Global Environmental Change 45 (2017) 47–62

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

A physically-based model of long-term food demand

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ARTICLE INFO

Keywords:
Food demand
Food demand projections
Food waste
Dietary change
Income inequality
Income elasticity
Urban
Rural
Integrated assessment models
Shared socio-economic pathways
Undernourishment

ABSTRACT

Reducing hunger while staying within planetary boundaries of pollution, land use and fresh water use is one of the most urgent sustainable development goals. It is imperative to understand future food demand, the agricultural system, and the interactions with other natural and human systems. Studying such interactions in the long-term future is often done with Integrated Assessment Modelling. In this paper we develop a new food demand model to make projections several decades ahead, having 46 detailed food categories and population segmented by income and urban vs rural. The core of our model is a set of relationships between income and dietary patterns, with differences between regions and income inequalities within a region. Hereby we take a different, more long-term-oriented approach than elasticity-based macro-economic models (Computable General Equilibrium (CGE) and Partial Equilibrium (PE) models). The physical and detailed nature of our model allows for fine-grained scenario exploration. We first apply the model to the newly developed Shared Socio-economic Pathways (SSP) scenarios, and then to additional sustainable development scenarios of food waste reduction and dietary change. We conclude that total demand for crops and grass could increase roughly 35–165% between 2010 and 2100, that this future demand growth can be tempered more effectively by replacing animal products than by reducing food waste, and that income-based consumption inequality persists and is a contributing factor to our estimate that 270 million people could still be undernourished in 2050.

1. Introduction

Food plays a major role in discussions on sustainable development. While providing sufficient food for all people worldwide is a key human development objective (as expressed for instance in Goal 2 of the Sustainable Development Goals (UN, 2015)), at the moment still nearly 1 billion people suffer from undernourishment (FAO, 2015a). Moreover, the production of food plays a role in several environmental problems. Agricultural production is one of the main causes of land degradation, freshwater scarcity, loss of biodiversity, the imbalance in the nitrogen and phosphorus cycles, and climate change (Millennium Ecosystem Assessment, 2005). At the same time, several forms of global environmental change also impact agricultural production, such as climate change, ozone pollution and water scarcity (Millennium Ecosystem Assessment, 2005). In understanding these relationships, it is important to note that agricultural systems do not only produce food crops for direct human consumption. In 2011, 50% of food crops (not including grass) were used as food, 29% for industrial uses (including biofuels), 13% as animal feed, 2% as seed, and 6% were wasted during storage and distribution (rounded percentages by tonne (fresh) (FAOSTAT, 2014)). The share of animal feed is much higher when grass is included, i.e. around 60% in dry matter tonnes (Stehfest et al., 2014). For studying the future role of the food system in the context of sustainable development, it is therefore important to account for complex interactions between development, dietary patterns, and the productive capacity of natural resources.

At the moment, several types of models look into future food demand, including economic Computable General Equilibrium (CGE) or Partial Equilibrium (PE) models. In these models, the future structure of an economy and the resulting demand for goods and services are estimated based on macro-economic data, income elasticities, own-price and cross-price elasticities, and substitution elasticities. The strong point of such macro-economic models is the consistent description of the agricultural sector, the connection between the supply and the demand side via price-mediated equilibriums, and the representation of food demand as part of the economy as a whole, allowing also to assess the propagation of indirect effects of future food demand across economic sectors. However, this approach also has limits, especially for

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http://dx.doi.org/10.1016/j.gloenvcha.2017.04.003
Received 22 September 2016; Accepted 10 April 2017

long-term projections of food demand. First of all, the income, price and substitution elasticities used in these models are often hard to calibrate empirically: it is not clear that published elasticity estimates accurately reflect the behaviour of consumers and producers (Woltjer et al., 2011). Secondly, while the detailed structure of macro-economic models adds value if production and consumption patterns remain close to the range of historical behaviour, it becomes progressively less suitable for longer-term projections, also because it is difficult to incorporate physical constraints which lie outside the historical range. Finally, it is not easy to account for income inequality and other heterogeneities among the population within these aggregated CGE approaches, though some have included a representation of inequality recently.

Other approaches for determining future food demand have been developed that focus more on the food systems in terms of physical flows. Many of these take the concept of so-called Engel curves describing relationships between food expenditure and income, and apply this concept to physical food consumption. One advantage of this approach is the ability to model non-rational behavioural trends and cultural preferences. Existing physical flow models, however, also have important limitations. Many of them only cover a limited number of products and do not capture local heterogeneity (neither urban-rural nor income differences). One of the more advanced physical, Engel-curve based food-demand models is described by Tilman and Clark (2014). We take a similar approach, but we explicitly include local income inequality and use a much more fine-grained set of regions based on geographic, political and cultural similarity. This allows the development of scenarios that better take into account the heterogeneity across the world. Further, we include various types of animal feed and their efficiencies to calculate the actual production volumes; the purpose in Tilman and Clark (2014) was to provide a more rough set of indicators of greenhouse gas emissions and consumer health.

The main purpose of this research is therefore to develop a global food demand model which is aimed (1) at long-term developments, (2) is therefore physically based by simulating calories, proteins and grams of food consumed per person per day, (3) incorporates heterogeneities between regions and income inequality in urban and rural populations within regions, and (4) has sufficiently detailed food categories in order to run dietary change scenarios with Integrated Assessment Models (IAMs) that project land use and other environmental impacts. The model is used to investigate how physical food demand based on Engel curves may develop in the long-term future, and to evaluate options for making the food system more sustainable.

First we introduce the overall structure of the new food demand model (Section 2.1), followed by a more detailed description (Section 2.2) and the scenario definition (Section 2.3). In Section 3 we present the main results, including heterogeneity between and within regions (Section 3.1.2), the number of undernourished people (Section 3.1.3) and the impact of measures that could reduce demand growth relative to the baseline scenario (Section 3.2). In Section 4 we discuss advantages and limitations of the model, including a sensitivity analysis and comparisons with other projections and household survey micro-data. Section 5 concludes with the main findings.

2. Methods

2.1. General model description

The model presented in this paper focuses on future food consumption. Here, 'consumption' is defined as the total amount of food actually consumed by humans. The term 'food use' includes consumption and 'waste in households' (including restaurants etc.). The calculation of food use is driven by a set of key drivers, i.e. population and income. The model is based on Engel's law, which states that households with lower incomes generally spend a larger share of their income on food (Engel, 1857). In Engel's study and many subsequent empirical studies, it is also shown that the absolute expenditure on food increases with income (albeit less than proportionally). In general, the average expenditure per calorie also increases with income, since richer households buy more luxury items and spend more on 'value added' such as service in restaurants or premium brands in supermarkets. This means that food use in physical terms (calories, weight or volume) increases even less proportionally with income. The income elasticity of demand is the percentage that demand increases (or decreases) for each percentage point increase in income. In other words, it is the sensitivity of demand to income changes, and should therefore decrease for higher incomes, regardless of whether demand is defined in physical or monetary terms. Since real income can increase dramatically over long time periods, decreasing income elasticities are an essential part of our long-term food demand model (see Section 2.2). Modelled food consumption is modified for scenario assumptions and leads to animal production and feed demand. Animals can be fed with grass ('grass use') or with crops such as maize or soy, which is called 'feed use'. Subsequently, feed, food and industrial use of crops are summed to total crop use. Finally, 'waste in distribution' is calculated, which includes waste in storage, distribution and retail, but excludes losses on the field (e.g. due to weather or pests) since these are accounted for in agricultural production models. Throughout this paper, we use the term 'use' for actual use as revealed by historical data and 'demand' (potential use) for future projections. We cannot project actual use for the future without explicitly considering supply constraints, and therefore call it 'demand'. Fig. 1 shows a conceptual diagram of the model.

2.1.1. Food categories

In the model, we have defined six major and 46 minor food categories in such a way that they (1) relate to the functions of food for end-users (Table 1), (2) relate to crop characteristics used in food production models, (3) show similar behaviour within the 6 major categories, and (4) allow detailed behavioural scenarios such as the substitution of pulses and soy for cattle meat. See Supporting information for the mapping of minor to major categories.

The major category 'luxuries' is mainly composed of the calorie-heavy food type sugar, and will be only marginally influenced by tea, coffee and spices. We decided to cluster these food types together because they serve roughly the same purpose, and because demand for these food types would increase with income in roughly the same way.

2.2. Calibration and detailed model description

2.2.1. Demand for major food categories

The FAO provides data in very detailed food categories, allowing the model to be calibrated. Fig. 2 shows historical food use for each of the six major categories aggregated from the Food Balance Sheets (FAOSTAT, 2014), plotted against logarithmic average income per region for the SSP-2 scenario in IMAGE regions (Dellink et al., 2015; Stehfest et al., 2014). Although there is much variation between regions and variability for each region, some very broad patterns can be observed. Historical food use increases with income for most categories, slightly decreases for pulses and remains constant for staples.

We use a log-linear relation between food demand and income because (1) it roughly matches the data in Fig. 2 and (2) log-linear relations with income are widely used in food demand modelling for their Engel behaviour (Aitchison and Brown, 1954; Banks et al., 1997) and the resulting lower income elasticity for higher incomes (see Supporting information).

The relation between income and demand is calibrated separately for our six major food categories. First, for each major food category a global slope is calibrated using linear least squares on yearly regional data weighted by population size, as shown in Fig. 2. A dummy variable is used for each region. With this approach we are able to distinguish whether low-income regions seem to follow the behaviour of high-income regions (which is the case for animal products) or whether

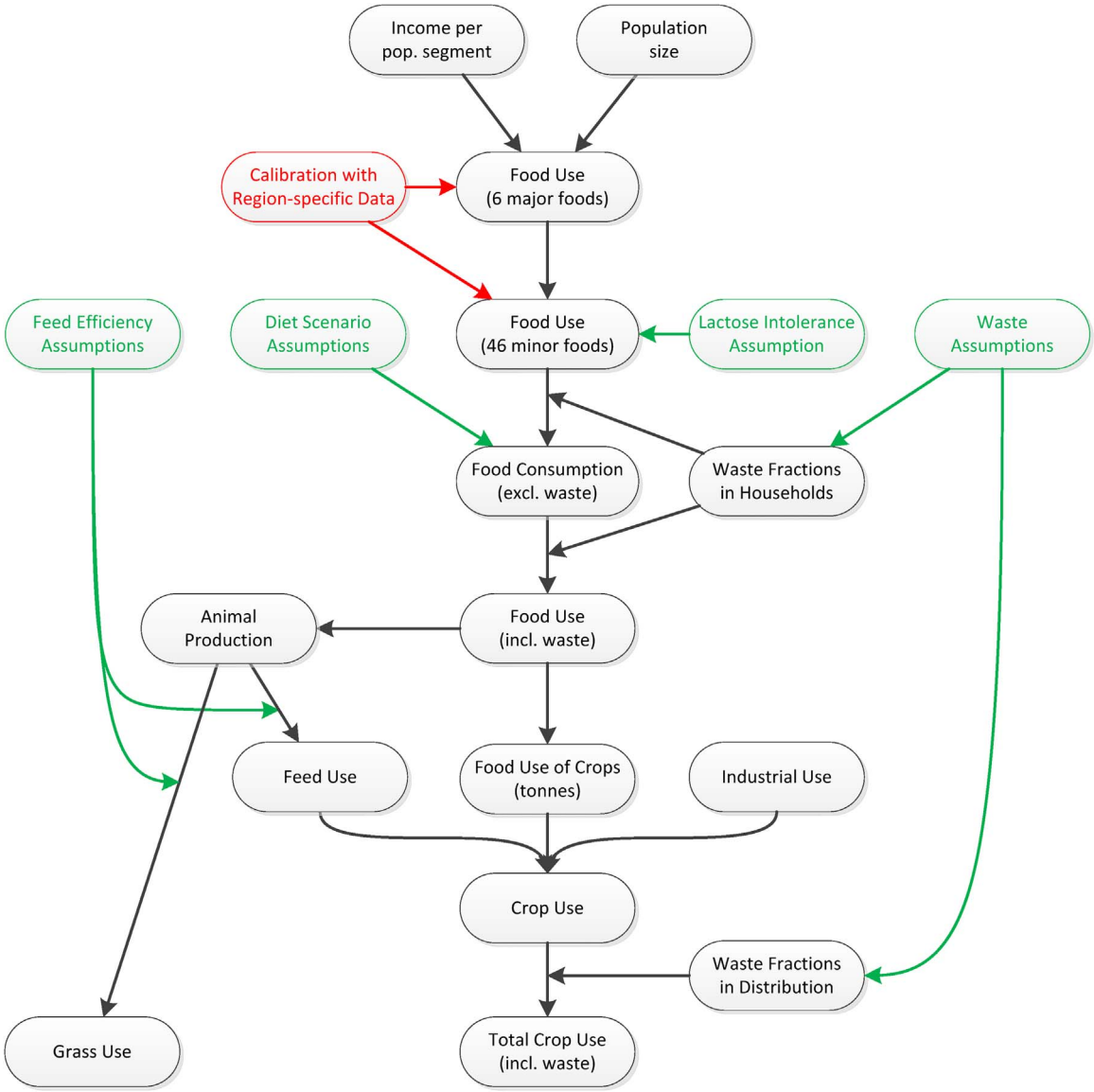

Fig. 1. Conceptual diagram of our physical food demand model. Region-specific data is used for calibration (in red). Various assumptions and scenario settings also influence the model (in green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

income and consumption levels are historically correlated by coincidence. For instance, low-income regions do not follow high-income regions in the case of staple use. Note that only the global slope is used for future projections, while the intercept is replaced by the starting point in 2011 for each region.

Next, the regional models are initialized at their respective values in 2011 and then follow the slope of the global model, i.e.:

$$D_{r,f}(t) = D_{r,f}^{2011} + a_f \ln\left(\frac{I_r(t)}{I_r^{2011}}\right) \tag{1}$$

Where $D_{r,f}$ is demand (kcal/capita) for major food category f in region r at time t, and $D_{r,f}^{2011}$ (kcal/capita) is the historical food use in 2011. I_r (constant 2000 PPP dollars/capita) denotes regional income and I_r^{2011} is the historical regional income in 2011. a_f (kcal/capita) is the calibrated

Table 1
End use functions for consumers, linked to six major food categories. A '+ +' means that the category (e.g. Animal) is a major contributor to the end use function (e.g. Protein). A single '+' indicates a lesser contribution. We developed these end use functions and contribution levels in a qualitative assessment – the exact contribution varies with the specific food type within a category and the method of preparation.

	Energy	Protein	Luxury, taste	Vitamins, minerals	Dietary fibres	Frying
Animal	+ +	+ +	+ +	+		
Fruit and Vegetables	+		+	+ +	+ +	
Luxuries (sugar, tea, coffee, alcohol, etc.)	+		+ +			
Oils and oilcrops	+ +	+	+		+	+ +
Pulses	+ +	+ +		+	+	
Staples (cereals, roots and tubers)	+ +	+			+	

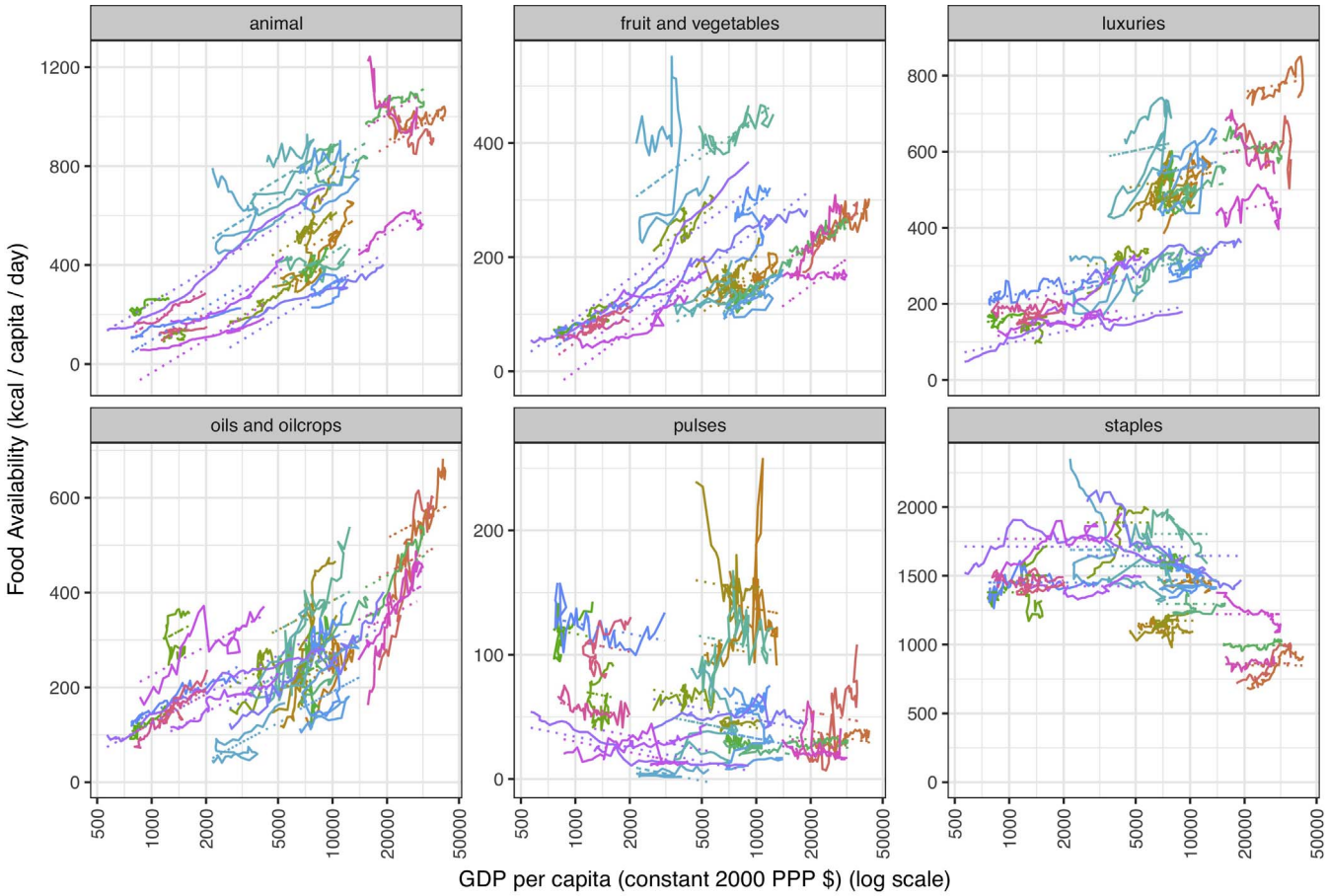

Fig. 2. Relations between income and historical food use for six major food categories. Food use (kcal/cap) on the vertical axis is regionally aggregated from FAOSTAT (2014) as described in the Supporting information. Regional average income on the horizontal axis is corrected for inflation and purchasing power (Stehfest et al., 2014). The dotted straight lines indicate the log-linear model with regional dummies. Region names are omitted to improve readability, but the full data are available in the Supporting information.

slope for the global model. The calibrated values for the slope are 193.3 for animal, 101.8 for fruit and vegetables, 43.3 for luxuries, 88.8 for oils and oilcrops, −12.5 for pulses, and −0.8 for staples.

We also investigated separately calibrated models for each region using only that region's data. In many cases, the regionally calibrated slopes were surprisingly similar to the global slope (see Supporting information Figs. S2 and S3). Regardless of this, regionally calibrated slopes are more sensitive to data for individual years, and the steeper the slope, the less likely it is for this trend to continue in the long run. For both these reasons we decided to disregard separate regional calibrations and use the global slopes instead.

Urban and rural income-based population quintiles with their corresponding average income are obtained from the TIMER model (Stehfest et al., 2014) (constructed from GINI coefficients using the Atlas method). The slope of the global income-relation is then applied to each quintile separately. The result is recalibrated such that regional average demand exactly matches the data in 2011 (FAOSTAT, 2014). This last step is necessary due to the log-linear relation between food demand and income, which means the average of population segments' modelled food demands is not the same as the food demand for the average income (for details see Supporting information).

In summary, the entire calibration procedure consists of three steps: (1) the global relations to income for 6 major categories using 1971–2011 data at regional level but calibrating only the global slope, (2) the initialization for each region separately using regional data but only for 2011, and (3) the correction for income inequality using income and population size per population segment in each region in 2011 (from TIMER).

2.2.1.1. Calibration results. The results of the calibration are shown in Fig. 3. For most major food categories, the model stays quite close to the regional data, even though the slope of the income-demand relation is not region-specific. The R-squared (squared correlation coefficient) of the time series of global average kcal/cap/day is 0.95 for total calories, 0.99 for animal products, 0.97 for fruit and vegetables, 0.42 for luxuries, 0.96 for oils and oilcrops, 0.18 for pulses and 0.52 for staples. See Supporting information Fig. S4 for the full matrix of all regions and aggregates, including values for R-squared.

2.2.2. Minor food categories and lactose intolerance

Modelled demand for major foods is decomposed into 46 minor food categories while accounting for historical cultural preferences (e.g. more milk in India vs. pork in China), using the relative fractions in 2011. Because regional diet preferences might converge in the long term due to globalization, the minor-in-major-fractions slowly transition from fully region-specific in 2011 to the population-weighted global average in 2150.

Lactose intolerance is much more prevalent in Latin America, Africa, and South and East Asia than it is in Europe, the former USSR, the USA, Australia and New Zealand. Therefore, per capita milk demand in these regions might not increase with income as much as for other animal products, although the production of cheese and lactose-free milk would allow some increase. In our model, we assume the average milk demand per region cannot increase more than 25% above the 2011 level for non-western regions (see Supporting information for details). When milk demand is constrained by this assumption, the demand for all other animal foods is increased to match total demand in the animal category.

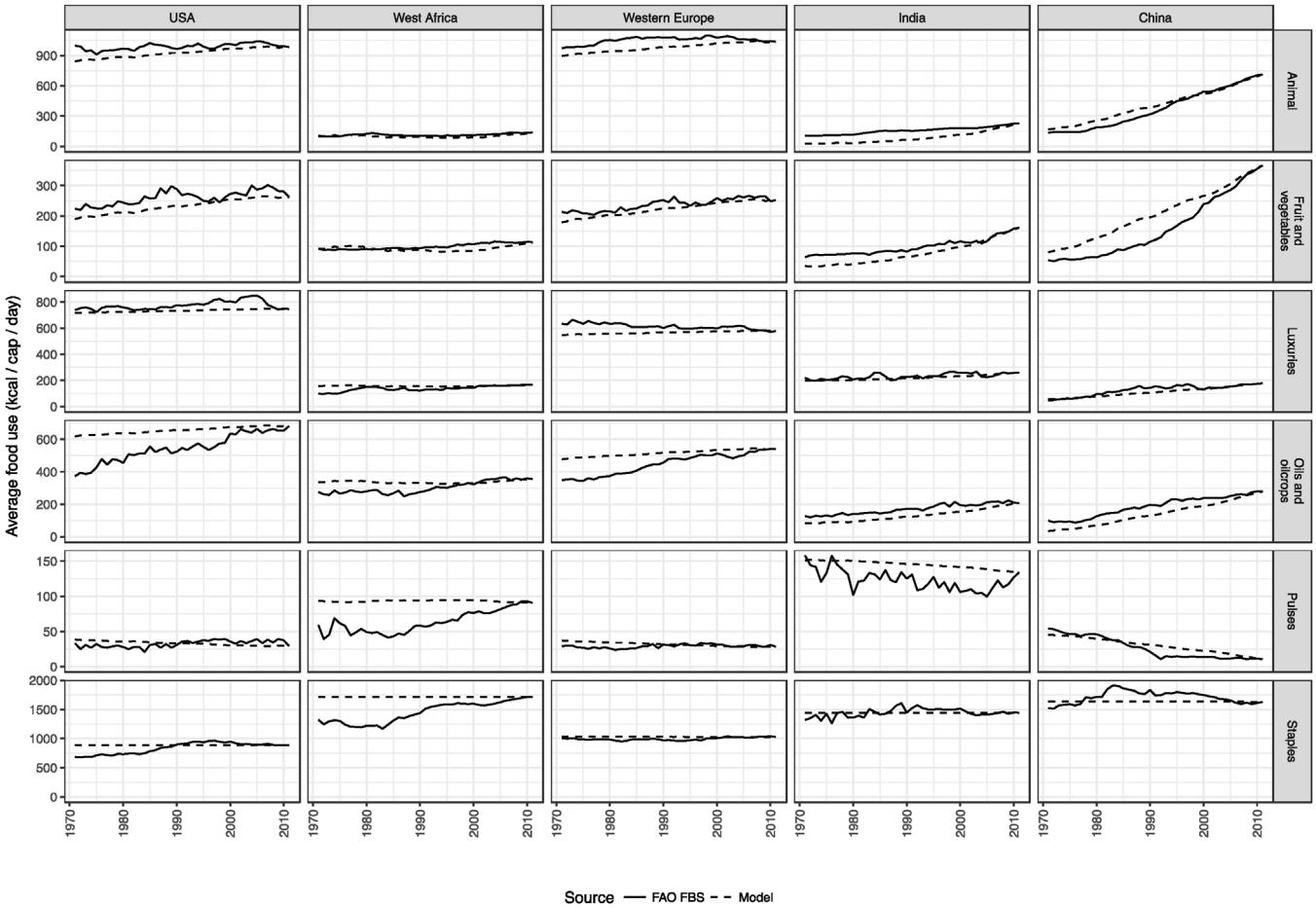

Fig. 3. Comparison between model and data for five selected regions and the six major food categories. The model (dashed lines) coincides with the data (solid lines) in 2011 due to initialization (step 2 in the calibration procedure).

2.2.3. Household waste and dietary change

For household waste we model the waste fraction with a log-linear relation to income, based on estimates in Gustavsson et al. (2013), and constrained between the current minimum and maximum waste fraction attained globally for each food (see Supporting information).

$$HWF_{r,m,p}(t) = \max(L_m, \min(H_m, w_{1m} + w_{2m}\ln(I_{r,p}(t)))) \quad (2)$$

$HWF_{r,m,p}(-)$ is the household waste fraction in region r for minor food category m and population segment p at time $t.L_m(-)$ and $H_m(-)$ are the current lowest and highest waste fractions globally. $w_{1m}(-)$ and $w_{2m}(-)$ are the calibrated intercept and slope and $I_{r,p}$(constant 2000 PPP dollars/capita) is the income specific to the population segment. Thus the waste fractions for various foods increase with income, for each population segment: poor populations waste less than rich populations in the same region. Household waste fractions are specified in terms of calories, and actual food consumption is calculated as food use minus household waste. Although the household waste fraction increases with income, the storage and distribution waste fraction is held constant (Section 2.2.5), and pre-harvest waste fractions generally decrease with increasing income (not modelled here, since this is covered by agricultural production models).

Diet scenarios are applied to the food consumption, and involve either prescribed consumption levels for various meats and eggs, or substituting plant proteins for animal proteins (see Section 2.3 for details). After the dietary changes, household waste is recalculated based on the new consumption pattern, resulting in a modified food demand.

If a scenario specifies household waste to be reduced compared to the baseline scenario, this does not increase food consumption but rather decreases total food demand (i.e. the sum of consumption and waste). Next, food calories are converted to tonnes and multiplied by the population size of each population segment, to arrive at regional aggregate food demand in tonnes.

2.2.4. Animal feed, industrial use and trade patterns

The CGE model MAGNET (Woltjer et al., 2011, 2014) is normally used for food demand-supply interactions in IMAGE (Stehfest et al., 2014). Here, we use output from the SSP scenarios in IMAGE-MAGNET (Doelman and et. al., in review, n.d.) only for (1) regional shares of global production of animal products, (2) animal feed efficiencies, (3) industrial (non-food) crop demand, and (4) regional shares of global production of crops. For each of these variables, the data for the historical period is based on FAO (up to 2007) while for the future period the relative changes of MAGNET are used. The reason for using existing MAGNET data is that these variables are not covered dynamically in the current model.

In our model, demand for animal products is converted to production per region by first equating global production to global demand and then applying the regional shares of global production from IMAGE for each year. Animal feed efficiencies are specified per region and combination of animal product and feed type, and are used to translate production of animal commodities into demand for feed crops and grass. Industrial (non-food) demand for food crops is specified per SSP scenario, but is not differentiated for the sustainable development scenarios. The sum of the crop demands for all uses (including distribution waste described below) can be translated into production volumes per region, using the regional shares of global production per crop from IMAGE-MAGNET. In this paper we focus on demand, not

production, but this step allows our demand model to be coupled with IMAGE for estimating other impacts such as land use or greenhouse gas emissions.

2.2.5. Distribution waste

Waste in the storage and distribution phase applies to all crop uses (food, feed and industry) and is calculated in terms of tonnes. Grass is a separate category which is not used for food or industry and for which we do not calculate distribution waste. Waste fractions are based on Food Balance Sheets (FAOSTAT, 2014), as follows:

$$DWF_{r,m}(t) = \frac{W_{r,m}(t)}{P_{r,m}(t) + IM_{r,m}(t) + S_{r,m}^{pos}(t)} \quad (3)$$

$DWF_{r,m}$ (dimensionless) is the distribution waste fraction in region r for minor food category m at time t. $W_{r,m}$ (tonne) denotes waste, $P_{r,m}$(tonne) production, $IM_{r,m}$ (tonne) import and $S_{r,m}^{pos}$ (tonne) stock withdrawals. The waste fractions from 2011 are carried forward into the future. An income-driven model similar to the household waste model could not be established, since data analysis did not reveal a clear relation between income and waste in storage/distribution.

2.2.6. Undernourished population

The model also enables estimation of the future number of undernourished people. We follow the FAO approach in assuming a lognormal distribution around the average food consumption and compare this to the region-specific minimum dietary energy requirement (FAO, 2015b). Different is that we assume a distribution for each population segment. Although each segment could have a different standard deviation, we have no information about this and therefore assume the same standard deviation for each population segment in a region. We subsequently calibrate the standard deviation in such a way that the resulting total number of undernourished people matches the FAO estimate (FAOSTAT, 2015) for each region over the historical period. For the future, we use the 2015 standard deviation, but assume a slow decrease to avoid implying unrealistically high consumption levels for the higher income classes. In order to keep the upper end of the distribution roughly the same as in 2015, the standard deviation is adjusted with a decrease of 2% per annum for China, Rest of Southern Africa, and Eastern Africa, 1.5% per annum for Western Africa, Indonesia and Rest of Central America, and 1% per annum for all other regions. (see Supporting information for details). Hasegawa et al. (2015) have shown how estimates of long-term undernourishment are influenced by population size, increasing mean consumption due to increasing income, the mean minimum dietary energy requirement, and the inequality of food distribution. New in our study is that inequality of income within a region is separated from the inequality of physical food consumption, and is shown to also have an effect on estimated undernourishment.

2.3. Scenarios

2.3.1. Socio-economic scenarios (SSPs)

We apply the model to the Shared Socio-economic Pathways (SSPs) to study the impact of potential future economic, demographic and technological developments in an internally consistent way (O'Neill et al., 2014). Although O'Neill et al. specify five different SSPs, we focus on SSP-1, 2 and 3 to illustrate the future possibilities ranging from 'cooperation for sustainability' (SSP-1) to 'fragmentation' (SSP-3). While the development of population and income have been quantified for the SSPs (Dellink et al., 2015; Kc and Lutz, 2014), other parameters are only described in qualitative terms. We therefore added assumptions on future behaviour regarding diets and food waste (Table 2).

For SSP-1 we assume a maximum consumption of 3500 kcal/cap/day, but we do not assume such a limit in general for all scenarios, since it is difficult to decide where exactly the limit should be. Physical limits both in terms of calories and kilograms will heavily depend on individual characteristics such as size, age, and habit, whereas our model only computes average consumption patterns for each population segment. However, due to the log-linear relation in our model, the change in consumption per capita for high income groups is very small and thus consumption is bounded in a practical sense. It should also be noted that lifestyle assumptions become much more important for high income levels.

2.3.2. Sustainable development scenarios

To explore the potential effects of lifestyle choices, we also specify a set of 'sustainable development scenarios', departing from the 'middle of the road' SSP-2 scenario (Table 3). By reducing food waste (Kummu et al., 2012) or changing diets (Pimentel and Pimentel, 2003), the future demand for crops (food and feed) and grass can be reduced (see Section 3.1.3). Demand reduction is a critical factor in avoiding the transgression of planetary boundaries and sharply rising food prices. The food waste assumptions take effect in an exponential fashion as described below. The diet assumptions are phased in linearly from 2011 to 2050.

The substitution of pulses and oilcrops for meat is done on a protein-for-protein basis. Only protein-rich oilcrops are used – mostly soybeans but also some groundnuts, sunflowerseed, sesameseed, and 'other oilcrops'. The composition of pulses and various oilcrops in the substitute is the same as in the unmodified regional diet. Because the calorie-to-protein ratio of the substitutes is higher, the amount of staples is adjusted to keep total caloric consumption constant.

The Low Meat Diet scenario is based on specific levels of meat consumption recommended by M.D. Walter C. Willett (at Harvard Medical School) as interpreted by Stehfest et al. (2009), and implemented as follows: 10.4 kcal/cap/day for cattle meat, 16.0 for pig meat, 32.3 for eggs, 33.2 for poultry meat and 13.0 kcal/cap/day for fish and seafood. Applying this diet globally leads to reduced meat consumption by rich populations while increasing it for the poorest populations up to the recommended level. Consumption of pulses, oilcrops, staples and luxuries is adjusted to keep total protein and calories constant, as in the other dietary change scenarios. Note that we only implement the recommendations regarding consumption of meat, fish and eggs – the consumption of dairy products (milk, cheese, yoghurt, etc.) and fruits and vegetables follows the reference scenario SSP-2.

Many authors suggest methods to reduce food waste (Godfray et al., 2010; Mena et al., 2011; Parfitt et al., 2010; Quested and Murphy, 2014), but it is difficult to estimate how much of current food waste could actually be avoided in practice. Kummu et al. (2012) use a life cycle analysis approach and assume at each stage of the supply chain and for each food category that the lowest waste fraction achieved by any region can be achieved by all others regions. To study the theoretical potential effects of waste reduction, we make similarly optimistic assumptions, noting that it will be difficult to achieve these waste reductions in practice. For the household waste reduction scenario, we set the current lowest waste fraction worldwide as a lower bound, for each food category. We then assume for all regions that the actual waste fraction tends towards the lower bound exponentially at 10% a year, thus closing the gap by 86% in 2030 and 98% in 2050. For waste in the storage/distribution phase, we assume all waste could be avoided (zero lower bound), but at a slower rate of 5% per year, thus reducing the distribution waste fraction by 62% in 2030 and 86% in 2050. The rationale for the slower reduction is that distribution waste is caused less by behaviour and more by the physical conditions and systems in place, such as the quality of cold chains (refrigeration throughout the supply chain to preserve fresh products).

Table 2
Scenario assumptions for SSP-1, SSP-2 and SSP-3.

	SSP-1	SSP-2	SSP-3
Population Growth	Peak around 8.5 billion in 2050.	Peak around 9.5 billion in 2070.	Around 13 billion in 2100 and increasing.
Average Income	About 81,000 in 2100.	About 59,000 in 2100.	About 22,000 in 2100, with larger regional differences.
GINI coefficient (global average of regional GINIs)	Decreases from 38.7 to 35.7 during 2011–2050.	Little change (39.2 to 39.4) during 2011–2050.	Increases from 39.8 to 44.4 during 2011–2050.
Urbanisation	93% urban in 2100.	80% urban in 2100.	58% urban in 2100.
Livestock feed efficiencies	High: efficiency parameters in each region converge 50% towards the levels of the most efficient region in SSP-2.	Medium: largely follows projections by FAO agricultural outlooks.	Low: efficiency stagnates at current levels in each region.
Food Waste	Households avoid up to 50% of avoidable waste. The distribution waste fraction is reduced by 2% annually.	No additional assumptions.	No additional assumptions.
Diets	Max. total consumption 3500 kcal/cap/day. 25% less animal products compared to income-based diet, compensated protein-for-protein by pulses and oilcrops. align=" < span class="	No additional assumptions.	20% more meat compared to income-based diet (no additional dairy products, pulses or oilcrops).

Table 3
Scenario specification for response scenarios based on SSP-2.

Scenario	Assumptions in addition to SSP-2
Household Waste Reduction	Households avoid up to 100% of avoidable waste.
Distribution Waste Reduction	The distribution waste fraction is reduced by 5% annually.
Combined Waste Reduction	Both of the above.
No Ruminant Meat	Meat from cows, sheep and goats is replaced by pulses and some oilcrops (mainly soy, see below).
Lacto-ovo-vegetarian	All meat is replaced by pulses and oilcrops, but eggs and milk products remain unchanged.
Low Meat Diet	Consumption of meat, fish and eggs is prescribed at fairly low levels, without changing other foods.

3. Results

3.1. SSP scenario projections

3.1.1. Food demand

Fig. 4 shows the results of our model applied to three of the Shared Socio-economic Pathways (SSPs). The upper panel shows the world average diet composition (kcal/capita). In SSP-1, per capita demand for calories grows quickly before 2050 due to increasing incomes, but slows down after 2050 partly due to household waste reduction and a maximum consumption of 3500 kcal/cap applied to each population segment (see Section 2.3). The transition to less animal-intensive diets is also clearly visible in the growth of oilcrops and pulses. SSP-2 diets keep increasing steadily in terms of overall calories and in particular animal products and fruit and vegetables, due to increasing income. By contrast, the growth of average calories per capita in SSP-3 slows down around 2030 because demand remains lower in many developing regions due to slow income growth, while their weight in the global average increases due to their high population growth.

The lower panel of Fig. 4, shows the differences between the three scenarios in terms of resulting tonnage. Total demand for crops and grass declines after 2050 in SSP-1, stabilizes around 2090 in SSP-2, and keeps growing steeply in SSP-3. The peak of demand in SSP-2 is 10.9 Gton, 48% higher than the peak in SSP-1 (7.4 Gton). Besides the different diet composition, other reasons for lower crop and grass demand in SSP-1 compared to SSP-2 are lower population growth, higher animal feed efficiency, and a 2% annual reduction of the distribution waste fraction. There is a small dip at 2050 for SSP-1 because we assumed that the dietary transition is complete in 2050. In SSP-3 demand keeps increasing rapidly whereas it levels off in SSP-2. The difference is largest in the 'feed grass' and 'food staples' categories. Demand for staples is higher in SSP-3 because there simply are more people. Since they remain relatively poor, demand for non-staple categories does not grow as quickly as in the other scenarios. The higher demand for grass is also partly due to higher population numbers, although per capita consumption of animal products is slightly lower in SSP-3. However, the main reasons are (1) slower improvement of feed efficiencies, and (2) more use of extensive rather than intensive farming systems to produce cattle meat and milk in SSP-3. The steep demand growth in SSP-3 might be above practical production capacity, and might therefore trigger feedbacks to lower consumption or more intensive production, especially regarding livestock systems.

3.1.2. Differences between and within regions

Fig. 5 highlights the modelled consumption inequality between population segments in the same region, which is of a similar magnitude as differences between regions. In 2011, modelled total dietary energy consumption ranges from 1877 to 2911 kcal/cap/day for the poorest rural quintiles of all regions, and from 2577 to 3598 for the richest urban quintiles. The gap between richest urban and poorest rural quintiles within a region ranges from 410 kcal/cap/day in Russia to 1226 in 'Rest of South America' (South America without Brazil).

The differences in diet composition are highlighted by the coloured bars in Fig. 5. According to the model, the 20% poorest rural inhabitants in West Africa could not afford any animal products in 2011, whereas the rural poorest in China consumed almost as many animal calories as the 20% richest urban dwellers in India and West Africa (but still much less than the poorest in Western Europe and USA). Note that rural inhabitants in developing countries may have access to meat from hunting, which is not covered by the statistics. The model for rich/poor population segments is derived solely from the income-demand relations based on national accounts.

As time moves on, developing regions slowly catch up with developed regions regarding physical consumption levels. The global gap between all the poorest rural quintiles of the regions decreases from 1034 kcal/cap/day in 2011 to 954 in 2050, and for the richest urban quintiles decreases from 1021 to 965. Within regions, the gap between the rural poor and the urban rich decreases only slightly, from 410 to 1226 kcal/cap/day in 2011 to 360–1037 in 2050. In all regions, the rural poor eat less in 2050 than the urban rich did in 2011. This highlights only the inequality between the population segments. Due to rapid urbanization in developing countries, the number of people in each rural segment decreases over time. This effect, combined with the overall consumption increases greatly reduces the estimated total number of undernourished people, as shown in Section 3.1.3.

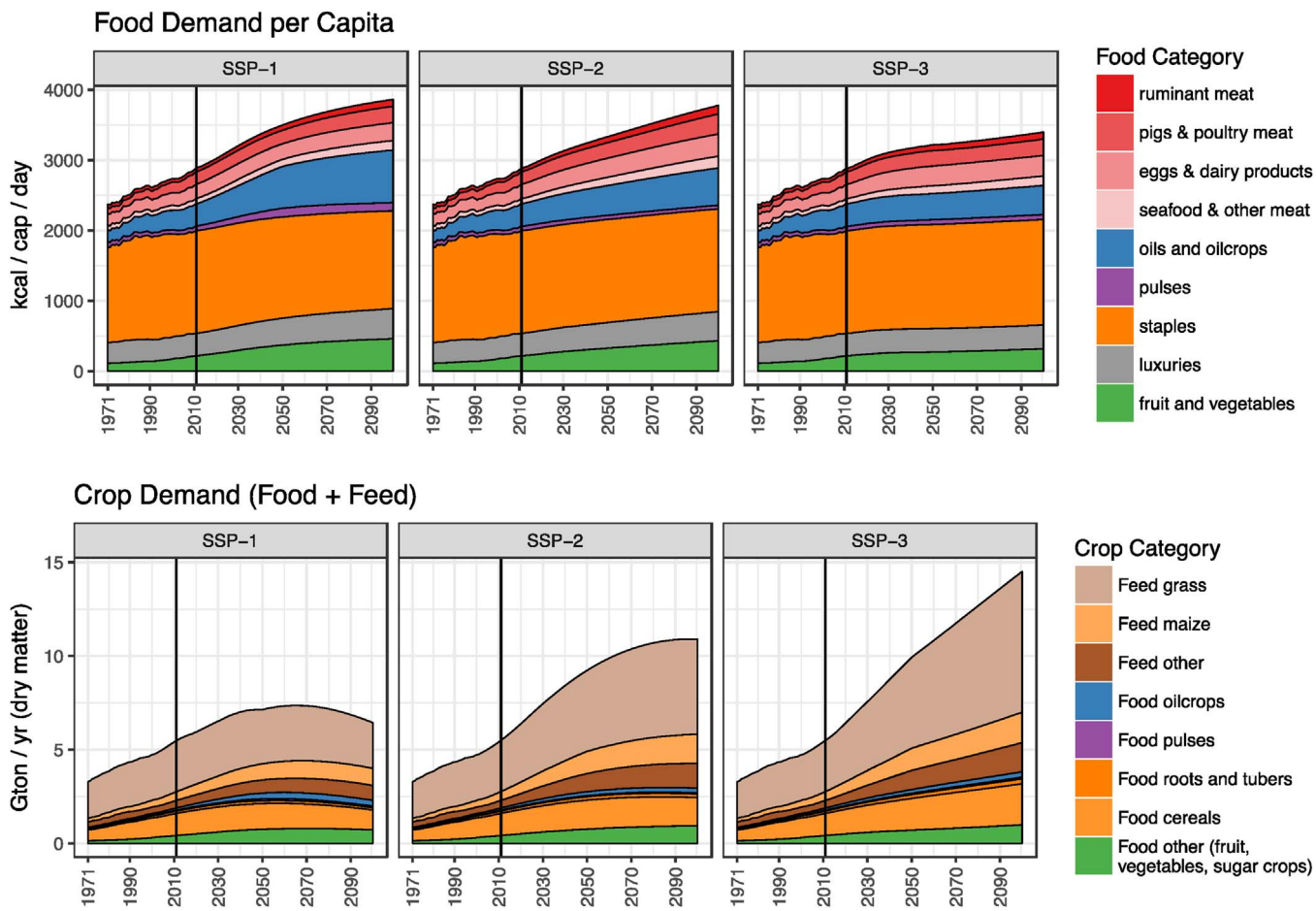

Fig. 4. Historical use (before 2011) and projected future demand (after 2011) for food and crops, for three socio-economic scenarios. The upper panel shows the global average diet composition in kcal per capita, as influenced by income, income inequality, scenario-specific diets and household waste. The lower panel shows the effects on total demand in dry matter tonnes (food, feed and grass), as influenced by population growth, the diets in the upper panel, livestock feed efficiencies, and distribution waste.

3.1.3. Undernourished population

Fig. 6 shows both the overall trend in estimated future undernourished population, and the effects of income inequality. We display two versions of SSP-2: a 'more equal' scenario in which the average income in each region still follows SSP-2 but the distribution of incomes around the average follows SSP-3, and a 'less equal' scenario with income inequality as in SSP-3. In absolute terms, the gap between the 'less equal income' and the 'more equal income' scenario is largest around 2040, with 41 million more undernourished people in the 'less equal income' scenario. The scenarios converge again after 2040, because population growth slows down over time while per capita income keeps increasing.

The overall trend in Fig. 6 is clearly decreasing: global undernourishment decreases from roughly 700 million people in 2015 to almost zero in 2100. The two main causes for this decrease are that (1) income growth allows average consumption to increase, and (2) the variance around the average consumption is assumed to decrease over time. As there is a natural limit to the amount consumed per person, the variance should decrease as the average consumption increases (see Supporting information for details). Without this variance reduction, our model would still project 250 million undernourished people in 2100.

In most regions undernourishment declines quickly, with the notable exception of Rest of Southern Africa (RSAF, i.e. excluding the country South Africa) and to a lesser extent Eastern Africa (EAF). In these regions, the number of undernourished people is projected to increase first, due to high population growth combined with a limited increase in consumption per capita. Also note that these estimates of undernourished population only hold when future demand is actually satisfied by increased food production (or imports) in every region.

3.2. Sustainable development scenarios

Fig. 7 shows the potential to reduce global demand for crops and grass by making sustainable lifestyle choices. Reducing demand compared to SSP-2 is crucial for global sustainability, since total demand would increase by 70% from 2010 to 2050, due to growing populations and incomes. Drastic waste reduction efforts in households and distribution systems have relatively little effect on total demand in 2050: up to 10% reduction compared to SSP-2 for both effects combined. In contrast, the substitution of plant proteins for animal proteins significantly reduces total demand for crops and grass, as shown in the dietary change scenarios. If only meat from ruminants (cattle, sheep and goats) would be globally substituted by plant proteins, grass demand would decrease 78% compared to SSP-2, and feed crop demand would decrease 28%, while increasing food crops demand by only 2%. A global transition to a lacto-ovo-vegetarian diet is not likely, but would reduce feed crops as significantly as grass demand: 68% and 78%, respectively, while increasing food crops demand by 10%. The final diet scenario is based on recommended low levels of meat consumption, which results in large reductions of meat consumption for wealthy populations and regions with a preference for meat, and a modest increase up to the recommended levels for poorer populations. This diet scenario may be more realistic, since meat is not eliminated completely and the rationale is based on health considerations. In this scenario, feed crops and grass demand are

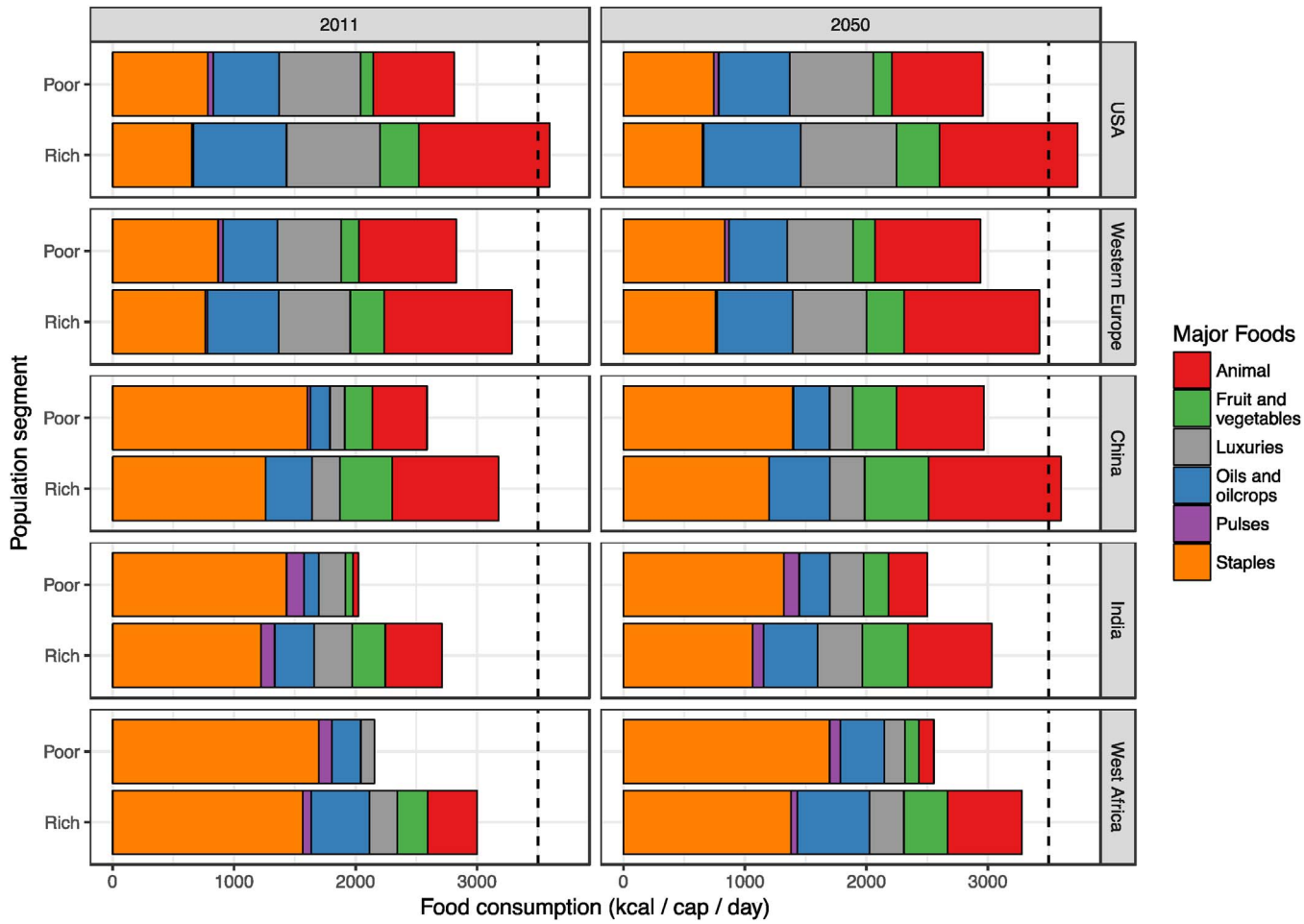

Fig. 5. Differences in food consumption projections (SSP-2) between and within regions. 'Poor' indicates the poorest rural quintile and 'Rich' the richest urban quintile. Differences between population segments in 2011 are modelled using the calibrated global income-demand-relations (Section 2.1). Food consumption (horizontal axis) excludes household waste, which also increases with income. The dashed line facilitates left-right comparison, and represents the level at which total consumption is constrained in SSP-1.

reduced by 55% and 66% compared to SSP-2, while increasing food crops demand by 7%. Total dry matter demand (for food, feed and grass) would be 41% lower than SSP-2 in 2050, and roughly the same as in 2010, although crops make up a larger fraction of the total.

4. Discussion

In this section we compare our food demand projections with previous projections from the literature (Section 4.1), compare our modelled consumption inequality within regions to data from national household surveys (Section 4.2), investigate the relative importance of the main drivers with a sensitivity analysis (Section 4.3), and end with limitations of our methodology and implications for further research (Section 4.4).

4.1. Comparison to other projections

Fig. 8 compares our model to FAO projections up to 2050. In the upper panel, our model projections for developing countries are generally in line with FAO, except 'other food' (mostly fruits, vegetables, eggs, butter, seafood and alcohol), for which our modelled demand increases substantially faster. Roughly a third of the gap can be explained by the faster income growth in our baseline projection (see also Fig. 9), since the dashed line is somewhat closer to the FAO projection.

In the lower panel of Fig. 8, the growth in total dietary calories (model) or grams (FAO) is shown for developing versus developed regions, for various continents, and for the global average diet. Most differences can be explained by our higher income growth, since the dashed lines (our model applied to FAO income) are generally close to the FAO projection. Remaining notable differences are East Asia, where FAO projects much slower consumption growth after 2011, and Sub-Saharan Africa, where FAO projects higher growth than our model would project with their income. However, even with indexing the comparison is not accurate since we project calories whereas FAO project grams, and the calorie density for aggregate categories may change over time (especially for 'other foods' and 'total food').

The FAO projection is at the low end or even below the range of model projections because 2050 income per capita in SSP-2 is 50% higher than in FAO, as explained by Valin et al. (2014). Our model is close to the lower end of the AgMIP10 range for Crops (middle panel) and in the centre for Livestock (right panel), resulting in an overall position in the lower half of the AgMIP10 range for Total calories (left panel).

In summary, our new approach yields results close to FAO projections and within the range of other model projections, although the method is quite different. Whereas FAO projections are a combination of modelling and input from country experts, and other models take a macro-economic perspective, our approach is characterized by a demand-side perspective, income-related behaviour (including waste), local inequality, and physical calculations. Our model is quite sensitive to projected income growth, since demand for animal products, oilcrops and fruit and vegetables increases rapidly with income. However, demand growth for milk products levels off because lactose intolerance

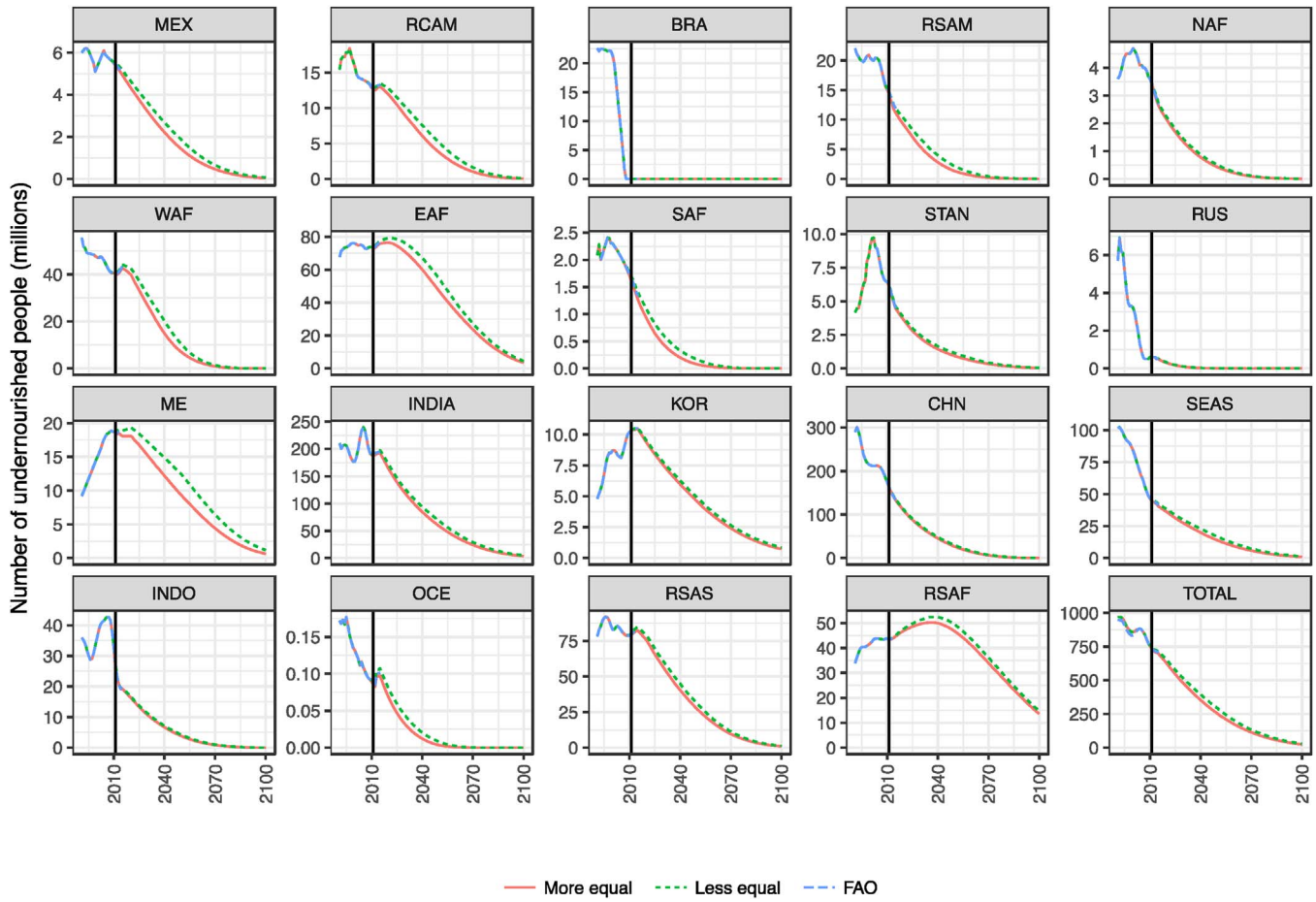

Fig. 6. Historical (FAO in blue) and future (model-based) estimates of the number of undernourished people per region. The global total is shown in the last panel. The effects of income inequality on estimated undernourished population are shown by comparing a 'more equal income' (SSP-1) (red solid lines) with a 'less equal income' (SSP-3) (green dashed lines) version of SSP-2. The estimation is only applied to countries for which the FAO estimates undernourishment. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is included in a physical, region-specific way. Note that the historical record does not provide information on the maximum level of dairy consumption. Since most lactose-intolerant regions still have relatively low incomes, a plateau would not have been reached historically. The only region with high income and high prevalence of lactose intolerance is Japan, where we see a slow decline after reaching a maximum that is a factor 2–3 lower compared to other rich countries (Fig. S9 in Supporting information), but this might also have been caused by cultural factors and/or supply-side restrictions.

4.2. Comparison to household surveys

One of the new features of our model is the disaggregation of regions to five urban and five rural income quintiles. Since the FAO Food Balance Sheets do not include sub-national disaggregation, we derive the income-demand relations from the global data. We then evaluate this approach by comparing our model to household survey data for two large countries with very different income levels. For a good evaluation, physical data for all food categories and population segments would be needed, but we only found a mix of physical and monetary data for India and only monetary for the USA (for an overview of datasets see Supporting information). Still, we present a comparison between model and data for these two very different countries.

In Fig. 10 we compare our model to a household survey from India (Desai et al., 2015). Since calories were not reported for all food categories in the survey, the 'inferred' consumption in the centre panels was derived by combining expenditure data in the survey with calories from FAOSTAT (2014) for specific food categories. Three things jump out. First, our model has higher average food use per capita than reported in the survey, even when inferred calories are included. One contributing factor is that we ignored expenditure on 'processed food' and 'eating out' from the survey results, since there was no way to match this to FAO categories. Secondly, the inequality between population segments in the model is low compared to the inferred data, but on the high end when comparing only to the actual calories reported in the survey. The inferred part of the food use (centre panels) is inaccurate for specific population segments, because the inference method assumes that everyone pays the same price per calorie. If richer segments pay higher prices per calorie, the real distribution would be more equal than shown here. On the other hand, the low inequality in the rightmost panels is to be expected, since calories were only reported for basic foods such as rice, pulses, milk and eggs − for which there should be little difference between rich and poor populations. Overall, the modelled inequality matches quite well with inequality based on the survey. Finally, we observe that the model corresponds quite well to the data regarding the increasing use of animal products, oilcrops, and fruit and vegetables with increasing income. However, use of staples also increases with income in the survey, whereas it remains constant in the model.

Fig. 11 compares our model to consumption aggregated and inferred from the USA Consumer Expenditure Survey 2011 (BLS, 2011). The kcal per capita values for the survey (right panels) were inferred from expenditure on each food category combined with overall food use according to FAOSTAT, since the survey only reports expenditure in dollar terms. 54% of expenditure could not be matched

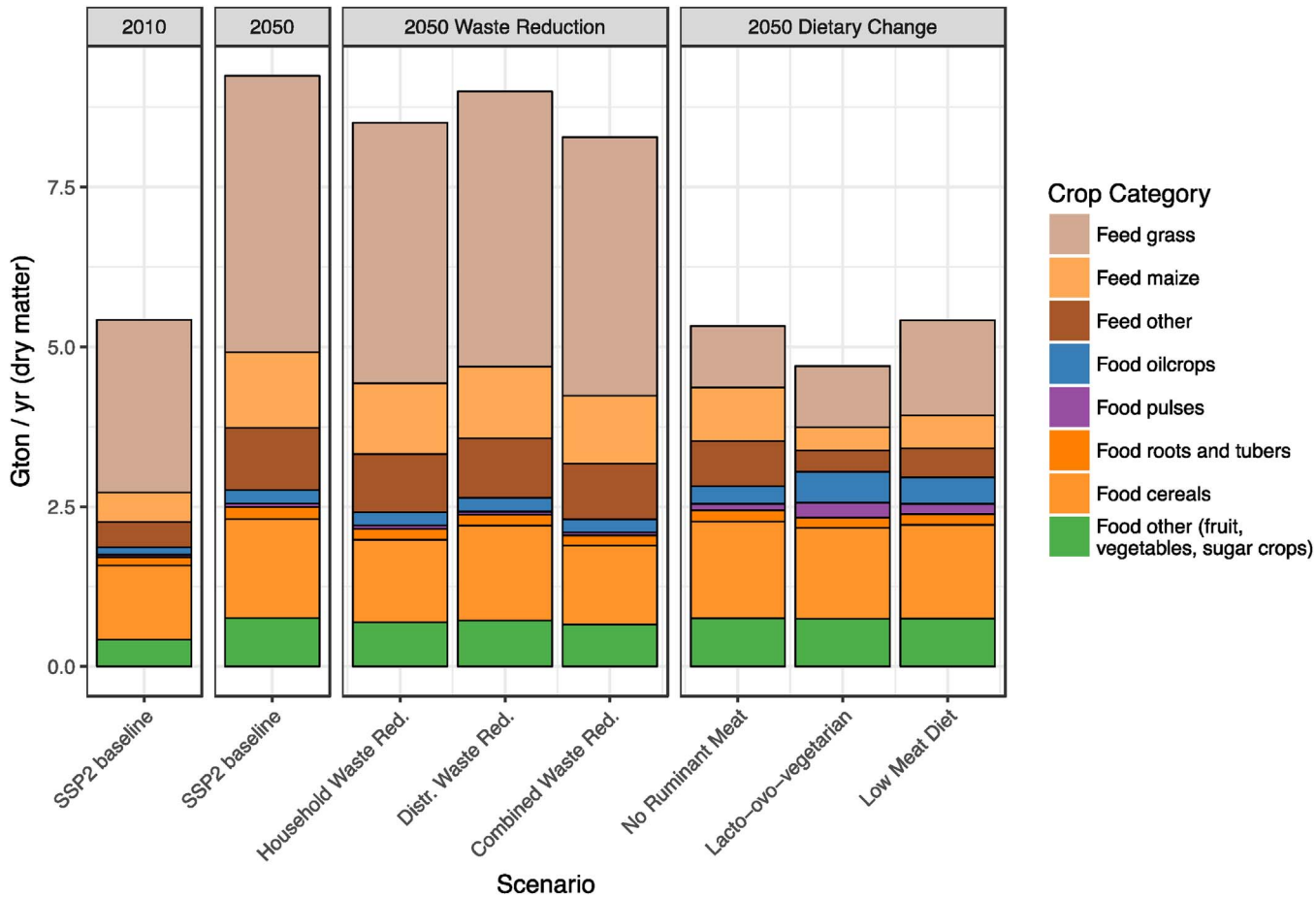

Fig. 7. Waste reduction and dietary change as solutions to reduce projected crop and grass demand: Total demand for food crops, feed crops and grass for the SSP-2 baseline in 2010 and 2050 (left), for three scenarios of food waste reduction (middle), and three scenarios of dietary change (right).

to a specific food category, so we assume such expenditure (e.g. restaurants) has the same composition as the rest of the diet. Since we have no other data, this inference method also assumes that prices per calorie are the same for rich and poor population segments. The food categories in Fig. 11 are sorted with the cheapest foods (per calorie) at the bottom and the most expensive at the top. Note that household waste is included in these numbers.

The main similarities between the model and survey are that total food use and use of milk and dairy, various meats, alcohol and oils all clearly increase with income. Interesting differences are the higher use of cereals among the rich in the survey, and the two poorest rural quintiles using more food than the middle quintile in the survey. The overall inequality is also much higher in the survey than in the model, but this may well be an artifact of using the same price per calorie for rich and poor populations. It is highly likely that the rich spend more per calorie in each food category, e.g. buying the top brands. Likewise, we cannot actually conclude that the urban rich in the survey drink more alcohol than the poor, because they may be buying only expensive wines. Since we have no additional information, it is unclear how unequal the distribution of calories is in reality.

4.3. Sensitivity analysis

The model and the SSP scenarios are built around a small set of ‘drivers’ which determine future food demand. Here we perform a sensitivity analysis to investigate the relative importance of the drivers. The scenarios for sensitivity analysis are variations on SSP-2 in which only one parameter is modified in each scenario. The modified parameter is based on SSP-1 or SSP-3 scenario settings, since these represent a realistic parameter space that does cover quite a wide range of potential future developments. In each case, the parameters are specified for each region separately. The resulting percentages deviation from SSP-2 are shown for the year 2050 and are calculated in terms of dry matter tonnes (see Table 2). The sensitivity of the model to alternative calibrations is discussed in the Supporting information.

We highlight a few observations about Table 4. Feed efficiency (top row) by definition has no effect on demand for plant-based food, but the inverse effects on animal feed demand are substantial. Effects of income per capita (second row) on animal feed demand are stronger than effects on plant-based food demand, because demand for staples hardly changes with income but constitutes a large part of the plant-based demand, thus dampening the increases from oilcrops, fruits and vegetables and luxuries. Population size (third row) has almost symmetric effects and affects plant-based food and animal feed in roughly the same way (there is no meat-to-feed multiplier effect here, because everything is measured in percentages). The numbers are not exactly the same because the higher/lower population size and the preference for animal products varies per region. The diet intensity parameter (fourth row) has no effect on food crop demand in the ‘high’ (SSP-3 diet) case, since the SSP-3 assumption is ‘20% more animal products without reducing oilcrops/pulses’. In the ‘low’ (SSP-1 diet) case, there is a small reducing effect on plant-based food demand, even though the assumption is ‘25% less animal products compensated by higher consumption of oilcrops and pulses’. This is due to the additional assumption of a maximum 3500 kcal/cap/day total consumption for each population segment. In summary, population size and income per capita are equally influential drivers for plant-based food demand. For animal feed, the most influential driver is the diet intensity, with a

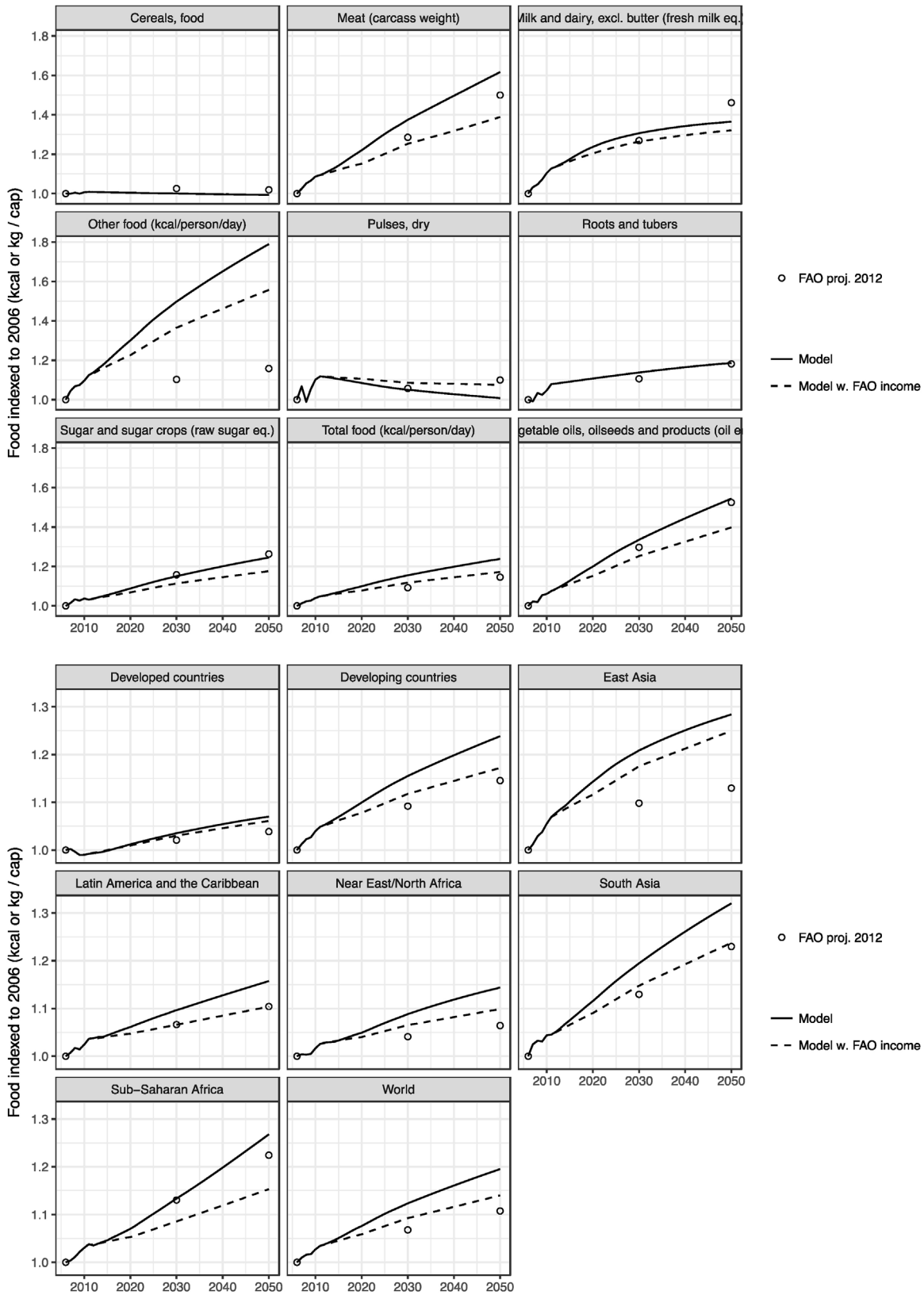

Fig. 8. Comparison of our SSP-2 food demand projection (solid lines) to FAO projection (dots) (Alexandratos et al., 2012). Since the SSP-2 scenario has higher income growth than the FAO, a model run with FAO income is included (dashed lines). Values were indexed to 2006 in order to compare calories with grams. The upper panel shows each food category for the developing countries. The lower panel shows total food for each country grouping. For other combinations see the Supporting information.

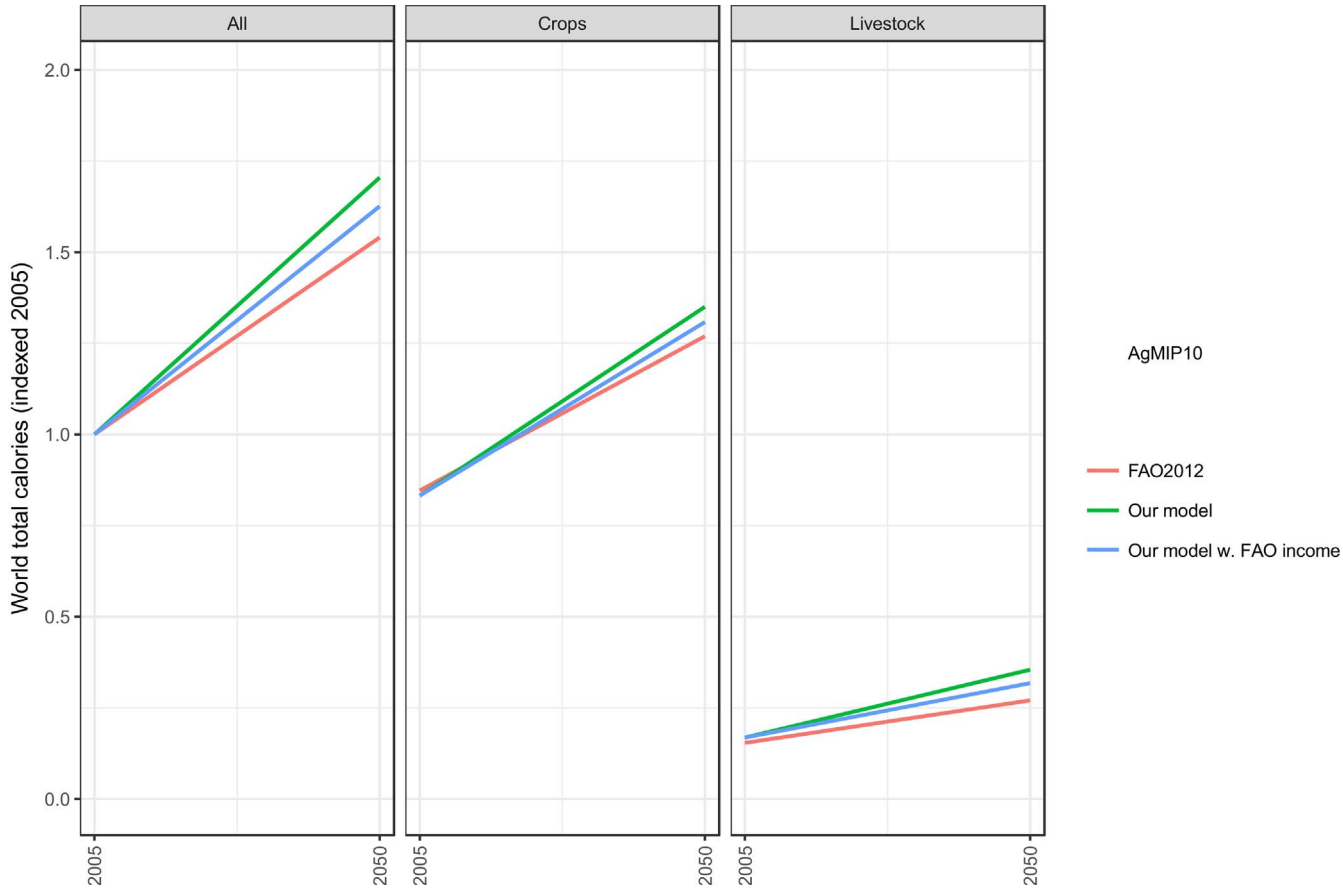

Fig. 9. Comparison to other food demand projections from literature. The grey area labelled 'AgMIP10' is the envelope of SSP-2 projections by 10 different models, and 'FAO2012' refers to estimates in Alexandratos et al. (2012), as reported by Valin et al. (2014). Projections were normalized with respect to total calories in 2005.

shared second place for feed efficiency and income per capita, and population size coming last.

Note that income inequality should also affect total demand and the rate at which demand increases. Due to the physical nature, the food categories with increasing demand (animal products, fruits/vegetables, luxuries, and oils and oilcrops) will encounter a saturation effect at some point for high incomes. Therefore, total demand under income inequality should be lower than under equality, for the same average income. Likewise, decreasing inequality should result in slightly faster demand growth. This effect exists in the model but is negligible, partly because income inequality changes very slowly compared to the change in income itself.

4.4. Limitations and further research

In our model, we have related future food demand directly to income levels. The comparison to historical data (Fig. 3) shows that income levels explain trends in historical food consumption well. We therefore use income as the main driver of our future projections (in addition to storyline elements). There are in fact good reasons to assume the sensitivity to prices in the future will be lower. First, literature indicates that price elasticity of expenditure (in dollars, at retail) decreases when income increases (Green et al., 2013), mostly because the percentage of income that is spent on food also decreases (Antle, 1999). Second, the gap between consumer prices and farm-gate prices, also generally increases with income (Antle, 1999), as more is spent on processing, packaging, advertising, or service in restaurants. As a result, the current model can provide important insights into future trends. At the same time, it would be an improvement to add price elasticities in subsequent versions of the model.

Since all projections show a large increase in future food demand, while further increasing production is getting progressively harder, we have explored two main solution directions for reducing demand growth: food waste reduction and dietary change. We found that waste reduction, although absolutely helpful, has a much lower potential impact on total crop and grass demand compared to dietary change. We estimate that the most aggressive efforts to reduce post-harvest food waste might reduce total demand by 10% in 2050 compared to the baseline. This is much lower than the 30% which is often quoted in mainstream media. Thus the potential of food waste reduction as a strategy for solving the future food crisis is overestimated in the public perception. Not only are the potential effects of dietary change much larger, the path to large-scale implementation is much clearer than for extensive food waste reduction. Therefore dietary change (less animal products and more plant-based) should receive more attention than food waste reduction, both from academics and the general public.

Future work on the urban/rural divide could include different food preferences (independent from income and price levels) (Huang and Bouis, 1996), and 'shielding' of rural markets from urban price swings and vice versa, which may have significant implications for estimating undernutrition (Gibson, 2013) in a similar way as urban markets can be influenced by global prices to a greater or lesser degree (FAO, 2011; Keats et al., 2010).

Our detailed physical model lends itself to estimating the consumption of not only total calories and protein, but also fat, sugar and alcohol consumption. Indicators or proxies could be used for dietary fibre and vitamins and minerals. With appropriate indicators of health risks, the model could inform discussions of long-term public health issues, for any scenario and with different risks for the five urban and five rural income quintiles.

The disaggregation of regional demand into demand for specific population segments highlights the need for household survey data that

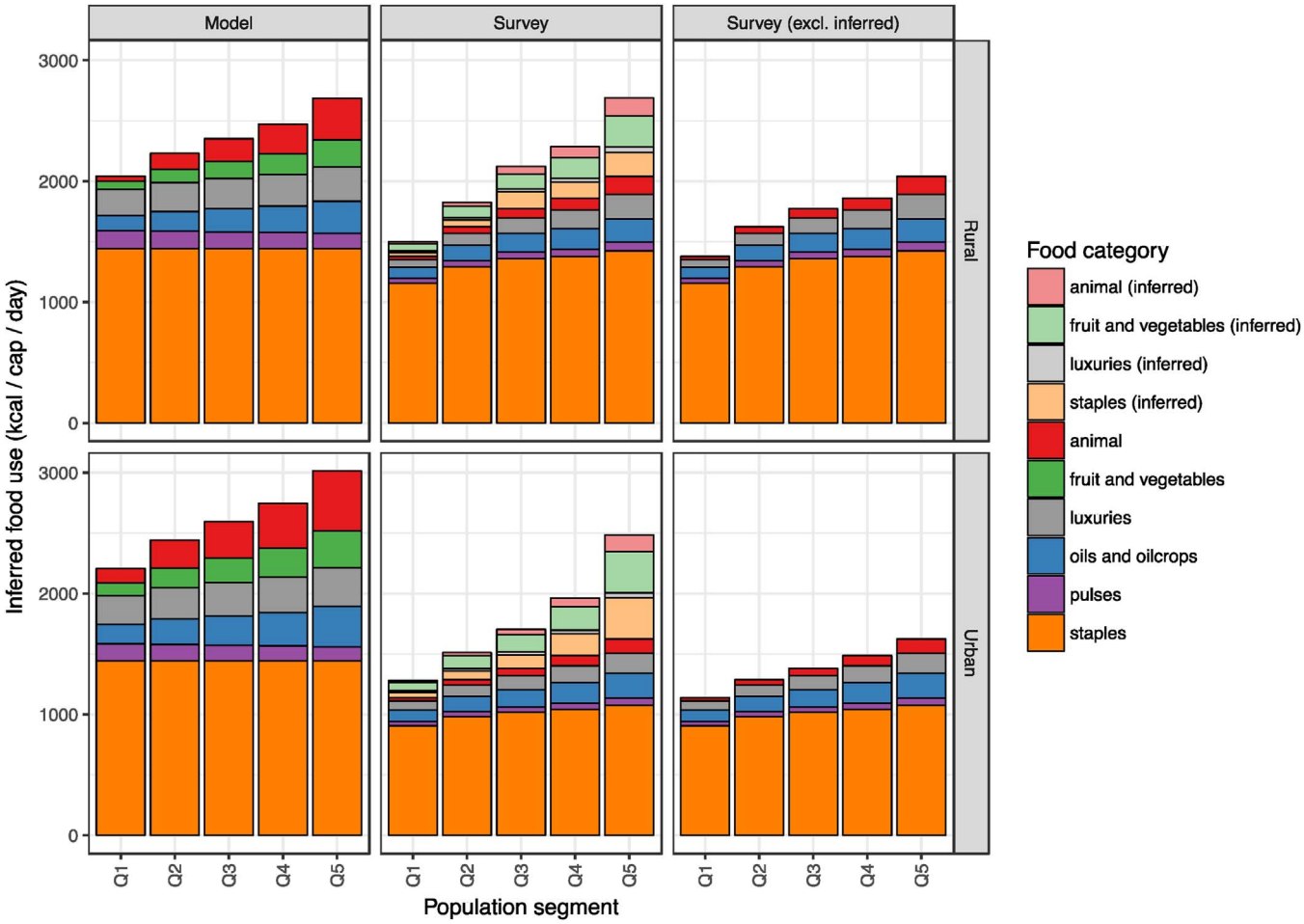

Fig. 10. Income-based inequality in the model compared to the India Human Development Survey-II. The leftmost panels show model output, the rightmost panels show the calories explicitly reported in the survey, and the centre panels show original survey data plus calories inferred from reported expenditure.

includes not only expenditure but also prices or physical quantities for all food categories. Without such data, there is no way to calibrate or validate any disaggregation method.

5. Conclusion

The new physical model provides insight into the physical and behavioural causes of future food demand, and opens new avenues for policy scenario analysis. The model is different from previous models in disaggregating regional populations to five urban and five rural income quintiles, in using more detailed food categories, and in using physical calculations for food waste, animal feed ratios, and diet scenarios. The model projections are generally in line with FAO projections and those of other models, but the physical-behavioural structure of the model is more suited to exploration of the distant future and also allows for more specific scenario studies. The model is detailed in terms of regions and food categories.

When applied to the SSP scenarios, the model projects global demand for crops and grass to increase from 5.5 Gton/yr in 2011 to a peak of 10.9 around 2090 in the baseline scenario SSP-2. In the 'fragmentation' scenario SSP-3, demand keeps increasing beyond 14.5 Gton/yr in 2100, but in the sustainability-oriented scenario SSP-1 demand peaks at 7.4 Gton/yr around 2050. The range of the demand increase among scenarios is wider for grass (11–175%) than for crops (59–152%, including both food and feed crops), highlighting the sensitivity of total dry matter demand to demand for animal products, the different types of animals, their feed mix, and their feed conversion efficiencies. In the projections, it is possible to directly examine impacts regarding average per capita caloric intake and its distribution among the population.

Growing food demand can be tempered most effectively by reducing the consumption of animal products, while food waste reduction can contribute to a lesser degree. We have introduced several scenarios to explore possibilities to mitigate the increasing demand for food products. A global transition to recommended low levels of meat consumption would reduce feed crops demand by 55% and grass demand by 66% compared to SSP-2 in 2050, while increasing food crop demand only 7%. Total crop and grass demand would drop by 41%. In contrast, even drastic waste reduction efforts in households and distribution systems only reduce total crop and grass demand by 10% compared to SSP-2 in 2050.

Modelled consumption inequality due to income inequality between population segments within a region is of the same magnitude as the inequality between regions. Total dietary energy consumption ranges from 1877 to 2911 kcal/cap/day for the poorest rural income quintiles of all regions, and from 2577 to 3598 kcal/cap/day for the richest urban quintiles of all regions. In all regions, the rural poor eat less in 2050 than the urban rich did in 2011.

The estimated global number of undernourished people in baseline scenario SSP-2 is projected to decrease from roughly 700 million in 2015 to roughly 270 million in 2050 and almost zero in 2100, depending on both income growth, a reduction of variance in food consumption within population segments, and income inequality between population segments. The projected number of undernourished people quickly declines in most regions, but first increases a little in Eastern Africa and Southern Africa (except the

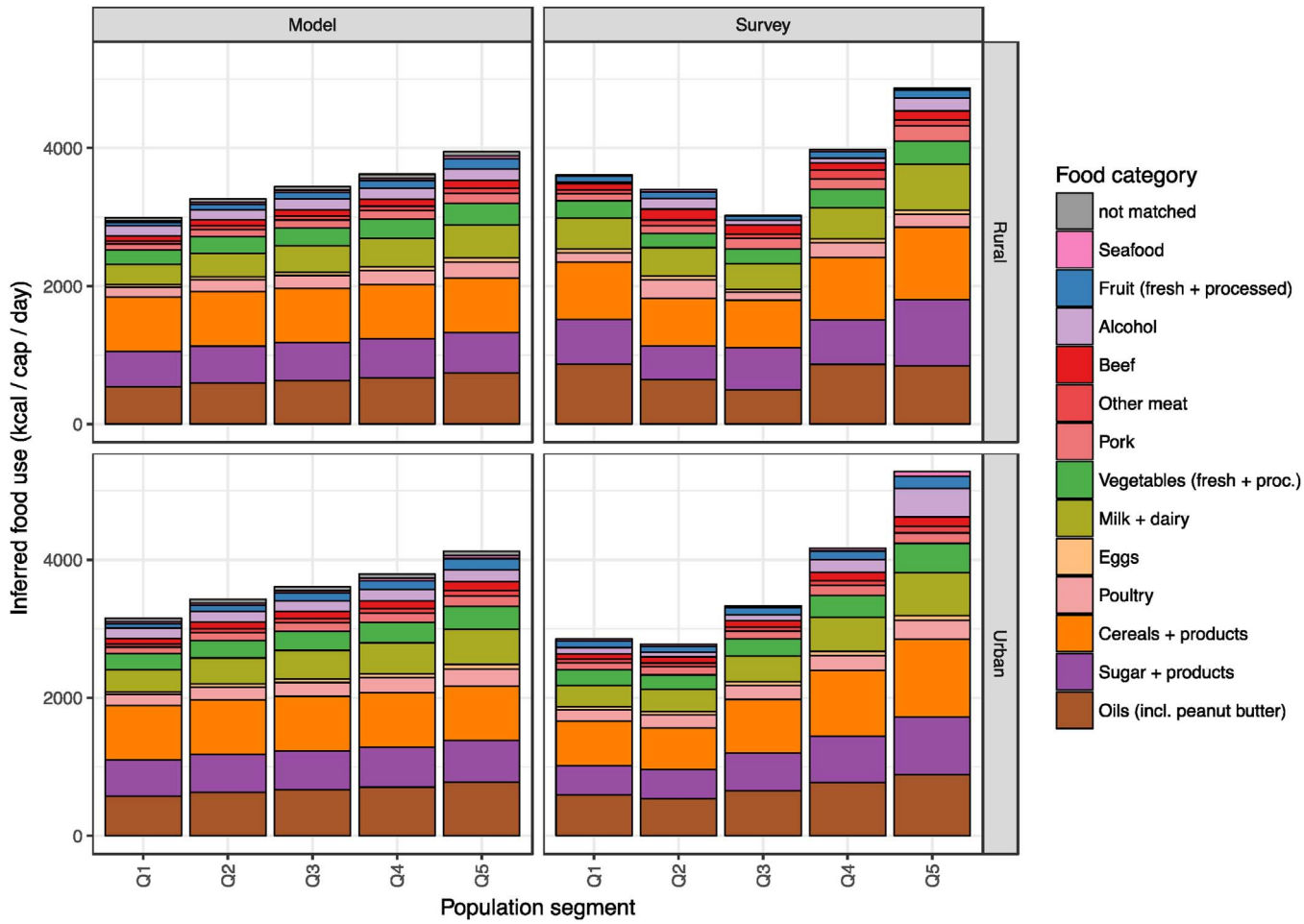

Fig. 11. Income-based inequality in the model compared to USA Consumer Expenditure Survey 2011.

Table 4
Sensitivity analysis of scenario drivers: The SSP-2 baseline scenario modified with region-specific parameter settings from SSP-1 or SSP-3. Percentages are calculated for 2050 in dry matter tonnes.

Parameters	Parameter settings		Plant-based food (food crops)		Animal feed (feed crops + grass)	
	Low	High	Low	High	Low	High
Feed efficiency	SSP-3	SSP-1	0%	0%	+13%	−17%
Income per capita	SSP-3	SSP-1	−7%	+6%	−12%	+11%
Population size	SSP-1	SSP-3	−7%	+7%	−4%	+3%
Diet composition	SSP-1	SSP-3	−2%	0%	−24%	+18%

country South Africa), due to high population growth and limited income growth in those regions. The degree to which the variance of consumption will decrease autonomously is highly uncertain, but in practice this effect could be achieved by better targeting food aid to at-risk individuals within countries. Novel to our approach is that the effect of income inequality is separated from the inequality of food distribution. A baseline SSP-2 scenario with higher (SSP-3) income inequality results in 41 million more undernourished people in 2040 than the same scenario with lower (SSP-1) income inequality.

Acknowledgements

The research leading to these results has received funding from the Rabobank Foundation.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gloenvcha.2017.04.003.

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