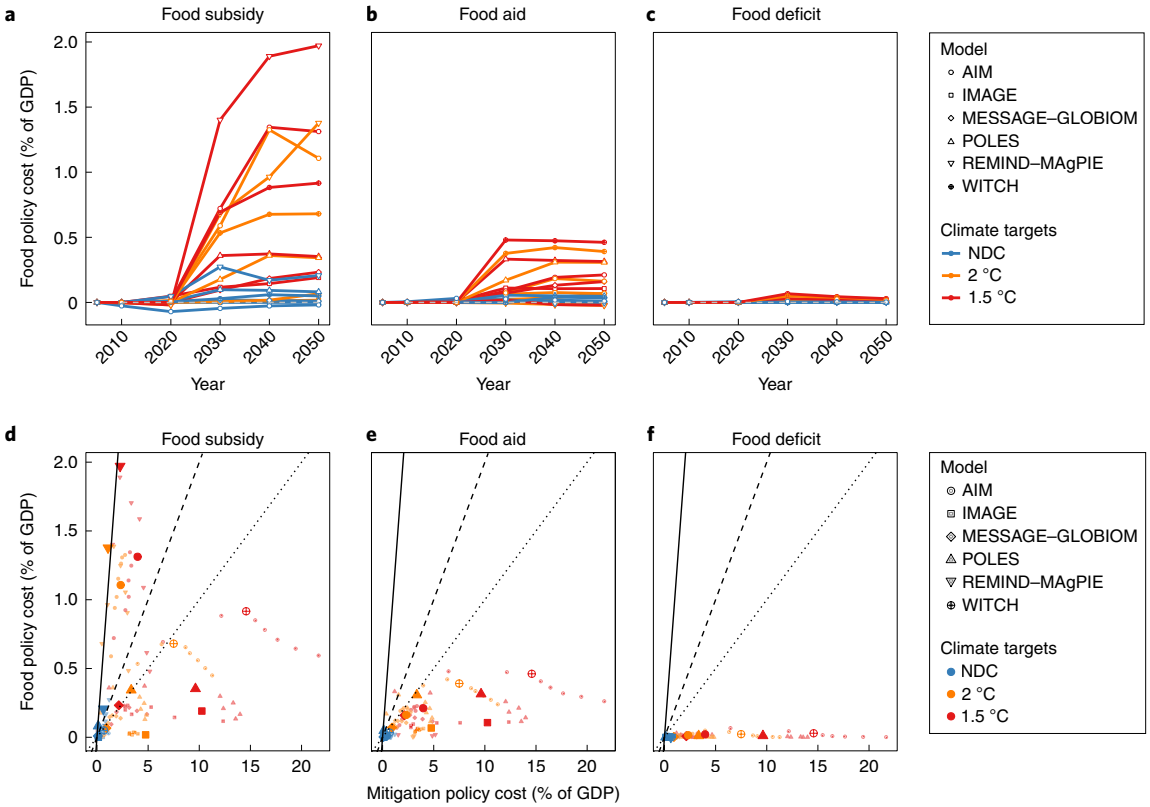

Fig. 5 | Complementary food policy cost compared with the mitigation cost. a,**d**, An additional agricultural subsidy in the mitigation scenarios. The 2050 plots are highlighted with big markers. **b**,**e**, Food aid derived from the agricultural demand decrease in the mitigation scenarios compared with the baseline scenario, multiplied by the agricultural price. **c**,**f**, Cost of food aid targeted at the population at risk of hunger. The *x* axes in **d**–**f** show the policy cost variable, which depends on the model (GDP loss is used for AIM, MESSAGE–GLOBIOM, REMIND–MAgPIE and WITCH. The area under the marginal abatement cost curve is used for IMAGE and POLES). The solid line is where the food policy cost is equal to the mitigation cost. The dotted and dashed lines have gradients 0.1 and 0.2, respectively.

However, when increases in food prices are caused by a carbon tax[10], the increased production costs are a result of carbon pricing and land rent, and income from increased spending tends to not 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[42,43]. These populations would suffer if food prices increased.

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

(4) Agricultural prices increase not only because of emissions pricing, but also because of other factors, such as bioenergy expansion. These other factors have 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[42,44]. These alternative measures can complement the use of emission price caps to alleviate risks to food security stemming from actions to mitigate climate change. However, alternative measures that rely on societal changes, such as switching diets and using advanced technologies, come with their own challenges. Therefore, a suite of complementary measures is needed 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 would 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[43]. In this sense, this study contributes to better understanding of the relationship between climate change and a different societal challenge (in this case, food security), which is also highlighted in the Intergovernmental Panel on Climate Change special report on the 1.5 °C (ref. [43]) scenario.

(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 to 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[46]; thus, the way mitigation policies are implemented in the agricultural sector can impact food security.

There are some caveats and limitations of this study. The uncertainty in the models demonstrated here sheds light on the drivers of uncertainty in the assessment of the population at risk of hunger. This uncertainty is caused by two main factors: carbon prices and food demand price elasticity. Several studies of agricultural economic multi-model intercomparison projects have been performed to determine the uncertainty among the models[47–50]. It might be necessary to focus more attention on price and income elasticity of food demand, since multi-model agricultural outcomes with extremely high carbon prices have not been widely addressed. In our analysis, we did not include the effects of climate change, but these should be investigated, including the consideration of extreme events. We believe that this study will provide a benchmark for future studies (Supplementary Note 4).

Methods

Overall methodology. We use six IAMs that sufficiently represent energy, emissions, land use and agriculture to assess the interaction between climate mitigation and food security. To investigate the agriculture and food security implications associated with climate change mitigation targets, we need models that are consistently able to capture the interaction of energy, agriculture and land-use markets and the all IAMs meet the above-mentioned standard. Each of the models 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, enabling us to deal with the model uncertainty and derive robust conclusions. Each IAM is described in brief below. Since most of the models have been used in previous IAM work[51] and the versions that have been used in this study are almost the same, the model descriptions are quite similar.

Four representative scenarios are examined, differing with the stringency of climate mitigation. The number of people at risk of hunger is implemented as a metric of food security; this 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 presented in Supplementary Table 2 and the model scope is shown in Supplementary Table 3), (2) definitions of the scenarios definition and (3) a description of the hunger estimation tool.

The relationship between model inputs and outputs is illustrated in Supplementary Fig. 1 (similar to Hall et al.[52], 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 Fig. 1). The amount of bioenergy use depends on the energy systems, particularly those in which technological costs (for example, cost of biomass-power generation) and model types (for example linear least-cost optimization, non-linear substitution functions)[53] are the main factors to determine the bioenergy amount. 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 (Fig. 4).

Model descriptions. AIM/CGE[22] is a recursive-type dynamic general equilibrium model that covers all regions of the world, which is divided into 17 regions. The model structure and mathematical formulae are described in ref. [54]. Production sectors were assumed to maximize profits with multi-nested constant elasticity substitution (CES) functions given intermediate inputs and primary-factor prices. The inputs of energy and value added in energy transformation, such as power sectors, were represented as a Leontief function. They were treated in this manner to deal with engineering energy-conversion efficiency appropriately in the energy-transformation sectors. Power generation from multiple energy technologies were combined with a logit function. This functional form was used to ensure energy balance, as the CES function does not guarantee an energy balance. Household expenditures were described by a linear expenditure system (LES) function. The parameters adopted in the LES function were recursively updated by income elasticity assumptions[29]. Land use was represented by a logit function[55]. In addition to energy-related CO_2, CO_2 from other sources and CH_4, N_2O and fluorinated gases were represented as GHGs in the model. Energy-related emissions were associated with fossil fuel use. Non-energy-related CO_2 emissions comprise land-use change and industrial processes. Land-use change CO_2 emissions were derived from changes in forest area multiplied by the carbon stock density, which was differentiated by global agroecological zones. Non-energy-related GHG emissions other than land-use change were modelled in proportion to the activity levels (such as outputs). Air pollutant gases (black carbon (BC), CO, NH_3, non-methane volatile organic compounds (NMVOC), NO_x, organic carbon (OC) and SO_2) were associated either with fuel combustion or activity level. Emissions coefficients changed over time; this relies on the assumed implementation of air-pollutant-removal technologies and legislation.

IMAGE 3.0 is a comprehensive integrated assessment framework that models interacting human and natural systems[56]. The framework comprises several sub-models representing land use, agricultural economy, the energy system, natural vegetation, hydrology and the climate system. The spatial resolutions in the sub-models differ. The socioeconomic components work at the level of 26 regions, while the environmental components work at the grid level to consider heterogeneities in environmental circumstances. The models interact through upscaling and downscaling algorithms.

The IMAGE-LandManagement model represents land use and crop production explicitly spatially modelled on a 5 min grid using an empirical land-use allocation algorithm. Livestock systems are modelled on 26 regions for intensive and extensive systems. Demand for agricultural production and intensification or extensification of the agricultural sector is provided by MAGNET, an agricultural economy model; MAGNET is a multi-regional, multi-sectoral, applied general-equilibrium model[57] that is based on neo-classical microeconomic theory. MAGNET 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 endogenous variables set by markets to achieve supply-and-demand equilibrium. The productivity developments are driven by a combination of assumptions on autonomous technological change provided by IMAGE-LandManagement and by economic processes modelled by MAGNET (that is, substitution between production factors). Land is modelled as an explicit production factor in MAGNET, that is described by a land supply curve and constructed with land availability information provided by IMAGE-LandManagement.

The energy system is represented by the energy simulation model TIMER which models 12 primary energy carriers. The TIMER model determines demand for bioenergy production 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 describe the carbon and hydrological cycles. LPJmL also provides potential crop yields. The simple climate model MAGICC is used to calculate climate change on the basis of GHG and air pollutants emissions calculated by IMAGE-LandManagement and TIMER.

Climate change mitigation policy was modelled by the FAIR-SimCAP model which uses carbon prices and MACs representing costs of mitigation actions to determine a cost-optimal emission pathway. Technical mitigation of non-CO_2 GHG emissions from agriculture was based on ref. [58]. Taxes on residual emissions were estimated with MAGNET. The costs of technical mitigation were also implemented as part of the tax. Avoided deforestation policy (for example, reducing emissions from deforestation and forest degradation (REDD) incentives) was calibrated to the carbon tax of FAIR-SimCAP and implemented in MAGNET through reduced land availability.

MESSAGE–GLOBIOM integrates the energy engineering system model MESSAGE (model for energy supply strategy alternatives and their general environmental impact) with the land-use model GLOBIOM (global biosphere management) via soft linkage into a single global integrated assessment modelling framework[24].

MESSAGE is a global model with a linear programming energy-engineering model. As a system engineering optimization model, MESSAGE is primarily used for global medium- to long-term energy system planning, energy policy analysis and relevant scenario development. The model represents an energy system with all its interdependencies from resource extraction, trade, conversion, transport and distribution, to the provision of energy end-use services such as lighting, space conditioning (heating and cooling), industrial production processes and transportation. The aggregated macroeconomic model MACRO is linked to MESSAGE to assess economic implications and to capture macroeconomic feedbacks of climate and energy policies[59].

Land-use dynamics were modelled with a partial-equilibrium model in GLOBIOM[12]. GLOBIOM represents the competition between different land-use-based activities. It includes a detailed representation of the agricultural (crop and livestock), forestry and bioenergy 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, including comprehensive GHG emissions from agriculture, forestry and other land use 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 global forest model G4M[60]. G4M models forest area change, carbon uptake and release by forests, and supply of bioenergy and timber.

MESSAGE–GLOBIOM covers all GHG-emitting sectors, including energy, industrial processes, agriculture and forestry. The emissions comprise CO_2, CH_4, N_2O and fluorinated gases (CF_4, C_2F_6, HFC125, HFC134a, HFC143a, HFC227ea, HFC245ca and SF_6) and other radiatively active substances, such as NO_x, volatile organic compounds (VOCs), CO, SO_2, BC and OC). MESSAGE–GLOBIOM is used in conjunction with MAGICC (model for greenhouse gas-induced climate change) v.6.8 (ref. [61]) for calculating climate outcomes such as 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 worldwide (Group of 20 (G20) countries, OECD and principal energy consumers) plus the European Union. The model covers 15

fuel-supply branches, 30 technologies in power production, 6 in other energy transformation, 15 final-demand sectors and corresponding GHG emissions. GDP is an exogenous input of the model, whereas resource prices, global technological progress in electricity generation technologies and price-induced lagged adjustments of energy supply and demand are endogenously determined. Mitigation policies are represented by implementation of carbon prices up to the level where emission reduction targets are met: carbon prices affect average energy prices through energy-efficiency responses on the demand side and the relative prices of different fuels and technologies, which lead to adjustments on both the demand side (for example, fuel switching) and the supply side (for example, investments in renewables). Non-CO_2 emissions in energy and industry sectors are represented by the marginal abatement cost curves derived from the literature. Projections for agriculture, land use, land-use change, and forestry emissions and food indicators are derived from the GLOBIOM model by using a dynamic look-up table of emissions depending on climate policy and biomass-energy use, calibrated on historical emissions and food demand (from United Nations Framework Convention on Climate Change, Emission Database for Global Atmospheric Research (EDGAR) and Food and Agriculture Organization). 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 this study, REMIND v.1.7 was used. REMIND represents five individual countries and six aggregated regions formed by the remaining countries. Intertemporal welfare for each region is optimized based on a Ramsey-type macroeconomic growth model. The model explicitly represents trade in final goods, primary energy carriers and emission allowances in the case of climate policy, and computes simultaneous and intertemporal market equilibria on the basis of an iterative procedure. Macroeconomic production factors are capital, labour and final energy. Economic outputs are used for investments in the macroeconomic 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 agroeconomic model. MAgPIE operates on a spatially explicit scale, in which 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, and the function is minimized such that the demand of agricultural products is fulfilled. Agricultural demand is aggregated at the level of ten geo-economic regions. Food demand is exogenously calculated on the basis of an econometric regression model. This regression model computes per capita caloric consumption on a national level, considering historical consumption patterns and future socio—economic assumptions such as population and income[64]. The demand implementation considers the long-term income effect on agricultural consumption, and the model is limited with respect to representing short-term demand adjustments to changes in prices. Material demand (non-food consumption) is assumed to be proportional to total food demand. Agricultural demand also comprises demand for animal feed (feed crops, fodder and grazed biomass) based on feed-basket content. Regional agricultural supply is endogenously determined within the model, taking into account production costs and spatially explicit agricultural productivity. The costs comprise 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] (inputs are local biophysical conditions (land, water and terrestrial carbon) and crop yields are provided on the gridded resolution (0.5°×0.5° geographic longitude–latitude) from the global Lund—Potsdam—Jena model with managed land. MAgPIE estimates CO_2, CH_4 and nitrogen-related emissions[66]. CO_2 emissions are computed from land-use change dynamics and consequent loss of terrestrial carbon stocks. Land conversion into cropland can occur from pasture, forest (pristine and unmanaged) and other natural-vegetation (for example, savannahs and shrublands) land pools. The reduction of GHGs is incentivized by imposed GHG prices. The price serves as an incentive to restrain land-use conversion and consequent carbon release in the form of CO_2 emissions. Reduction of CH_4 and N emissions are possible by applying technical mitigation with additional costs, also triggered by GHG emission pricing.

WITCH-GLOBIOM (World Induced Technical Change Hybrid) is an IAM used to assess climate change mitigation and adaptation policies. It is developed and maintained at the Centro Euro-Mediterraneo sui Cambiamenti Climatici. WITCH-GLOBIOM is a global dynamic model that integrates the most important drivers of climate change into a unified framework. An intertemporal optimal macroeconomic growth model captures the long-term economic growth. A relatively compact representation of the energy sector is 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 as a set with a varying number of macroregions. Thirteen representative native regions have been used here; for each region, the model generates the intertemporally 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. The endogenous representation of research-and-development diffusion and innovation processes is a distinguishing feature of WITCH. This feature allows a description of how research-and-development investments in energy efficiency and carbon-free technologies integrate the mitigation options currently available. Non-CO_2 emissions in energy and industry are modelled with marginal abatement cost curves. As for agriculture projections, land use, land-use change, and forestry emissions and food indicators are derived from the GLOBIOM model in a similar way to POLES, calibrated on historical emissions and food demand (from UNFCCC, FAO and EDGAR).

More details can be found in refs. [27,67], and full documentation is available at http://doc.witchmodel.org/.

Scenario definition. We employed four scenarios in this study as listed below:

(1) Baseline: does not include climate policy but includes currently planned non-climate policy such as energy policies.
(2) NDC: currently planned policies and NDCs are reflected. Thus, the emissions meet the NDC targets for 2025 and 2030. After 2030, the same emissions reduction effort carried out before 2030 is assumed.
(3) 2 °C: currently planned policies and cost-effective mitigation pathway with global cumulative CO_2 emissions constraint as 1,000 $GtCO_2$ from 2011 to 2100 is adopted. This level of mitigation efforts likely (>66% change) enables the global mean temperature increase to stay below 2 °C. The emission reduction starts from 2020.
(4) 1.5 °C: currently planned policies and 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 1.5 °C by roughly 50%. The emission reduction starts from 2020.

Estimation of the 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 approach used in AIM and IMAGE. GLOBIOM recently published a quantification of the number of people at risk of hunger[13]. Moreover, the GLOBIOM emulator, which is a simplified version of land-use and agricultural model, is 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 area. Thus, the combination of the IAMs and the hunger estimation tool were sufficient for our purposes to represent agricultural and land-use changes.

The narrow definition of undernourishment or hunger is a state of energy (or calorie) deprivation lasting more than one year; this does not include the short-term effects of temporary crises[68,69]. Moreover, this feature does not include inadequate intake of other essential micronutrients[68]. The number of people at risk of hunger as a proportion of the total population is calculated using equation (1):

$$\mathrm{Risk}_t = \mathrm{POP}_t \times \mathrm{PoU}_t \tag{1}$$

where t is the year, Risk_t is the population at risk of hunger in year t, POP_t is the total population in year t, and PoU_t is the proportion of the population at risk of hunger in year t.

According to the FAO methodology[70], the proportion of the population at risk of hunger is defined using equations (2)–(4). The proportion is calculated using three parameters: the mean calorie consumption per person per day, 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 consumption distribution within a country is assumed to be a log-normal distribution. We then count the proportion of the population consuming less than the mean minimum dietary energy requirement as the population at risk of hunger. The log-normal distribution has key two parameters that determine its shape: the mean (μ_t) and the variance (σ_t), as in equation (2). These parameters can be derived from cal and CV as shown in equations (3) and (4).

Each IAM reports the mean food calorie consumption per person per day. We standardize the base year calorie consumption to the figure reported by the FAO and the base year calories are multiplied by the change ratio of IAM future scenarios to the base year. We then compute the standardized calorie consumption to obtain a consistent number for those at risk of hunger. In this process, since the IAMs are regionally aggregated values, they are downscaled to the individual country level by taking the base year value reported by FAO and using the future change ratio from IAMs. The CV is obtained from a household survey reported by the FAO, ranging from 0 to 1. This CV is weighted on the basis of population in the base year and aggregated to a 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 it is assumed that future CV changes of each region are based on the current regional values.

$$\mathrm{PoU}_t = \Phi\left(\log M_t - \mu\left(\mathrm{cal}_t, \sigma_t\right)/\sigma_t\right) \tag{2}$$

$$\mu\left(\mathrm{cal}_t \sigma_t\right) = \log_e \mathrm{cal}_t - \sigma_t^2/2 \tag{3}$$

$$\sigma_t = \left[\log_e\left(\mathrm{CV}^2 + 1\right)\right]^{0.5} \tag{4}$$

where M_t is the mean minimum dietary energy requirement in year t, CV_t is the coefficient of variation of the international distribution of dietary energy consumption in year t, Φ is the standard normal cumulative distribution and cal_t is the 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 base year information at the country level[71–73] and an adjustment coefficient differentiating age and sex groups[72] with the population dynamics in age and sex group structure[73], as in equations (5) and (6).

$$M_t = M_{\text{base}} \times \frac{\text{MER}_t}{\text{MER}_{\text{base}}} \tag{5}$$

$$\text{MER}_t = \frac{\sum_{i,j} \text{RMER}_{i,j} \cdot P_{\text{class}\ i,j,t}}{\sum_{i,j} P_{\text{class}\ i,j,t}} \tag{6}$$

where i is age group, j is sex, M_{base} is mean minimum dietary energy requirement per person in the base year, MER_t is mean adjustment coefficient of minimum energy requirements per person in year t, MER_{base} is mean adjustment coefficient of the minimum energy requirements per person in the base year, $\text{RMER}_{i,j}$ is adjustment coefficient for the minimum energy requirements per person of age i and sex j and $P_{\text{class}\,i,j,t}$ is population of age i and sex j in year t.

Data availability

Scenario data are accessible online via the CD-LINKS Scenario Database at https://db1.ene.iiasa.ac.at/CDLINKSDB. Data derived from the original scenario database, which are shown as figures but are not in the above database, are available upon reasonable request from the corresponding author.

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Author contributions

S.Fujimori, V.K. and K.R. designed the research; S.Fujimori carried out analysis of the modelling results, created figures and wrote the draft of the paper; T.H. and Y.O. carried out hunger estimation tool simulation; S.Fujimori and T.H. provided AIM data; J.Doelman, J.K., H.v.M. and D.v.V. provided IMAGE data; O.F., S.Frank and P.H. provided MESSAGE–GLOBIOM data; J.Després and A.S. provided POLES data; B.L.B., F.H. and A.P. provided REMIND–MAgPIE data; V.B., L.D. and J.E. provided WITCH data; J.C. edited English language; and all authors contributed to the discussion and interpretation of the results.

Competing interests

The authors declare no competing interests.

Additional information

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