Supplementary material for

Scenarios for the Risk of Hunger in the Twenty-first Century using

Shared Socioeconomic Pathways

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S1. Methodology for calculating the population at risk of hunger

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 (FAO 2012a). Furthermore, this does not include inadequate intake of other essential nutrients (FAO 2012a).

The population at risk of hunger is a proportion of the total population and is calculated using Eq. 1.

\[ Risk_t = \frac{POP_t}{POP} \cdot PoU_t \]  

(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 (FAO 2008), 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 intake 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 obey a standard normal cumulative 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 standard normal cumulative distribution has two parameters, the mean \( \mu \) and the variance \( \sigma \), as in Eq. 2. The parameters \( \mu \) and \( \sigma \) can be represented using the mean food calorie intake per person per day (cal) and the coefficient of variation of the domestic distribution of dietary energy consumption (\( CV \)) as Eqs. 3 and 4.

The weight-based consumption of food goods calculated by the computable general equilibrium (CGE) model is converted into the calorie-based consumption using conversion factors for each commodity, and this is used as the mean food calorie intake per person per day (cal). Calories per 100 g (FAO 2007) are weighted on the basis of production data in the base year and aggregated to the commodity classification to obtain the conversion factors. In this process, only the edible parts of commodities are considered for food consumption by using the edible parts ratios (FAO 2007). The \( CV \) is an indicator of food security observed in a household survey conducted by the FAO.
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.

\[ PoU_t = \Phi \left( \log M_t - \frac{\mu(cal_t, \sigma_t)}{\sigma_t} \right) \]  
(Eq. 2)

\[ \mu(cal_t, \sigma_t) = \log e \cdot cal_t - \frac{\sigma_t^2}{2} \]  
(Eq. 3)

\[ \sigma_t = \left[ \log_e \left( CV_t^2 + 1 \right) \right]^{0.5} \]  
(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 \( t \)
\( \Phi \) : 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 using the mean minimum dietary energy requirement in the base year at the country level (FAO 2013b), adjustment coefficient for the minimum energy requirements per person in different age and sex groups (Table S1) (FAO/WHO 1973) and the population of each age and sex group in each year (IIASA 2012), as in Eqs. 5 and 6.

\[ M_t = M_{base} \cdot \frac{MER_t}{MER_{base}} \]  
(Eq. 5)

\[ MER_t = \frac{\sum_{i,j} RMER_{i,j} \cdot P_{class_{i,j,t}}}{\sum_{i,j} P_{class_{i,j,t}}} \]  
(Eq. 6)

where,
i: age group;
j: sex;
\( M_{base} \) : 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 \( j \);
\( P_{class_{i,j,t}} \) : population of age \( i \) and sex \( j \) in year \( t \).
**Table S1** Adjustment coefficients for the minimum energy requirements per person in different age and sex groups ($RMER_{ij}$) (average = 1.0)

| Age group (years) | Male  | Female |
|-------------------|-------|--------|
| 0-4               | 0.46  | 0.59   |
| 5-9               | 0.75  | 0.97   |
| 10-14             | 0.97  | 1.13   |
| 15-19             | 1.02  | 1.05   |
| 20-39             | 1.00  | 1.00   |
| 40-40             | 0.95  | 0.95   |
| 50-59             | 0.90  | 0.90   |
| 60-69             | 0.80  | 0.80   |
| 70+               | 0.70  | 0.70   |

Note: this table is based on Table 26 in FAO/WHO(1973)
S2. Methodology for the decomposition analysis of the future risk of hunger

The expansion of Eq. 2 shows that the change in the population at risk of hunger can be decomposed into several factors. A method for calculating the effect of each factor is described below.

The partial differentiation of Eq. 2 by $\sigma_{cal}$ gives Eq. 7.

$$dPoU_t = \frac{\partial \Phi_i}{\partial \sigma_t} d\sigma_t + \frac{\partial \Phi_i}{\partial cal_t} dcal_t$$

\hspace{1cm} (Eq. 7)

Differentiation of Eq. 1 by $Risk$ gives Eq. 8.

$$dRisk_i = \frac{\partial Risk_i}{\partial POP_t} dPOP_t + \frac{\partial Risk_i}{\partial PoU_t} dPoU_t$$

$$= PoU_t \cdot dPOP_t + POP_t \cdot dPoU_t$$

$$\frac{dRisk_i}{Risk_i} = \frac{PoU_t \cdot dPOP_t + POP_t \cdot dPoU_t}{PoU_t \cdot POP_t}$$

$$= \frac{dPOP_t}{POP_t} + \frac{1}{PoU_t} \left[ \frac{\partial \Phi_i}{\partial \sigma_t} d\sigma_t + \frac{\partial \Phi_i}{\partial cal_t} dcal_t \right] + \epsilon_i \quad \text{(by Eq.7)}$$

$$= IPOP_t + \frac{1}{PoU_t} \left( ICV_t + ICAL_t + ITRD_t \right) + \epsilon_i$$

\hspace{1cm} (Eq. 8)

where,

$IPOP_t$ : change in the population at risk of hunger caused by the change in population in year $t$ [-]

$ICV_t$ : change in the population at risk of hunger caused by the change in CV in year $t$ [-]

$ICAL_t$ : change in the population at risk of hunger caused by the change in food calorie intake in year $t$ [-]

$ITRD_t$ : change in the population at risk of hunger caused by the change in trade in year $t$ [-]

$\epsilon_i$ : residual of year $t$

Multiplying both sides of Eq. 8 by $Risk$ gives Eq. 9.

$$dRisk_i = Risk_i \cdot IPOP_t + \frac{Risk_i}{PoU_t} \cdot ICV_t + \frac{Risk_i}{PoU_t} \cdot ICAL_t + \frac{Risk_i}{PoU_t} \cdot ITRD_t + \epsilon_i$$

$$= FaPOP_t + FaCV_t + FaCAL_t + FaTRD_t + \epsilon_i$$

\hspace{1cm} (Eq. 9)
with

\[ \begin{align*}
F_{aPOP} &= \text{Risk}_t \cdot IP_{OP_t} \\
F_{aCV} &= \text{Risk}_t \cdot IC_{V_t} \\
F_{aCAL} &= \text{Risk}_t \cdot IC_{AL_t} \\
F_{aTRD} &= \text{Risk}_t \cdot ITRD_t
\end{align*} \]

where

- \( d\text{Risk}_t \): annual change in the population at risk of hunger in year \( t \) [person/year]
- \( F_{aPOP} \): annual change in the population at risk of hunger caused by the change in population in year \( t \) [person/year]
- \( F_{aCV} \): annual change in the population at risk of hunger caused by the change in CV in year \( t \) [person/year]
- \( F_{aCAL} \): annual change in the population at risk of hunger caused by the change in food calorie intake in year \( t \) [person/year]
- \( F_{aTRD} \): annual change in the population at risk of hunger caused by the change in trade in year \( t \) [person/year]

Equation 9 presents how the change in the population at risk of hunger in year \( t \) can be decomposed into the change in four factors: population, variation in food distribution, per-capita food calorie intake and trade.

The summation of Eq. 9 from the base year to year \( t \), gives Eq. 10.

\[
\text{Risk}_t = \text{Risk}_{t_{base}} + \left( d\text{Risk}_{t_{base}+1} + \cdots + d\text{Risk}_t \right) \\
= \text{Risk}_{t_{base}} + \sum_{t_{base}<t\leq t} d\text{Risk}_t,
\]

(Eq. 10)

Therefore, the cumulative change in the population at risk of hunger from the base year to year \( t \) is described as the sum of the cumulative change in the four factors, as Eq. 11.

\[
\text{Risk}_t = \text{Risk}_{t_{base}} = \sum_{t_{base}<t\leq t} d\text{Risk}_t, \\
= \sum_{t_{base}<t\leq t} \left( F_{aPOP} + F_{aCV} + F_{aCAL} + F_{aTRD} \right) + \epsilon_t \\
= F_{POP} + F_{CV} + F_{CAL} + F_{TRD} + \epsilon_t
\]

(Eq. 11)

with

- \( F_{POP} = \sum_{t_{base}<t\leq t} \left( Fa_{POP} \right) \)
- \( F_{CV} = \sum_{t_{base}<t\leq t} \left( Fa_{CV} \right) \)
- \( F_{CAL} = \sum_{t_{base}<t\leq t} \left( Fa_{CAL} \right) \)
- \( F_{TRD} = \sum_{t_{base}<t\leq t} \left( Fa_{TRD} \right) \)
where

- $FPOP_t$: cumulative change in the population at risk of hunger caused by the change in population from base year to year $t$ [person]
- $FCV_t$: cumulative change in the population at risk of hunger caused by the change in CV from base year to year $t$ [person]
- $FCAL_t$: cumulative change in the population at risk of hunger caused by the change in food calorie intake from base year to year $t$ [person]
- $FTRD_t$: cumulative change in the population at risk of hunger caused by the change in trade from base year to year $t$ [person]

Using this formula, it is possible to describe the cumulative change in the population at risk of hunger from the base year to year $t$ as Eqs. 12 to 15.

\[
FPOP_t = \sum_{\text{base} < t \leq T} (FPOP_t) = \sum_{\text{base} < t \leq T} (\text{Risk}_t \cdot IPOP_t) \quad \text{(Eq. 12)}
\]

\[
FCV_t = \sum_{\text{base} < t \leq T} (FCV_t) = \sum_{\text{base} < t \leq T} \left( \frac{\text{Risk}_t}{PoU_t} \cdot ICV_t \right) \quad \text{(Eq. 13)}
\]

\[
FCAL_t = \sum_{\text{base} < t \leq T} (FCAL_t) = \sum_{\text{base} < t \leq T} \left( \frac{\text{Risk}_t}{PoU_t} \cdot ICAL_t \right) \quad \text{(Eq. 14)}
\]

\[
FTRD_t = \sum_{\text{base} < t \leq T} (FTRD_t) = \sum_{\text{base} < t \leq T} \left( \frac{\text{Risk}_t}{PoU_t} \cdot ITRD_t \right) \quad \text{(Eq. 15)}
\]

To calculate $FPOP, FCV, FCAL,$ and $FTRD,$ the method used to calculate $IPOP, ICV, ICAL,$ and $ITRD$ is described below.

First, the effects of a change in population on the change in the population at risk of hunger ($IPOP$) can be calculated with Eq. 16.

\[
IPOP_t = \frac{\partial POP_t}{\partial POP} = \frac{(POP_{t+1} - POP_t)}{POP_t} \quad \text{(Eq. 16)}
\]

Next, the effects of a change in the variation of food distribution on the change in the population at risk of hunger ($ICV$) can be calculated with Eq. 17 by assuming an approximation.

\[
ICV_t = \frac{\partial \Phi_t}{\partial \sigma_t} \approx \frac{\partial \Phi_t}{\partial \sigma_t} = \Phi_t \left( \sigma_{t+1} \right) - \Phi_t \left( \sigma_t \right)
\]

\[
= \Phi \left( \frac{\log(M_t) - \mu(cal_t, \sigma_{t+1})}{\sigma_{t+1}} \right) - \Phi \left( \frac{\log(M_t) - \mu(cal_t, \sigma_t)}{\sigma_t} \right) \quad \text{(Eq. 17)}
\]

Finally, the effects of the change in the per-capita food calorie intake ($ICAL$) and trade ($ITRD$) are calculated with Eqs. 18 and 19.
Using the above formula, the effects of the four factors on the population at risk of hunger are calculated.

First, the cumulative change in the population at risk of hunger caused by population change ($FPOP$) is calculated by assigning Eq. 16 to Eq. 12.

Next, the cumulative change in the population at risk of hunger caused by a change in the variation of food distribution ($FCV$) is calculated by assigning Eq. 17 to Eq. 13.

Then, the cumulative change in the population at risk of hunger caused by a change in the per-capita food calorie intake ($FCAL$) is calculated by assigning Eq. 18 to Eq. 14.

Fourth, the cumulative change in the population at risk of hunger caused by a change in trade ($FTRD$) is calculated by assigning Eq. 19 to Eq. 15.

Finally, the residual ($\varepsilon_t$) is calculated as Eq. 20.

\[
\varepsilon_t = (\text{Risk}_t - \text{Risk}_{base}) - (FPOP_t + FCY_t + FCAL_t + FTRD_t)
\]  

(Eq. 20)
S3. Global CGE Model

S3.1 General description

The global Asia-Pacific Integrated Model/Computable General Equilibrium (AIM/CGE) model used in (Fujimori 2012) is based on the standard CGE model created by the International Food Policy Research Institute (Löfgren et al. 2002). In the model, supply, demand, investment, and trade are described using individual behavioral functions that respond to changes in the price of production factors and commodities, as well as changes in technology and preference parameters.

The CGE model contains 17 regions and countries and 26 sectors and commodities. Production functions are formulated as multi-nested constant elasticity substitution (CES) functions. Household demand is formulated as linear expenditure system (LES) functions (not minimization of risk of hunger). For trade, substitution between domestic and imported commodities is based on the Armington assumption, and the CES function is used for the aggregation of domestic and imported commodities. Disaggregation between exports and domestic supply is described by a constant elasticity transformation (CET) function. A single international trade market is assumed for each traded commodity. Allocation of land by sector is formulated as a multi-nominal logit function to reflect differences in substitutability across land categories with land rent. See (Fujimori 2012) for more details on the structure of the CGE model.

S3.2 Consumption

Household consumption is described in terms of LES functions derived from an original function that defines spending on individual commodities has having a linear relation with total consumption spending, based on the assumption that each household maximizes a “Stone-Geary” utility function subject to the consumption expenditure constraint. The parameters of the formulas were calibrated using income elasticity values (Nganou 2005). The income elasticity of food demand for each region and commodity was prepared from the per-capita food consumption and gross domestic product (GDP) data reported in Bruinsma et al. (Bruinsma 2010). The income elasticity for livestock products was changed according to the future income increase, while the value for crops was fixed. The elasticity of livestock products was calculated using a function estimated from time-series cross-country data on meat calorie intake and income (Figure S4). The parameters were updated recursively to realize the assumed income elasticity. The intermediate input coefficients of agricultural commodities,
except for the intermediate input as feed, were also adjusted according to income
elasticity.

There are two laws that describe the relationship between food consumption and
wealth: Engel’s Law and Bennett’s Law. Engel’s Law holds that the proportion of food
expenditure to total expenditure declines with increasing wealth, whereas Bennett’s
Law holds that the starchy staples portion of food consumption decreases with
increasing wealth. The LES function used here partly describes the two laws. First,
Engel’s Law is described in the following context. The income elasticities of food
commodities for industrial countries are low and those for developing countries are high.
There is a wide range between the two regions. By contrast, there is no wide range
between the two regions in the income elasticities of other commodities (i.e., 1.11 (the
United States of America; USA) to 1.53 (Rest of Africa; XAF) for the transport sector
and 0.74 (USA) to 1.03 (XAF) for the construction or pulp and paper sector). Based on
the assumed elasticities, the proportion of food expenditure to the total expenditure
decreases markedly in the industrial regions and declines gradually in the developing
regions, along with the future income increase. In addition, Bennett’s Law is described
in the following context. The elasticities for cereal crops are much lower than those for
livestock products (i.e., −0.06 to 0.22 for cereal crops and 0.12 to 0.62 for dairy cattle).
Using these elasticities, the starchy staples portion of food consumption decreases with
increasing wealth.

S3.3 Trade

Substitution between domestic and imported commodities is based on the
Armington assumption, and the CES function is used to aggregate domestic and
imported commodities. Disaggregation between exports and domestic supply is
described using a constant elasticity transformation (CET) function. The substitution
elasticity applied to trade functions is assumed to be 0.8 (Löfgren et al. 2002), and a
single international trade market is assumed for each traded commodity.

The CGE model is a recursive model calculated in 1-year steps, and the
calculations for each year are based on the results of the previous year. In particular,
calculation of the capital stock is based on information from the previous year. The
model differentiates old and new capital stocks. The production functions for labor and
capital were formulated as constant elasticity substitution (CES) functions, which have
multi-nested structures. To quantify the assumed scenarios, we set labor and total factor
productivity so that the total labor supply was proportional to the changes in population.
Existing capital is given by the previous year’s capital, and new capital is added by
investment. To obtain GDP growth, we adjusted an efficiency factor that represented total factor productivity (TFP) in the CES function.

**S3.4 Land nesting strategy in the CGE Model**

The CGE model has a land nesting strategy, which is similar to the treatments in Sands and Kim (Sands and Kim 2008) and Wise and Calvin (Wise and Calvin 2011). Land is categorized in one of three ecological zones, and there is a land market for each zone. The allocation of land by sector is formulated as a multi-nominal logit function to reflect differences in substitutability across land categories with land rent. As such, the function assumes that land owners in each region and agro-ecological zone (AEZ) decide on land sharing among options with the land rent depending on the production on each land (*i.e.*, crops, livestock, and wood products).

Figure S1 shows the nesting diagram of land with the AEZ classification. We assessed all land, except desert, rock, ice, tundra, and built-up land. There are 18 AEZ classifications. At the top is all land, which is divided into two main types: forest and non-forest land. The forest land node contains two competing uses: primary forest (unmanaged forest) and secondary forest (managed forest). The non-forest land can be divided into grassland and cropland. The grassland can be divided into primary grassland (unmanaged pasture) and grazing grassland (managed pasture that feeds marketed livestock), which is in turn subdivided into each type of livestock (1 to n). The cropland is divided into cropland for each crop (1 to n) and fallow land.

One approach using the nesting strategies is based on the assumption that the land regions are small enough that all competing options are equally substitutable. This assumption implies that it is as easy to switch from forest to wheat as it is to switch from corn to wheat. However, this conversion would not happen unless wheat was more profitable than forest or corn. Consequently, the function assumes that the land owners in each region and AEZ subregion decide on land sharing among options depending on the land rent from the production on each land (*i.e.*, crops, livestock, and wood products). To calibrate the function for both managed and unmanaged land in the base year, we used the mean base-year land rent of the managed land as that of the unmanaged land because no data for unmanaged land are available. The carbon stock on forest land is evaluated using price in the case of a climate mitigation scenario. The land rent of forest includes both revenue from wood products and the price of the carbon stock.
**S3.5 Data**

The base-year social accounting matrix is prepared by reconciling data from the Global Trade Analysis Project (GTAP) database (Dimaranan 2006) with data from industrial (OECD 2005; UNIDO 2009), trade (UN 2006), energy (IEA 2009a, b), and agricultural (FAO 2009) statistics, national accounts (UN 2007), and input-output tables (OECD 2010). The concept behind the reconciliation method is discussed in Fujimori and Matsuoka (Fujimori and Matsuoka 2011). The land database was prepared based on Representative Concentration Pathways (RCP) data (Hurtt et al. 2011) and the GTAP database (Lee et al. 2009).
S4. Future assumptions of relevant elements

Specific assumptions for parameters related to food and hunger risk are described below.

S4.1 Irrigation growth rate
Irrigation expansion brings about a change in future yields. High, intermediate, and low irrigation growth rates were assumed based on existing research (Hanasaki et al. 2013).

S4.2 Crop yields
Exogenous crop yield was input to the model and crop yield was calculated endogenously within the model from crop production divided by the area cultivated for crops. Therefore, the model assesses whether the exogenous yields depart significantly from the estimates of existing studies by comparing the endogenous yields with existing studies.

Technology development and irrigation expansion were considered as factors that bring about a change in future yields. First, the yield changes due to technology development were set in line with the Shared Socioeconomic Pathways (SSPs) to express the range of estimates in existing research. High and low changes in crop yields for rain-fed and irrigation-fed cultivation were assumed by using the Agricultural Model Intercomparison and Improvement Project (AgMIP) assumptions (von Lampe et al. 2014) as intermediate assumptions. Then, the changes in yield due to irrigation expansion were calculated from 1) the crop yields for rain-fed and irrigation-fed cultivation and 2) the above-mentioned irrigation growth rates.

High crop yields reduce challenges to both adaptation and mitigation. High crop yields lead to intensive land use, decreased land demand, and increased land-based adaptive capacity for cropland expansion under climate change. They also decrease the mitigation challenge by increasing the land area for energy crop production and decreasing emissions from deforestation. Higher crop yields might increase the mitigation challenge by increasing the emissions from nitrous fertilizer, but they might influence the mitigation challenge less than they influence emissions from deforestation.

The characteristics of crop yields can be interpreted easily using the concepts of SSP1–4, but not for SSP5. For SSP5, we determined high yield from the viewpoint of the challenge of adaptation.
Figure S2 compares the yields estimated with the above methods to existing research. Comparing the values for 2050, the highest estimate among SSPs, SSP5 was slightly lower than those of the International Food Policy Research Institute (IFPRI) (Rosegrant 2002) and Global Orchestration (GO) scenario of the Millennium Ecosystem Assessment (MA) (Alcamo 2005).

Figure S2 Comparison of crop yields with existing studies (Rosegrant 2002; Alcamo 2005; Alexandratos and Bruinsma 2012; FAO 2013a). SSP1–5 represent the results of this study. The values in existing studies were adjusted for 2005.

S4.3 Land productivity of livestock and wood products
High land productivity (production per unit area) of livestock and wood products lowers both the challenges to adaptation and mitigation. High land productivity for these products leads to the intensive use of land, decreases land demand, and increases the land-based adaptive capacity for cropland expansion under climate change. It also decreases the mitigation challenge by increasing the land area available for energy crop production.

The characteristics of land productivity cannot be interpreted easily using the concept of SSP5. We determined high productivity for SSP5 from the perspective of the challenge of adaptation.
The assumptions for livestock productivity were set to cover the range of estimates for pasture area in existing research. The scenario with the strongest contraction of pasture within the AgMIP results (Schmitz et al. 2014) was used for the optimistic assumption and the Order from Strength (OS) scenario of Alcamo (Alcamo 2005), which involves the greatest expansion of pasture, was used as the pessimistic assumption. The average of the two was used as the intermediate assumption. The assumptions for wood productivity were set in line with the storyline of the SSPs.

**S4.4 Forest management**
Forest management lowers the challenge to mitigation by decreasing deforestation and its accompanying emissions. Forest management was described by changing the price elasticity of land use change. The assumptions for price elasticity were set in line with the SSPs. In the optimistic scenario, in which forest regulation is strict and deforestation is difficult, the elasticity was low; in the pessimistic scenario, in which forest regulation is weak and deforestation is easy, the elasticity was set high. The intermediate scenario fixed the price elasticity at current levels. For SSP5, which describes a high mitigation challenge, low wood productivity and weak forest management were assumed.

**S4.5 Inequality in food distribution in a country**
Future changes in the inequality of food distribution in a country were considered by changing the coefficient of variation (CV) of the distribution of dietary energy consumption among households within the country along with income growth. When the proportion of the population corresponding to different per-capita dietary energy consumption levels is assumed to be a lognormal function \( LN(\mu, \sigma^2) \) (\( \mu \), mean; \( \sigma \), standard deviation), the CV can be estimated as \( CV = \sigma / \mu \) (FAO 2008). A higher CV means that the food consumption level varies more widely in the country and food is distributed more unequally. For the same mean consumption, the percentage of the population at risk of hunger would be higher in a country with a high CV. CV is one of the parameters used to calculate the percentage of the population at risk of hunger (See chapter 1 of the Supplementary Material).

Future change in the CV was assumed based on observed data. A function between CV and income was estimated using nation-level observations for 2005 (FAO 2013b) (Figure S3) and used for the intermediate assumption. The function was shifted in elastic and inelastic directions of CV against income growth to express the range of the distribution of low-income level (less than US $10,000 per person). These functions
were used to change the inequality of food distribution according to future income changes. CV was not allowed to fall below the lowest observed value of 0.2.

![Coeficient of variation (CV) of the domestic distribution of dietary energy consumption vs GDP per capita](image)

**Figure S3** Observed and assumed relationships between income and the equality of food domestic distribution.

**S4.6 Income elasticity of food demand**

In the model, food consumption was calculated from income and the income elasticity of food demand. The income elasticity implicitly describes the increase in food consumption and change in diet with income growth. High elasticity of meat demand to income growth means a large increase in meat consumption with income growth.

Future change in the income elasticity of meat consumption was assumed based on observed data. A function between the per-capita meat consumption and income was estimated from nation-level values observed for 1980–2009 (Figure S4), and used as intermediate assumptions. The function was shifted in elastic and inelastic directions of meat consumption against income growth to express the range of the distribution of observed values. These functions were used to change the future income elasticity of meat consumption responding to income growth.

A high meat diet increases the challenges to both mitigation and adaptation. Greater meat consumption leads to greater feed consumption and requires more
cropland and pasture and decreases the land-based adaptation capacity to produce crops under climate change. It also increases the challenge to mitigation by increasing emissions from the livestock sectors and increasing land conversion (Stehfest et al. 2009). Therefore, high elasticity of meat demand to income growth, which indicates a large increase in meat consumption with income growth, was interpreted as a pessimistic assumption in terms of adaptation challenge.

For crop products, no relationship was identified between crop consumption and income, so Bruinsma’s (Bruinsma 2006) values were taken as constant throughout the period for all SSPs. The rate of food loss is assumed to be constant at the current level for the future.

\[ y = 60.0 \cdot \ln x - 399.8 \]
\[ y = 87.8 \cdot \ln x - 545.3 \text{ (Observed data; } R^2 = 0.57) \]
\[ y = 130 \cdot \ln x - 833.0 \]

**Figure S4** Observed and assumed relationship between income and meat-based calorie intake. Time-series and across-country data on the meat calorie intake and income (1980–2009, source World Bank (WorldBank 2013) for income and FAO (FAO 2012b) for calorie intake)

**S4.7 International trade**

Globalization in international trade was described by changing the substitution elasticity applied to the trade function. The assumptions for elasticity were set in line with the
SSPs. The elasticity was assumed to be 0.8 (Löfgren et al. 2002) for the base year. In the globalization scenario, the substitution elasticity was assumed to increase from the base year for each year studied; for the regionalized scenario, the elasticity was assumed to decline. In the intermediate scenario, elasticity was assumed to stay at current levels.
S5. Comparison with existing studies

The per-capita food consumption, which is an element that greatly affects the risk of hunger, was compared with existing research. Figures S5 and S6 compare the per-capita food calorie intake and meat consumption, respectively. The range in the estimates in this study for 2050 have a similar range to estimates in existing studies and there were no significant outliers. The food consumption is high in SSP5, although the scenario assumed low income elasticity for meat demand. This was primarily the result of drastic income growth. In the model, food consumption is calculated from income and the income elasticity of food demand. The income elasticity implicitly assumes an increase in food consumption and change in diet along with income growth and an increase in economic level. Note that these values include food loss. The highest food consumption in 2050 is 3883 kcal/cap/day, the AgMIP high value estimated with the CGE model called FARM (Valin et al. 2014); the lowest is 2970 kcal/cap/day in the estimate of the Adapting Mosaic (AM) scenario of Alcamo (2005).

Figure S5 Comparison of the per-capita food consumption estimated in this study and existing studies (Alcamo 2005; Alexandratos and Bruinsma 2012; FAO 2013a; Valin et al. 2014). SSP1–5 represent the results of this study.
Figures S7-S9 compare cropland, pasture and forest areas with existing research. The estimates for these areas in this study were within the range of existing research and did not depart significantly from existing findings. There were significant differences for cropland area among SSPs resulting from differing assumptions for food consumption, crop yield, and trade. In SSP1, which assumes high yields, the area of cropland declined, whereas in SSP3, which assumes low yields, the area of cropland increased. Food consumption increased drastically in SSP5, but SSP5 also assumes the highest yields among the SSPs, and then the increase in the area of cropland was small. In existing research, there was a large range in the estimates of Tilman et al. (2011). Tilman et al. (2011) gave estimates from 1686 to 2936 million ha. For existing research, the highest value in 2050 was the 2936 million ha in Tilman et al. (2011) and the lowest was RCP 6.0 (van Vuuren et al. 2011).
Figure S7 Comparison of the cropland area estimated in the study and existing studies (Alcamo 2005; Alexandratos and Bruinsma 2012; FAO 2013a; Rosegrant 2002; Schmitz et al. 2014; Tilman et al. 2011; van Vuuren et al. 2011). SSP1–5 represent the results of this study.

Figure S8 Comparison of the grazing land area estimated in this study and existing studies (Alcamo 2005; FAO 2013a; Schmitz et al. 2014; van Vuuren et al. 2011). SSP1–5 represent the results of this study.
**Figure S9** Comparison of the forest area estimated in the study and existing studies (Alcamo 2005; FAO 2013a; Tilman *et al.* 2011)). SSP1–5 represent the results of this study.

**S6. Trade functions of the models**

Food trade is one of key issues in this study because food trade can alleviate the impacts on the risk of hunger. In the model, food trade is described as follows by using the CES function with the Armington assumption (Fujimori 2012). The methodology has the advantage of differentiating domestic and imported commodities. As shown in the second formula, the import-domestic demand ratio increases with the domestic demand-import price ratio, in that more of a commodity is imported when imports become less expensive than domestic products, although the model does not allow for a drastic change in the shares of the two commodities when the share parameter \( \delta_{x_i} \) is very small. As a result, the contribution of a change in trade to reducing the risk of hunger was limited in the analysis.

Another description of trade in economic models is net trade, *i.e.*, simply the gap between domestic production and consumption (Kyle *et al.* 2011; Rosegrant 2002)). The description allows a drastic change in trade, but taxes and tariffs are not considered and there is no economic theory behind the function and no reproducible parameters for this. Different trade functions have different merits and demerits. It might be difficult to
say that the CES function is not appropriate for the analysis. The trade representation is one of the challenges in the modeling activities.

**Composite Supply (Armington) Function**

\[
QQ_{r,c} = \alpha_r^f \cdot \left( \delta_r^f \cdot QM_{r,c} - \rho_r^f \cdot QD_{r,c} \right)^{\frac{1}{\rho_r^f}}, \quad \forall r \in R
\]

- \(QQ_{r,c}\): quantity of goods supplied to domestic market (composite supply),
- \(QD_{r,c}\): quantity sold domestically of domestic output,
- \(QM_{r,c}\): quantity of imports of commodity,
- \(\alpha_r^f\): an Armington function shift parameter,
- \(\delta_r^f\): an Armington function share parameter,
- \(\rho_r^f\): an Armington function exponent.

**Import-Domestic Demand Ratio**

\[
\frac{QM_{r,c}}{QD_{r,c}} = \left( \frac{PDD_{r,c}}{PM_{r,c}} \cdot \frac{\delta_r^f}{1 - \delta_r^f} \right)^{\frac{1}{\rho_r^f}}, \quad \forall r \in R
\]

- \(PDD_{r,c}\): demand price for a commodity produced and sold domestically,
- \(PM_{r,c}\): composite commodity price (including import tax and transaction costs).

**Figure S10** The five SSPs in a conceptual space of challenges to adaptation and mitigation and scenarios for food security (based on O’Neill et al. 2014)
**Figure S11** Population and income assumed for the five SSPs (IIASA 2012).

**Figure S12** Comparison of the population at risk of hunger estimated in this study and existing studies (Alexandratos and Bruinsma 2012; Arnell et al. 2002; Parry et al. 2005; Parry et al. 2004; Schmidhuber and Tubiello 2007)). SSP1–5 represent the results of this study.
Figure S13 Average prices of crops (rice, wheat, other cereal grains, oil crops, sugar crops and other crops) across regions and SSPs estimated in this study.

Figure S14 Average prices of livestock products (meat cattle, daily cattle and other livestock) across regions and SSPs estimated in this study.
Figure S15 Observed and estimated relationships between income and food calorie intake. Blue indicates observations for 1980–2009; red shows the estimates in this study.

Figure S16 Observed and estimated relationships between income and meat-based calorie intake
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