Global-scale projection and its sensitivity analysis of the health burden attributable to childhood undernutrition under the latest scenario framework for climate change research

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Abstract
This study assessed the health burden attributable to childhood underweight through 2050 focusing on disability-adjusted life years (DALYs), by considering the latest scenarios for climate change studies (representative concentration pathways and shared socioeconomic pathways (SSPs)) and conducting sensitivity analysis. A regression model for estimating DALYs attributable to childhood underweight (DAtU) was developed using the relationship between DAtU and childhood stunting. We combined a global computable general equilibrium model, a crop model, and two regression models to assess the future health burden. We found that (i) world total DAtU decreases from 2005 by 28–63% in 2050 depending on the socioeconomic scenarios. Per capita DAtU also decreases in all regions under either scenario in 2050, but the decreases vary significantly by regions and scenarios. (ii) The impact of climate change is relatively small in the framework of this study but, on the other hand, socioeconomic conditions have a great impact on the future health burden. (iii) Parameter uncertainty of the regression models is the second largest factor on uncertainty of the result following the changes in socioeconomic condition, and uncertainty derived from the difference in global circulation models is the smallest in the framework of this study.

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1. Introduction

There are growing concerns that future food security will be negatively affected by various factors, such as changes in socioeconomic and climate conditions. As undernourishment is one of the most serious problems related to the food crisis, the United Nations Millennium Summit in 2000 established the target of reducing the proportion of people suffering from hunger by half between 1990 and 2015 in the Millennium Development Goals (MDGs). Today, about 850 million people are suffering from undernourishment (FAO 2013a). Undernourishment negatively affects human health, especially that of young children. About one-third of the burden of disease in children <5 years of age is attributable to undernutrition (Black et al. 2008). ‘Undernourishment’ or ‘proportion of people undernourished (PoU)’ indicate the part of the population with food consumption below the minimum energy requirement, and are a theoretical model-based estimate from calorie distribution developed by the FAO. On the other hand, ‘undernutrition’ is a term referring to a physical state (Lloyd et al. 2011). The health burden attributable to undernutrition includes not only nutritional deficiencies but also diarrheal disease, respiratory infections, measles, and so on (WHO 2009). Childhood undernutrition may result in a permanent reduction in future earning capacity and can have an impact on the economic development of a country (FAO 2010). The health burden attributable to childhood undernutrition is thus among the most severe problems in the world. The impact of future changes in socioeconomic and climate conditions on human health needs to be quantified so as to chart a course for decision-making.

Changes in climate conditions could have an impact on undernutrition through affecting future crop yields. It is important to consider socioeconomic aspects since per capita food availability varies depending on population and the economic situation in the country. Further, undernutrition is caused not only by a lack of food but also by poor water, sanitation provision, low levels of women’s education and so on (UNICEF 1990). Only a limited number of studies have assessed future undernutrition under scenarios for climate change research, which include socioeconomic aspects. McMichael et al. (2004) projected the number of climate-attributable undernourished children in 2030 and Ebi (2008) estimated the cost of treatment. Nelson et al. (2009, 2010) modeled childhood underweight using food availability and three socioeconomic conditions (life expectancy, female enrollment in secondary school and access to safe water). Lloyd et al. (2011) developed a model to estimate childhood stunting using GDP per capita to represent socioeconomic conditions so that future socioeconomic changes can be taken into account. Children are considered moderately stunted/underweight if they are more than two standard deviations below the mean expected height/weight for their age, and severely stunted/underweight if they are more than three standard deviations below the mean (de Onis and Blossner 2003). Lloyd et al. (2011) and other recent studies (Parry et al. 2004, Nelson et al. 2009, 2010), which are using SRES climate change scenarios, concluded that climate change is likely to have negative effects on future undernutrition.

There is room to expand the previous studies in terms of two aspects. Firstly, a new scenario framework was recently developed for the Intergovernmental Panel on Climate Change (IPCC)’s Fifth Assessment Report (AR5). No group has thus far provided quantitative estimates of future undernutrition based on this scenario framework. The second is an indicator to assess the health burden. Though childhood stunting and underweight have been used as measures for undernutrition in previous studies (Nelson et al. 2010, Lloyd et al. 2011), we used an indicator called disability-adjusted life years (DALYs) to assess the burden more comprehensively (Murray and Lopez (1996)). DALYs accounts for not only the years of life lost due to disease but also the years of life spent living with disability due to disease. One DALY can be thought of as one lost year of ‘healthy’ life, and the burden of disease can be thought of as a measurement of the gap between the current health status and an ideal situation where everyone lives into old age, free of disease and disability. DALYs are calculated as the sum of the years of life lost due to premature mortality and the years lost due to disability (WHO 2009). WHO (2009) found that childhood underweight had the greatest impact on DALYs in the world and in low-income countries among 24 risk factors. Lim et al (2012) expanded the assessment of burden of disease using latest data and 67 risk factors. In 2010, though the world leading risk factor was high blood pressure, childhood underweight was still the leading risk factor in Sub-Saharan African countries, where food insecurity is a serious problem (Lim et al 2012). DALYs attributable to childhood underweight (DaU) is thus preferable to assess future undernutrition.

The aim of this study is to estimate the future health burden attributable to undernutrition by using DALYs, with
consideration of uncertainties in following procedures. (1) To clarify the impact of changes in climate conditions and socioeconomic conditions (i.e. population and GDP growth) using the latest scenario framework. (2) To conduct sensitivity analysis on differences in climate models and changes in a social inequality (i.e. GINI coefficient). Uncertainty in regression model parameters is also investigated. Details about climate models and GINI coefficient are described later in this paper.

2. Materials and methods

2.1. Brief overview

An overview of this study is shown in figure 1. In this section, we first explain the data and secondly describe the framework of the latest scenario. We then outline the models used in this study. Finally, settings for sensitivity analysis are explained in the end of this chapter. We use the term ‘stunting model’ to describe a model for estimating stunting and ‘DAtU model’ to describe a model for DAtU.

We note that DAtU is an indicator derived from underweight, not from stunting. It is accordingly preferable to use underweight to estimate DAtU. However, we quantify the relationship between DAtU and stunting in consideration of three issues: (1) data on DALYs attributable to childhood stunting are not available; (2) projection data to drive the model to estimate underweight used in Nelson et al (2009, 2010) are not available; and (3) stunting and underweight are both indicators of the level of undernutrition, and underweight can indicate stunting (Black et al 2008).

2.2. Data

Data related to DALYs and DAtU were obtained from WHO (2013a). DALYs data are available at the country and regional levels, whereas DAtU data are accessible only at the regional level. To parameterize the DAtU model, the number of regional level DAtU data may not be enough. We made an attempt to estimate country-level DAtU using the concept of population-attributable fraction (PAF) and regional level DAtU. PAF indicates the contribution of a specific risk factor, childhood underweight in this study, to a disease or death (WHO 2009).

We acquired the country-level per capita GDP and GINI coefficient, which is an economic measure of income inequality, from World Bank (2013), PoU data from FAO (2013b), and stunting data from WHO (2013b). To develop the stunting model, stunting data were matched to PoU data within a one-year period. Per capita GDP and GINI coefficient estimates were matched as closely as possible to the stunting data. The data set covered the period of 1990–2008 and contained 240 records with complete data. The data were organized following Lloyd et al (2011). Additionally, we assembled per capita GDP, GINI coefficient, and PoU data in 2004 to develop the DAtU model, as both DALYs and DAtU were available for 2004. The GINI coefficient was matched as closely as possible to 2004. We then prepared 89 records with complete data.

| Table 1. The combination of scenarios (BAU: business as usual, policy: climate policy). ‘BAU’/‘policy’ indicate the future without/with a climate policy for the mitigation of climate change. The existence of the climate policy is represented by the difference in the radiative forcing level and with the climate policy future radiative forcing level will be lower. We assumed six scenarios in total by reference to Hanasaki et al (2013). |
|-----------------------------------------|-----------|-----------|-----------|
| RCP2.6                                  | RCP4.5    | RCP8.5    |
| SSP1 Policy                             | SSP1 BAU  | SSP2 BAU  |
| SSP2 policy                             | SSP2 policy | SSP2 BAU  |
| SSP3 policy                             | SSP3 policy | SSP3 BAU  |

Estimates of future population and per capita GDP were obtained from SSP database (SSP 2012), and we used the current GINI coefficient for the future estimates of DAtU because no reliable projections of the GINI coefficient are available.

2.3. The latest scenario framework

We considered a two-pronged scenario framework, which consists of socioeconomic and climate aspects. As quantitative socioeconomic conditions, we used future projections of population and per capita GDP provided by shared socioeconomic pathways (SSPs) (O’Neill et al 2014). SSPs describe five representative future visions based on challenges to mitigation and challenges to adaptation (figure S4, supplementary information). We used three of five SSPs: SSP1, SSP2, and SSP3, which are respectively characterized as ‘sustainable,’ ‘middle of the road,’ and ‘fragmentation’ scenarios. SSP1 is an optimistic scenario assuming a low population growth rate and a high economic growth rate for the world. SSP3 is a pessimistic scenario with a high population growth rate and a low economic growth, and SSP2 is an intermediate scenario between SSP1 and SSP3. See figure S5 in supplementary information for details of future population and GDP.

We used radiative forcing levels described by representative concentration pathways (RCPs) (van Vuuren et al 2011) and future climate conditions represented by 12 global circulation models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). We considered three RCPs whose predicted radiative forcing levels in 2100 are 2.6, 4.5, and 8.5 [W m⁻²] (RCP2.6, RCP4.5, and RCP8.5, respectively). Changes in temperature in 2050 from the reference year (1991–2000) are 1.8, 2.2, and 2.8 degree for RCP2.6, 4.5 and 8.5, respectively (see figure S6 in the supplementary information). Futures without climate change (i.e. present climate) were not considered in this study.

SSPs and RCPs were developed independently unlike SRES scenarios and all combinations of SSPs and RCPs can be considered in theory. However, along the narratives of the challenges for the mitigation in SSPs (figure S4), we combined SSPs and RCPs as shown in table 1 by reference to Hanasaki et al (2013) in order to assume reasonable...
scenarios. Since SSPs do not include any climate policy and are considered as business as usual (BAU) scenario in terms of GHG emissions, ‘Policy’ scenarios, which include the climate policy for the mitigation of climate change, were also assumed for each SSP. The difference between ‘BAU’ and ‘Policy’ was represented by the change in RCPs (i.e. future radiative forcing level of ‘Policy’ will be lower than that of ‘BAU’). For example, we first combined SSP1 and RCP4.5 as a ‘BAU’ scenario considering the narratives of SSP1 (table 1). We then assumed the combination of SSP1 and RCP2.6, which has lower radiative forcing level than RCP4.5 does, as a ‘Policy’ scenario.

The estimates of the health burden cover from 2005 to 2050. The world is classified into 17 regions and we selected nine regions for the future analysis based on the presence of undernourished people (table 2).

2.4. Model description

(a) Models for estimating PoU

We used future PoU from Hasegawa et al (2014). To incorporate socioeconomic and climate conditions, they combined two models: the M-GAEZ crop model (Masutomi et al, 2009) and a global computable general equilibrium (CGE) economic model (Fujimori et al, 2012). We chose the models used in Hasegawa et al (2014) because although there are several recent studies (Nelson et al, 2010, Hertel et al, 2010, Lobell et al, 2013), which have assessed future food systems using economic models, most are based on SRES and previous phase of CMIP (CMIP3).

The M-GAEZ crop model calculates crop yield in 2.5° grid cells at a global scale with consideration for environmental factors such as climate, soil conditions, and atmospheric CO2 concentration. The global CGE model is an economic model in which supply, demand, investment, and trade are described in terms of individual behavioral functions. The change in crop yields calculated by M-GAEZ was fed into the CGE model to obtain projections of future production and consumption. We used the average food consumption obtained from 12 GCMs for the analysis. To calculate the PoU they used the function estimated from PoU and the mean per-capita calorie intake across countries from FAO data. See Hasegawa et al (2014) for more detail.

(b) Stunting model

We estimated stunting in children <5 years of age from PoU, GDP per capita, and the GINI coefficient. We followed Lloyd et al (2011) to develop the stunting model, which is represented by general equations (1) and (2):

\[ y_{ij} = \alpha_k + \beta_k x_j + \gamma_k w_j + \theta_k x_j w_j \]  
\[ y_{ij} = 1 - y_{ij2} - y_{ij3} \]

for every \( i, j; k = 2, 3 \), where \( y_{ij} \) is the proportion of children <5 years of age stunted in country \( i \) and region \( j \) at level \( k \), where \( k = 1 \) in the case of no/mild stunting, 2 for moderate stunting, or 3 for severe stunting; \( x_j \) is food causes of stunting, represented by the PoU in country \( i \), region \( j \); and \( w_j \) is nonfood causes of stunting, represented by the ‘development score’, which is driven by per capita GDP and the GINI coefficient (see Lloyd et al (2011) for details), in country \( i \), region \( j \). The parameters \( \alpha_k, \beta_k, \gamma_k, \) and \( \theta_k \) are to be determined. Table 3 shows the result for the parameterization. For the parameterization and the validation of the stunting model, see supplementary information S1.

(c) DAtU model

Our outcome of interest is DAtU. As explained in section 2.2, we estimated country-level DAtU since the data were not available. A general procedure of calculating country-level DAtU is as follows: (1) calculating regional level PAF of each disease from DALYs and DAtU (2) modeling the relationship between regional level PAF and per capita GDP and the GINI coefficient (see Lloyd et al (2011) for details), in country \( i \), region \( j \). The parameters \( \varphi \) and \( \psi \) are to be determined. A detailed description of the method to estimate country-level DAtU is given in supplementary information S3.

We developed a model to estimate DAtU using stunting in children, which is estimated from the stunting model; the model is represented by equation (3):

\[ \log (DAtU_{ij}) = \varphi + \psi y_{ij} \]  
\[ \text{for every } i, j \]

where DAtU_{ij} is DAtU in country \( i \), region \( j \); \( y_{ij} \) is the ‘stunting score’, which is composed of moderate and severe stunting with a ratio of 4:6 (see supplementary information S2 for details), in country \( i \), region \( j \). The parameters \( \varphi \) and \( \psi \) are to be determined.

Using dataset described in section 2.4, a linear relationship was noted between the country-level stunting score and the natural logarithm of DAtU per 1000 persons (figure 2(a)). We randomly selected and reserved 20% of the data set and parameterized the equation (3) using the rest (80%) of the data. This process was repeated 10,000 times.

After calculating mean parameter estimates, we also parameterized the equation using the full data set. As a result, we obtained similar parameter estimates to the ones calculated from
the trial repeated 10 000 times. We adopted the latter method and parameter estimates (table 3) because the purpose of the parameterization is to develop the best model for the data set.

To validate the DAtU model, we aggregated predicted country-level DAtU into regional level DAtU because observed country-level DAtU data were not available from WHO. We note that the model was validated using the same data as for the calibration, because of the data limitations, and regions used here are those defined in table S2 in supplementary information. Predicted and observed values were well correlated, with a correlation coefficient of 0.88 (figure 2(b)). Because this validation was done in the log scale, the higher the value is the larger the difference between the predicted and observed values is in the actual (i.e. unlogged) scale (figure S3 in the supplementary information).

GINI coefficient indicates more inequality. We note that changes in the GINI coefficient are considered only in the explanatory variable of the stunting model, though they also have an impact on future estimates of PoU. The impact of changes in the GINI coefficient is expected to be larger when its effect on PoU is considered.

2.5. Settings for sensitivity analysis

We quantified uncertainties derived from three factors: GCMs (i.e. climate models), the regression models (i.e. the stunting model and the DAtU model), and GINI coefficient.

We used 12 GCMs and each GCM calculates future climate conditions differently even for same RCP as seen in figure S6 (supplementary information). These differences make the results uncertain. GCM uncertainty therefore refers 'within-RCP' uncertainty.

We used the plausible ranges for the regression model parameters to estimate the regression model uncertainty (table 3). We assumed normal distributions for each parameter except parameter $\beta_1$, which was assumed to have a uniform distribution. Monte–Carlo simulation (10,000 times) was conducted to evaluate the uncertainty.

We used the current GINI coefficient for future estimation of the health burden because future estimates of GINI coefficient are not available. However, the future GINI coefficient is considered to vary as socioeconomic conditions change. We therefore created simple scenarios of a future GINI coefficient for SSP3 BAU independently from the original SSP scenarios so that we evaluate the impact of changes in the GINI coefficient. We arbitrarily assumed a world where the GINI coefficient in each region increases by 30% by 2050 but does not exceed 0.6, which is currently the worst level in the world, in line with historical trend. An increase in GINI coefficient indicates more inequality. We note that changes in the GINI coefficient are considered only in the explanatory variable of the stunting model, though they also have an impact on future estimates of PoU. The impact of changes in the GINI coefficient is expected to be larger when its effect on PoU is considered.

3. Results

3.1. Estimates of future DAtU under the latest scenario framework

(a) World total DAtU

Figure 3 shows world total DAtU in 2005, 2030 and 2050 for all scenarios. The health burden decreases by 2030 in the world in either scenario. It decreases from the 2005 level (57.4 million DALYs) by 36.4 million DALYs (63%), 30.4 million DALYs (53%) and 16.2 million DALYs (28%) for SSP1 BAU, SSP2 BAU and SSP3 BAU scenario, respectively. DAtU decreases further by 2050 to 11.6 million DALYs (80% decrease from 2005) and 17.0 million DALYs (70% decrease from 2005) for SSP1 BAU and SSP2 BAU, whereas it slightly increases to 43.7 million DALYs (6% increase from 2030) for SSP3 BAU. Even though per capita DAtU in the world in SSP3 scenario decreases by 2050 (explained in figure 4), the impact of population increase in SSP3 offsets the decrease in per capita DAtU.

Figure 3 also shows that the difference in Policy and BAU scenarios, which indicates the impact of climate change, is little in all SSP scenarios in both 2030 and 2050. The differences between BAU and Policy scenarios are 0.2%, 0.5%, and 2.0% in 2050 for SSP1, SSP2, and SSP3, respectively. On the other hand, there are obvious differences in socioeconomic scenarios. The health burden of SSP2 and SSP3 are larger than that of SSP1 by 29% (6.0 million DALYs) and 96% (20.1 million DALYs) in 2030 and by 46% (5.4 million DALYs) and 277% (32.1 million DALYs) in 2050.

(b) Regional level DAtU

Figure 4 shows world and regional level DAtU per 1000 persons from 2005 to 2050 with uncertainties in 2050 derived from GCMs, the regression models, and GINI coefficient. We chose three scenarios to show in the figure (SSP1 Policy, SSP2 Policy, and SSP3 BAU) because the differences in Policy and BAU scenarios are too small to see in the figure.

| Table 3. Parameters of the stunting model and the DAtU model (DAtU: DALYs attributable to childhood underweight). The plausible ranges (expressed by ±) for the parameters except $\beta_1$ indicate the standard error of estimates for 10 000 replications. The range for $\beta_1$ shows 1–10 percentile value (see Lloyd et al 2011 for detailed information). |
|-----------------|-----------------|-----------------|-----------------|
| **Stunting model** | **DAtU model** | **Stunting model** | **DAtU model** |
| **** | $\beta_1$ | $\alpha_k$ | $\gamma_k$ | $\theta_k$ | $\varphi$ | $\psi$ |
|**Moderate ($k=2$)** | 0.411 (0.215–0.480) | 0.003 ± 0.006 | 0.250 ± 0.013 | −0.436 ± 0.022 | −0.210 ± 0.100 | 18.573 ± 0.559 |
|**Severe ($k=3$)** | 0.188 (0.050–0.260) | −0.050 ± 0.008 | 0.264 ± 0.020 | −0.047 ± 0.037 | 0.003 ± 0.006 | 0.250 ± 0.013 | −0.436 ± 0.022 | −0.210 ± 0.100 | 18.573 ± 0.559 |

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even in regional level. In 2005, the world average DATU per 1000 persons is 10.87.

In 2050 for SSP1 scenario, DATU decreases to 2.04 DALYs/1000persons in Sub-Saharan Africa and to less than 2.00 DALYs/1000persons in the other regions. The burden decreases from the 2005 level, for example in Southeast Asia, Rest of Asia, and Sub-Saharan Africa, by 60%, 91%, and 91% in 2050. The world average burden in 2050 for SSP1 is 1.65 DALYs/1000persons (a 85% decrease from 2005), which is less than the current level of burden in Middle East (2.14 DALYs/1000persons). Although the burden in 2050 for SSP2 is larger than that for SSP1 in all regions, it also decreases to 3.00 DALYs/1000persons or less except in Sub-Saharan Africa, where the burden is 3.50 DALYs/1000persons. Even for SSP3 scenario, the health burden in all regions decreases by 2050 from 2005. However, it is higher compared with that for SSP1 and SSP2 scenarios, and it remains high in 2050 in some regions. For instance, DATU in Sub-Saharan Africa and Rest of Asia in 2050 are 10.85 and 6.12 DALYs/1000persons. The world average for SSP3 in 2050 is 4.87 DALYs/1000persons (a 55% decrease from 2005).

3.2. Sensitivity analysis

GCM difference is a minor factor in uncertainties in the world and all regions compared with other factors. The impacts of GCM difference on the health burden in the world are 0.5%, 0.9%, and 2.5% in 2050, for SSP1, SSP2, and SSP3 scenarios, respectively. Because these values are small, the error bars for GCM uncertainty in figure 4 are hard to distinguish. GCM uncertainty is expected to be small if changes in climate conditions have little impact on DATU as GCM uncertainty refers to ‘within-RCP’ uncertainty.

Error bars for uncertainty derived from the stunting model and the DATU model indicate standard errors of 10,000 times replications. The impacts of the stunting model uncertainty on the burden in the world are 6%, 8%, and 17% in 2050 for SSP1, SSP2, and SSP3. Because the burden in SSP3 scenario is high, the relative impact in SSP3 is the smallest among the three scenarios. However, the impact of SSP3 is the largest in an absolute term. The impacts of the DATU model are, on the other hand, 10%, 11%, and 13% for SSP1, SSP2, and SSP3. Uncertainty of the stunting model is larger than that of the DATU model in the world and most regions.

For GINI coefficient, the lower line of the error bar indicates DATU without the scenario and the upper line shows DATU with the scenario. The health burden increases when the GINI coefficient scenario is taken into account. The impact of change in GINI coefficient, which was determined based on arbitrary assumptions, in the world for SSP3 is 9.4% in 2050, which is following the uncertainty of the stunting model and the DATU model.

Input data for estimating future DATU and conducting sensitivity analysis (GDP, population, climate conditions from different GCMs, and GINI coefficient) are provided in supplementary information (figures S5–S7). See Hasegawa et al. (2014) for PoU. Plausible ranges of the regression models are shown in table 3.

4. Discussion

4.1. The impact of socioeconomic conditions

Our results show that changes in socioeconomic conditions (i.e., population and GDP) have a greater impact on the health burden than changes in climate conditions do. In our modeling framework socioeconomic conditions influence undernutrition through the changes in PoU, which is calculated from food availability, and ‘nonfood’ causes of stunting. Future food availability and PoU estimates are highly dependent on socioeconomic conditions compared to climate conditions (Hasegawa et al. 2014). In addition, ‘nonfood’ causes of stunting, which are represented by per capita GDP and GINI coefficient, reflect socioeconomic conditions. Population increase results in a decrease of per capita food availability. Economic growth increases per capita food consumption and decreases ‘nonfood’ causes of stunting. This is considered to be one of the reasons for the great impact of socioeconomic conditions on DATU.
DATU per capita decreases by 2050 in all regions for all SSP scenarios. However, the impact of change in socioeconomic condition differs among regions. In regions with high level of health burden in 2005 (i.e. Sub-Saharan Africa, India, and Rest of Asia), the differences between SSP1 and SSP3 scenario are large in 2050, with the percentage of 432%, 105%, and 278%, respectively. On the other hand, in regions such as Rest of South America, Brazil and Former Soviet Union regions, the differences are relatively small compared with those in the former regions, with the percentage of 4%, 21%, and 15%. This indicates that the impact of future socioeconomic conditions on the health burden is greater in the former regions than in the latter regions.

4.2. Uncertainty in the impact of climate change

It is worth assessing the difference in crop models and economic models. However, regional level future food consumption or PoU based on other crop and economic models are not available in public except the food consumption from Nelson et al (2009) (hereafter Nelson). Nelson estimated the future calorie intake using the Decision Support System for Agrotechnology Transfer (DSSAT) crop model and a partial equilibrium model (IMPACT), whereas we used the M-GAEZ crop model and a CGE model (described as AIM in this section). Because the calorie intake of Nelson based on the SRES, their results are not directly comparable to ours, which is based on the latest scenario framework. However, we brought the SRES scenarios into line with the latest scenario, as described in the table in figure 5. We evaluated the impact of the difference in the study framework by calculating DATU using the future calorie availability from Nelson.

Figure 5 shows world total DATU per 1000 persons in 2005 and 2050 for the scenarios with and without climate change. DATU of our study is described as AIM and DATU obtained based on the future calorie intake from Nelson as IMPACT. The health burden in 2050 without climate change is almost at the same level for AIM and IMPACT, and it shows that it is, to some extent, reasonable to compare DATU obtained from the calorie intake of Nelson to ours. Conversely, there is a huge difference between AIM and IMPACT for the scenario with climate change, with IMPACT showing much greater burden in 2050.

Because the impact of climate change on DATU for AIM was small, we investigated if climate change affects crop yields and calorie intake in our study framework. The impact of climate and socioeconomic on future crop yields and food availability is shown in the supplementary information S5. Crop yields, especially that of wheat, were affected by climate change but the impact of climate change on calorie availability was relatively small (tables S4 and S5). Future crop yields were calculated from the climate conditions with the crop model and food availability was estimated from crop yields with the economic model, which includes socioeconomic aspects. This indicates that some factors assumed in the economic model, such as price elasticity and ease of expanding cropland, can be critical factors to assess the impact of climate change. Recent studies (Nelson et al 2014 and Schmitz et al 2014) investigated these aspects quantitatively (See supplementary information S6 for the further discussion).

4.3. Scenario combinations

We assumed six scenarios shown in table 1 by reference to Hanasaki et al (2013). However, scenario combinations of SSPs and RCPs, especially in terms of how to deal with the climate policy, are still under discussion. Hanasaki et al (2013) refers that the scenario combinations assumed in the paper are tentative and that they may need to be revised. We
therefore calculated and checked the future DAU using scenario combinations, which were not considered in this study (i.e. SSP1/RCP8.5, SSP2/RCP2.6, and SSP3/RCP8.5). We then investigated if climate matters when the results of RCP2.6 and RCP8.5 are compared for each SSP. We found that the impact of climate change was still small compared with that of socioeconomics even under this experimental condition.

4.4. Discussion of modeling the DAU model in the log scale

As is seen in figure 2(a), DAU changes in logarithm scale among countries and regions. We therefore think it is somehow reasonable to model and discuss DAU in log scale, at least as a first step. The difference between regions over time may become clearer when seen in log scale. However, it is preferable if DAU can be modeled in the actual (unlogged) scale because, for example, the validation result in the actual scale is not as good as in the log scale. Even though the correlation coefficient in the actual scale for the model validation slightly increased ($R = 0.97$), the discussion with the correlation is questionable since there are obvious differences between observed and fitted value in the actual scale (figure S4 in supplementary information). We note that the figures of DAU were shown in the actual scale (figures 3–5) in this paper in order to interpret absolute estimates and percent changes in DAU easily.

5. Conclusion

This study evaluated the future health burden attributable to undernutrition, with consideration of uncertainty by using the latest scenario framework for climate change research and conducting sensitivity analysis. We focused on DAU to assess the health burden and developed a model to estimate DAU using childhood stunting. A logarithmic relationship between childhood stunting and DAU was proposed for the DAU model. We combined a global CGE model, a crop model, and two regression models.

Our results show that per capita DAU decreases by 2050 under all scenarios in all regions. Even with the consideration of population change, world total DAU decreases by 2050 in SSP1 and SSP2 scenario, whereas it decreases by 2030 and remains almost same from 2030 to 2050 in SSP3. In this study framework, socioeconomic condition has the greatest

Figure 4. World and regional level DAU per 1000 persons for each SSP scenario from 2005 to 2050. Error bars shown in the right of the boxes indicate uncertainties in 2050 derived from GCM differences (G), the stunting model (S), the DAU model (D), and GINI coefficient scenario (Gi). 12 GCMs are considered for calculating GCM uncertainty. In most regions, GCM uncertainty is too small to see. Uncertainties of two regression models are calculated by Monte–Carlo simulation using the plausible ranges of model parameters. GINI coefficient scenario is created only for SSP3 scenario.

Figure 5. World total DAU per 1000 persons in 2005 and 2050. In 2050, DAU of our study is described as AIM and DAU estimated using the future food consumption from Nelson et al (2009) as IMPACT. Four scenarios are shown for 2050: AIM with/without climate change and IMPACT with/without climate change.
impact on the future health burden. Parameter uncertainty of the regression models is the second largest factor on uncertainty of the result.

Although changes in climate conditions and differences in GCMs are minor factors on the health burden in the framework of this study, their impact could have varied significantly if our study had been based on other assumptions, for example about price elasticity and the ease of cropland expansion. Further studies, such as identifying critical assumptions in the study framework, and performing sensitivity analysis on these factors, are needed to evaluate the impact of changes in climate condition more comprehensively.

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