




Sensitivity analysis of global food and nutrition modelling

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Abstract

Computational models are often used to explore the future of the global food system, including the implications for human nutrition, an essential aspect of sustainability. However, the confidence that can be placed in the outputs of these models is often poorly quantified. Here, a sensitivity analysis of the DELTA Model® - a linear mass balance model calculating global nutrient supply using global and regional food balance sheet, processing, waste, inedible portion, composition, and bioavailability datasets - is conducted. First, a one-at-a-time analysis, varying 4019 underpinning datapoints from the above datasets individually by $\pm 50\%$ was conducted to identify those with the greatest impact on calculated global nutrient supply. The most influential values from this initial analysis were then carried forward into a multiple value sensitivity analysis, where all possible combinations of $\pm 50\%$ variations were simulated. Values related to cereals supply, waste, and nutritional value were the most influential on model output, with selenium, cystine, and carbohydrate supply the most sensitive nutrients. When compared to global nutrient requirements, variations in the calculated supply of some nutrients led to qualitative changes from a sufficient global supply to an insufficient supply. These results, while indicative rather than precise estimates of uncertainty, emphasise the critical importance of accurate cereals data in food system models, provide insight on the degree of sensitivity of similar linear models, and should encourage broader application of sensitivity analysis in the field.

Keywords Nutrient adequacy · Uncertainty analysis · Micronutrient · Amino acids

1 Introduction

There is a necessity for the global food system to transform to address the challenges that exist across the full breadth of sustainability: economic, environmental, and social (Fao, 2018; FAO/WHO, 2019). However, there is a lack of consensus on the actions needed to address these challenges, due to the inherent difficulty in fully predicting the consequences of proposed interventions. Computational modelling tools have become highly useful for investigating future scenarios under various pathways and to provide support for specific actions in the present day.

Many computational models exist for such investigations of future scenarios. These vary in their scope, methodology, and resolution. Several notable examples exist. The IMPACT model (Robinson et al., 2024), a partial equilibrium scenario testing model built on a combination of economic, water, and crop submodels has been recently used to investigate net food system emissions under various future scenarios (Almaraz et al., 2023) and in the development of the EAT-Lancet planetary health diet (Willett et al., 2019). The GLEAM model is a global analysis tool for assessing livestock input and output dynamics, allowing regional investigation of the environmental performance of different livestock systems (Macleod et al., 2018). Finally, the MAg-PIE model, a spatially explicit economic and land use model (Dietrich et al., 2019), has been recently used to forecast global variation in crop productivity growth (Wang et al., 2020) and understand the costs of food system transformation (Ruggeri Laderchi et al., 2024).

The majority of models developed to date have an economic and/or environmental focus. However, a key feature of a sustainable food system is its ability to deliver “food

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security and nutrition for all” (Fao, 2018). Fewer models have investigated the implications of future food system scenarios for human nutrition. Notable exceptions are the CiFoS model (Simon et al., 2024), which examines future scenarios for a circular food system and the impacts on food and nutrient supply (although this is yet to be applied to global scenarios); some recent applications of the IMPACT model including micronutrient availability (Beach et al., 2019; Rosegrant et al., 2024); and the Nutrient Balance Sheets (Lividini & Masters, 2022) and the GENuS model (Smith et al., 2016), which both calculate flows of food nutrients from production to consumption between 1961–2018 to understand global and national nutrient (under) supply. A final example is the DELTA Model®, previously developed by the Sustainable Nutrition Initiative®, which is an open access, online computational tool for examining how global food supply matches with global nutrient need under various future scenarios (Smith et al., 2021), with more recent use examining the importance of specific food groups in global nutrient supply (Smith et al., 2022a, b) and examining global nutrient losses and waste (Beuving et al., 2024).

The accuracy of any model is highly dependent on the quality of the underpinning data. Where there is uncertainty in the underpinning data, this uncertainty will be carried through to some extent into the model outputs. This is often noted and sometimes partially analysed in publications using food system models, but not comprehensively assessed (Lividini & Masters, 2022; Smith et al., 2016, 2021). More specifically, model authors rarely discuss the degree of sensitivity of specific model outputs to variations in the underpinning data, despite the fact this may lead to false conclusions if sensitivities are not well accounted for. The scarcity of sensitivity and uncertainty analyses for food system models means that our confidence in their predictions is currently poorly quantified, meaning that our confidence in any action based on their predictions is similarly limited.

We address this limitation and perform a sensitivity analysis of the DELTA Model® to quantify confidence in its predictions. Moreover, our work will inform the confidence that may be placed in outputs of models using similar underlying data. The DELTA Model® is an appropriate example of a global food system model considering nutrition, as it relies on a linear mass balance calculation engine (similar to approaches elsewhere), enjoys negligible runtime compared to models with similar scope, and leverages open access data commonly used by similar models (such as the Food and Agriculture Organization (FAO) Food Balance Sheets (Fao, 2024) and United States Department of Agriculture (USDA) food composition data (USDA, 2020)). Thus, it is a sensible candidate for an initial sensitivity analysis, allowing partial

generalizability of conclusions to other models and indicating the value of undertaking these analyses to other model developers.

We hypothesise that the impact of the underpinning data on model output (that is, nutrient supply to the global population for a range of essential nutrients) will vary substantially depending on the type of data considered. For example, we expect that total food supply data will have a stronger role in determining total nutrient supply than will consumer waste rates, given that food supply from production precedes consumer waste in the supply chain. A sensitivity analysis will indicate the areas of the underpinning data with the greatest impact on model output, allowing greater attention to be given to improving the reliability of these data in the future. We also hypothesise that the degree to which model output will be impacted will vary for supply of different nutrients, given the high variability in nutrient composition between foods. The sensitivity analysis will indicate the relative degree of confidence we can have in model conclusions for different nutrients, which is of high relevance to international research and policy that relies on models to study global food production and distribution, food security, and malnutrition.

2 Methods

2.1 The DELTA Model®

The DELTA Model® is a deterministic linear mass balance model, which calculates total nutrient supply to the global population based on total global food production and supply chain dynamics. A detailed explanation of the calculation methodology can be found elsewhere (Smith et al., 2021), but an overview is provided in Fig. 1 and below.

The calculation begins with the FAO Food Balance Sheets (FBS), which contain annual global production (at national resolution) of 100 food commodities (e.g. soya-beans, apples, etc.), and indication of their end use (food, feed, losses, etc.) (Fao, 2024). The food use of these commodities is then adjusted using estimates produced by FAO and others for inedible portions (Food and Agriculture Organization, 1989; USDA, 2020) (e.g. apple cores), consumer waste (Fao, 2011), and processing losses (Fao, 1997; United States Department of Agriculture Economic Research Service, 1992). The total amount of food remaining at this point is considered as representative of food consumed by the global population each year, with 2020 the baseline year for the model. The data for this baseline year is the result of a weighted linear interpolation of the previous 20 years, to prevent single year anomalies or errors from significantly shifting the baseline data or model outputs.

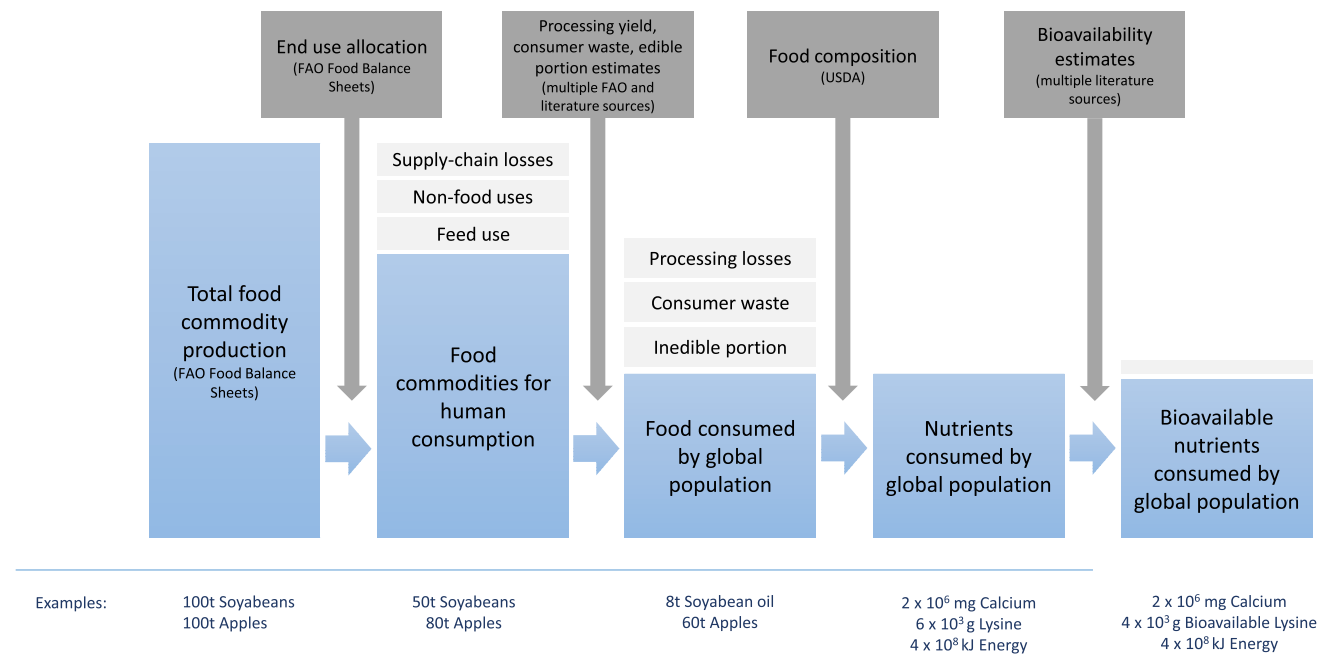


Fig. 1 Calculation methodology of the DELTA Model®. Data sources are indicated, with full explanations in the text. The model begins with total production of food balance sheet commodities, then estimates the

This quantity of the 100 commodities is then matched to food composition data (USDA, 2020), using a weighted average of several relevant compositions to derive an overall representative composition for each commodity. These weightings were derived from the same sources as inedible portion and processing data, and are visible within the model's user interface (Sustainable Nutrition Initiative®, 2024). This allows calculation of the total quantity of nutrients consumed by the global population for 29 nutrients (see Fig. 2 for full list). Lastly, the quantities of protein and the amino acids are adjusted for digestibility according to their food source using literature data (Gilani et al., 2012; Moughan et al., 2012).

2.2 Sensitivity analysis

We chose to assess the sensitivity of the model's calculated 2020 global nutrient supply (hereafter referred to as the baseline) to variations in the underlying data (as opposed to model structure or assumptions). The proportional deviation from the baseline supply for each of the 29 nutrients was calculated by dividing the newly calculated nutrient supply value (after varying the underlying data) for each nutrient by its supply value in the baseline. To quantify total variation across all nutrients, these values were also summed to give a single overall indicator of variation. These values were then used to identify both the variations in the underpinning data that created the greatest overall deviation in

amount eaten (after non-food and waste adjustment), before converting this food data into nutrient data and making bioavailability adjustments for protein and the indispensable amino acids

model calculated global nutrient supply, and the nutrients most sensitive to these variations.

The underpinning data to be varied were grouped based on data source and function in the model. For example, one group includes all food composition data, while another includes all consumer waste data. The groups used are shown in Table 1.

Given that the total number of datapoints that could be varied across the groups listed in Table 1 was 4019, it was not computationally feasible to conduct a comprehensive sensitivity analysis in which every permutation of variations was assessed. Instead, the individual values with the greatest impact on model output from each group were determined, and a combinatorial sensitivity analysis conducted using this subset of values. An analogous example of this method has been used recently in the life cycle analysis field (Kim et al., 2022).

Initially, a one-at-a-time sensitivity analysis was carried out individually on each datapoint in each data group. The model calculation was run twice for each datapoint, with each value increased by 50%, and then decreased by 50%, respectively. 50% is a high degree of variation, but given the linear nature of the model, the choice of variation is unimportant for ranking the individual datapoints with the greatest impact on model results. The resulting impact on model output was indicated by the percentage deviation in the nutrient supply estimates between the newly generated model output and the baseline, summed across all nutrients.

	Inedible portion		Consumer waste		Processing yields		Food allocation		Food item composition		Protein and amino acid digestibility	
	Vegetables, other	Poultry Meat	Asia, Cereals	Americas, Cereals	Cream and Butter	Soyabean oil	Wheat and products	Rice and products	Selenium, Wheat and products	Vitamin C, Vegetables; other	Cystine, Wheat and products	Cystine, Rice and products
Macronutrients	Energy	0%	1%	4%	2%	1%	3%	10%	13%	0%	0%	0%
	Protein	0%	1%	3%	1%	2%	0%	11%	9%	0%	0%	0%
	Fat	0%	1%	1%	0%	2%	11%	1%	2%	0%	0%	0%
	Fibre	2%	0%	3%	1%	0%	0%	14%	4%	0%	0%	0%
	Carbohydrates	0%	0%	6%	2%	0%	0%	14%	19%	0%	0%	0%
Minerals	Calcium	1%	1%	1%	0%	8%	0%	2%	3%	0%	0%	0%
	Copper	1%	0%	3%	1%	0%	0%	9%	10%	0%	0%	0%
	Iron	1%	1%	3%	1%	0%	0%	11%	7%	0%	0%	0%
	Magnesium	1%	0%	4%	2%	1%	0%	10%	11%	0%	0%	0%
	Phosphorus	1%	1%	3%	1%	3%	0%	9%	10%	0%	0%	0%
	Potassium	2%	0%	2%	1%	2%	0%	4%	4%	0%	0%	0%
	Selenium	0%	1%	4%	2%	1%	0%	27%	6%	21%	0%	0%
	Zinc	1%	1%	3%	1%	2%	0%	9%	12%	0%	0%	0%
Vitamins	Folate	2%	0%	2%	1%	1%	0%	7%	3%	0%	0%	0%
	Riboflavin	1%	1%	2%	1%	5%	0%	4%	3%	0%	0%	0%
	Thiamin	1%	0%	4%	1%	1%	0%	11%	9%	0%	0%	0%
	Vitamin A	3%	2%	0%	0%	3%	0%	0%	0%	0%	0%	0%
	Vitamin B5	1%	1%	4%	2%	2%	0%	5%	16%	0%	0%	0%
	Vitamin B6	2%	1%	3%	1%	1%	0%	5%	10%	0%	0%	0%
	Vitamin B12	0%	1%	0%	0%	5%	0%	0%	0%	0%	0%	0%
	Vitamin C	4%	0%	0%	0%	0%	0%	0%	0%	21%	0%	0%
	Vitamin E	1%	0%	1%	0%	1%	10%	2%	2%	0%	0%	0%
Amino acids	Cystine	0%	1%	4%	2%	1%	0%	17%	12%	0%	0%	13%
	Histidine	0%	2%	3%	1%	2%	0%	10%	9%	0%	0%	0%
	Leucine	0%	1%	3%	1%	3%	0%	10%	9%	0%	0%	0%
	Lysine	0%	2%	2%	1%	3%	0%	4%	6%	0%	0%	0%
	Methionine	0%	2%	3%	1%	2%	0%	9%	10%	0%	0%	0%
	Threonine	0%	2%	3%	1%	2%	0%	8%	8%	0%	0%	0%
	Tryptophan	0%	1%	3%	1%	2%	0%	13%	9%	0%	0%	0%
Summed variation	27%	25%	79%	32%	56%	24%	237%	218%	21%	21%	13%	11%

Fig. 2 Percentage variation in model output for each nutrient following a $\pm 50\%$ variation in the underlying datapoints during the one-at-a-time analysis (results for two most influential datapoints in each data group shown). Darker colouring indicates larger values

Table 1 Groupings of model data for the sensitivity analysis

Group	Example (unit)	Number of datapoints in the data group
Food supply	Total mass of milk for human food use (tonnes per year)	100
Inedible portion	Inedible portion of coconuts (i.e. husks) as a percentage of total coconut mass (%)	100
Processing yields	Tonnes of soyabean oil produced per tonne of soyabeans processed (dimensionless)	84
Consumer waste	Percentage of cereal mass, excluding inedible portion, that reaches the average European consumer but is not consumed* (%)	35
Food item composition	Calcium content of rice (mg/100 g)	2900
Protein and amino acid digestibility	Digestible lysine in peas as a percentage of total lysine content in peas (%)	800

*Note that consumer waste is the only dataset for which region-specific data (rather than global averages intended to be representative) are used. This reflects both the high regional variation in consumer waste rates and the resolution of the data sourced

Thereafter, the two datapoints in each of the six data groups with the greatest impact on model output (greatest summed percentage variation across all nutrients) were identified. These twelve values were taken forward into a multiple value sensitivity analysis. Each additional datapoint included in the multiple value sensitivity analysis exponentially increases the number of model runs required, therefore two per data group were selected as both computationally feasible and analytically useful for determining

the relative impact of datapoints in different data groups. In the multiple value sensitivity analysis, every combination of a 50% increase and 50% decrease of each value (4096 combinations in total) was run in the model. The percentage deviation in calculated supply of each nutrient was recorded in each model run. 50% was chosen for consistency with the one-at-a-time analysis, not because it is an appropriate level of variation to expect in every datapoint. However, in the absence of data for how much each of the underlying

datapoints could reasonably be expected to vary by, 50% was chosen as a “worst case scenario”. See the discussion for the limitations of this approach.

3 Results

3.1 One-at-a-time analysis

Initially, each value in each underpinning data group set was assessed for its impact on model output (inferred from the summed percentage variation across the 29 output nutrients). The results are presented here per data group (Fig. 2), with full results included in the Supplementary Material.

The datapoints for food supply of individual commodities causing the greatest variation in output were “Wheat and products”, “Rice and products”, “Milk, whole”, and “Vegetables, other”. This is unsurprising, as these four commodities are also the four with the greatest tonnage used as food globally, although with some re-ordering (vegetables, rice, milk, wheat is the order of greatest food supply mass). Further, the impact of these food supply values on total variation in model output was nearly three times greater than that of any other data group. Selenium, carbohydrates, and cystine were the nutrients most strongly affected by variation in the food supply of wheat and rice (Fig. 2). Therefore, estimates of total food supply have a much more significant impact on overall calculated nutrient supply than any other group of underpinning data.

In the inedible portion data group, the estimates for “Vegetables, other” and “Poultry meat” had the greatest impact on model output (Fig. 2). These are not the commodities with the largest inedible portion estimates in the dataset, indicating that the interaction between inedible portion size, food supply quantity, and nutrient content for these commodities has led to them having the greatest impact on model output in this data group.

In the processing yields data group, the estimated yield for cream and butter production from whole milk had the greatest impact on model output, with more than double the impact of the next datapoint, soyabean oil extraction, which only impacted energy, fat, and vitamin E supply (Fig. 2).

In the consumer waste data group, the estimates for cereals wasted in Asia and to a lesser extent in the Americas had the greatest impact on model output. This is to be expected given the size of these populations, and thus the amount of food waste generated, as well as the prevalence of cereals in the diet.

For the food item composition data group, the selenium content of “Wheat and products” and the vitamin C content of “Vegetables, other” had the greatest impact on model

output, reflecting the importance of these foods in supplying these nutrients globally.

For the bioavailability data group, the cystine bioavailability from “Wheat and products” and also from “Rice and products” had the greatest impact on model output, again reflecting the importance of cereals in protein and amino acid supply.

3.2 Multiple value analysis

The variation in model calculated nutrient supply for each nutrient was examined under every permutation of a 50% increase or a 50% decrease in the two most influential values in each data group. Two values from each of the six data groups either increasing or decreasing gave a total of 4096 permutations to run in the model. On completion of these model runs, the largest observed percentage variation for each nutrient was extracted and is displayed in Fig. 3.

The most sensitive nutrients were cystine and selenium, with over 80% maximum variation in output. This is to be expected, given that the selenium composition of wheat and the bioavailability of cystine from wheat and from rice were all values included in this multiple value sensitivity analysis, and the results shown in Fig. 2. The next most sensitive nutrients were carbohydrates and energy, with a maximum 44% and 35% variation, respectively. All other nutrients had less than 32% maximum variation. The least sensitive nutrients were vitamin B12 (6% maximum variation) and vitamin A (7%). As would be expected, the greatest increases in calculated nutrient supply resulted from the combination of 50% increases to the Food supply, composition, digestibility, and processing yield datapoints, and 50% decreases to the inedible portion and waste datapoints. The greatest decreases in calculated nutrient supply resulted from changes to these datapoints in the opposite direction.

It is also valuable to consider whether the observed variations would lead to a change in whether or not the model calculated sufficient or insufficient global supply of each nutrient. The DELTA Model® estimates that supply of all nutrients except calcium and vitamin E was sufficient in 2020. However, as shown in Fig. 3, the variation exhibited in this sensitivity analysis encompassed undersupply for energy, protein, fibre, carbohydrate, iron, magnesium, potassium, selenium, zinc, riboflavin, vitamin A, and cystine – 12 of the 29 nutrients assessed. On the other hand, it did not encompass sufficient supply for either calcium or vitamin E. These results are a combination of both the degree of sensitivity of supply of each nutrient and the current level of supply compared to requirement.

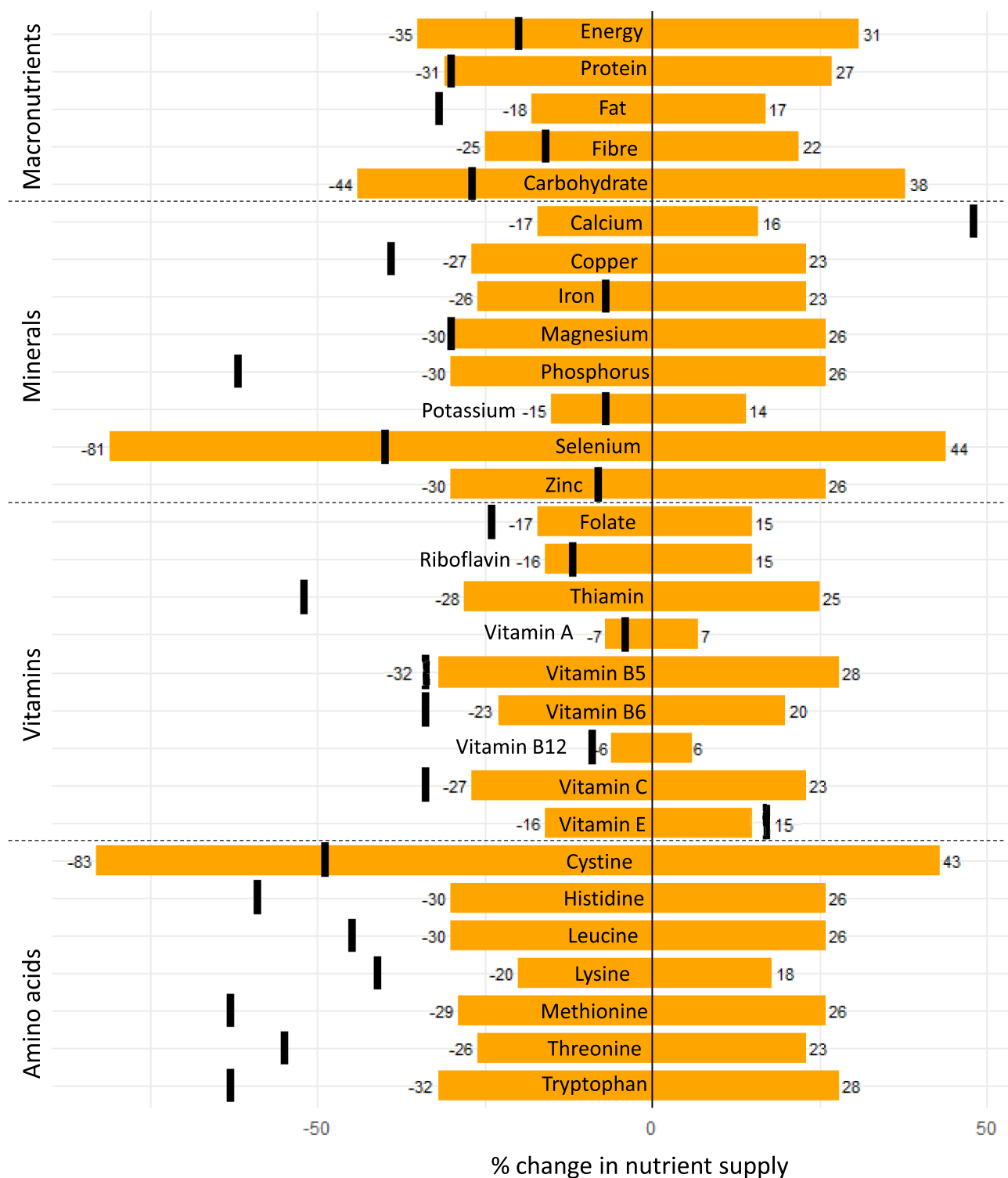


Fig. 3 Maximum positive and negative percentage change in model calculated nutrient supply during global sensitivity analysis. Orange bars display the range from maximum positive to negative change in calculated supply, with label numbers indicating the % value. The thick black bars indicate global requirement for each nutrient, as cal-

culated by the DELTA Model®, for comparison. For example, the global energy requirement (thick black bar) is 20% lower than model calculated energy supply (indicated by the vertical line at 0), but the range found in the sensitivity analysis (-35% to 31%) encompasses this value

4 Discussion

A sensitivity analysis of the DELTA Model® capturing nutrient supply from the 2020 global food system indicated both the underlying data with the greatest impact on model output, and the nutrients most sensitive to changes in this underlying data. Estimates of total food supply have the most significant impact on overall nutrient supply, more than double that of any other group of underpinning data. Cereal-related datapoints emerged commonly across multiple data groups as having the greatest impact on model outcomes (Fig. 2). These results are unsurprising: cereals are the food group produced in the greatest quantities globally and contribute close to half of dietary energy globally (Fao, 2023), thus are major contributors to global nutrient supply.

Given that cereal-related datapoints were heavily represented in the multiple value sensitivity analysis, the nutrients most sensitive to variations in the underlying data were also those for which cereals are a rich source in the global food system: selenium, cystine, and carbohydrates. Indeed, the DELTA Model® estimates that >50% of 2020 global supply of each of these nutrients comes from the cereals food group. For food system modellers, this emphasises that quality data for the production, consumption, waste, and nutritional profile of cereals is paramount for reliable conclusions on global nutrition.

Other nutrients showing sensitivity to datapoints not related to cereals were vitamin C, which was highly sensitive to the composition of the “Vegetables; other” food item, and vitamin E, which was highly sensitive to the processing yield of soyabean oil. The DELTA Model® estimates that 50 mg/capita/day of vitamin C came from vegetables in 2020, half of the demographically-weighted global requirement and more than one third of total global supply. For vitamin E, a little over 0.5 mg/capita/day came from soyabean oil, only around 5% of global supply. However, the DELTA Model® estimated a 2020 global undersupply of vitamin E against requirements. Thus, it could be said that the vitamin E sensitivity is more critical than that of vitamin C from the perspective of understanding adequacy of nutrient supply. However, it should be noted that vitamin E is an understudied nutrient, with few estimates of global intake or deficiency rates, which would be valuable to corroborate the model-estimated undersupply.

Vitamins B12 and A showed the least variation during the multiple value sensitivity analysis and little variation in the one-at-a-time analysis (Fig. 3). Vitamin B12 is found in animal-sourced foods, as is around half of global vitamin A supply (Smith et al., 2021). The only values impacting animal-sourced foods included in the multiple value sensitivity analysis were the inedible portion of poultry meat and

the processing yield of milk to butter and cream, explaining the low variation in these two nutrients.

This is important as both modelling studies on food supply and observational studies of populations identify nutrients such as vitamin A and B12, iron, zinc, and calcium as undersupplied or with relatively high rates of insufficient intakes or deficiency in many parts of the world (Beal et al., 2017; Roser, 2017; Smith et al., 2021; Lividini & Masters, 2022; Passarelli et al., 2022; Stevens et al., 2022). That these nutrients did not emerge as especially sensitive here is interesting. Partly this is a result of the data selected for the multiple value sensitivity analysis containing few animal-sourced foods, but it is surprising that iron and zinc were relatively unaffected by the variation in cereal-related data, given they are important global sources of these nutrients. This provides greater confidence in model estimates of iron and zinc supply and adequacy, which is valuable given the global focus on tackling iron and zinc deficiency.

By assessing the impact of 50% variations in underlying datapoints, our sensitivity analysis took an extreme view. In the worst case scenario of up to 12 critical datapoints in the underlying data being inaccurate by 50%, model outputs could also be incorrect by over 80% for some nutrients. While this may read as alarming, it is important to recognise how unlikely such scenarios are. For example, it is highly unlikely that global estimates of wheat and rice food supply are incorrect by 50%, as this translates to a misallocation of around 584 million tonnes of food. Moreover, this data is drawn from a widely trusted UN agency source, with a robust data collection methodology and was here averaged over multiple years and viewed at a global scale, contributing to reliability (Fao, 2001; Thar et al., 2020). However, for other datapoints, 50% may be within a realistic range of uncertainty. For example, determining a food’s content of cystine (one of the influential values in our analysis and an output nutrient showing high variability) for food composition tables is challenging due to the volatile nature of sulphur amino acids (Raab & Feldmann, 2019), and food composition data in general has been shown to vary substantially depending on various environmental and genetic factors (Elmadfa & Meyer, 2010).

The reliability and representativeness of the other data sources varies. For example, there exist widely acknowledged limitations to and gaps in currently available estimates of consumer waste (Xue et al., 2017; Spang et al., 2019); the inedible portion for a food item will vary between cultures; and protein and amino acid digestibility, while robustly measured, is sufficiently novel that data does not exist for all food items. These limitations acknowledged, we believe that a 50% variation represents an appropriate “worst case” for global modelling.

Our final sensitivity analysis was targeted in its approach due to computational feasibility, using only the most influential values from the comprehensive one-at-a-time analysis in our multiple value sensitivity analysis. Therefore, greater maximum variations may exist for each nutrient, particularly if more composition values were varied. For example, nearly half of global calcium supply is calculated to come from milk (Smith et al., 2022c), thus if the calcium composition for milk were varied, this would be expected to have a strong impact on the global calcium supply, but no impact on any other nutrient. However, undertaking a comprehensive global sensitivity analysis is not computationally feasible, given the 4019 values that exist in the underpinning data, requiring 10^{1209} model executions to perform a comprehensive global analysis using the current method. Our results provide indicative confidence levels (and relative confidence between nutrients) that can be placed in model predictions for each nutrient, and prioritises areas of the underpinning data that must be high quality to assure confidence in model outcomes. If a specific nutrient were of particular interest to the food system modelling community, it would be possible to repeat the one-at-a-time and multiple value sensitivity analyses focusing specifically on variability in that nutrient in the output. This variability could also be compared to global requirement, to quantify the degree of change necessary in each or a combination of parameters that would lead to the model estimating a global nutrient undersupply. This approach would identify the most important datapoints influencing supply calculation for a specific nutrient and quantify more precisely our confidence in model-estimated sufficiency of that specific nutrient.

An alternative approach to the $\pm 50\%$ used here would be to use expert opinion and literature data to inform reasonable distributions of uncertainty for each datapoint in each data group, and to then run a sensitivity analysis using these distributions, perhaps ignoring values with uncertainty below a certain cutoff (Kim et al., 2022), or relying on Bayesian sensitivity analysis (Berger et al., 1994). However, defining the reasonable and informative distributions would be a large, challenging, and subjective task. It would be feasible for a small number of datapoints and would be an independent commensurate research work in itself. Identifying an approach that allows for more comprehensive sensitivity analyses more reflective of the actual variation in the underlying data, while still being computationally feasible, would be beneficial to the field of nutrition modelling.

The opportunity exists to take a similar analytical approach to assessing sensitivity at a regional or national level. Several of the underlying datasets, notably the FBS, have this degree of data resolution. Undertaking this analysis for every country would face the computational difficulties mentioned above, but it would be feasible instead to identify

regions or countries of interest from a nutrient (under)supply perspective and assess how robust model conclusions are at this more localised level. For example, it would be valuable to understand the sensitivity of nutrient supply to cereals data in regions where cereals are a larger part of diet than the global average and where micronutrient deficiency is most common, such as sub-Saharan Africa and South-East Asia (Beal et al., 2017). Such an exercise would likely identify different datapoints that are more important in these more specific contexts compared to the global analysis.

In the present work, we have considered nutrition data, while other models (that do not consider nutrition to the same extent) also model environmental and economic outcomes. The importance of model sensitivity as demonstrated here should strongly encourage the developers of these other models to undertake sensitivity analyses to quantify the reliability of the conclusions of their own models. Our conclusions are only generalisable to models with similar linear approaches and similar underpinning data sources. Non-linear models and optimisation models may be far more sensitive, or far more unpredictable in their sensitivities, or exhibit emergent behaviours unlike those captured here. To assess the sensitivity to variations in a small number of datapoints, one could use Monte Carlo (Sobol', 2001) or more greedy algorithms (Li et al., 2016; Schulte & Nissen, 2023), but the computational tractability would be extremely challenging for the number of datapoints considered in this work.

5 Conclusion

The sensitivity analysis of the DELTA Model® indicated that uncertainty in data related to the food supply, waste, and nutritional value of cereals has the greatest impact on estimated nutrient supply, and that subsequently nutrients commonly associated with cereals, including selenium, cystine, and carbohydrates, were the most sensitive to variations in these data. While our results should only be seen as indicative of the areas of greatest concern rather than precise estimates of uncertainty, this work emphasises that reliable cereal data is foundational for food policy, nutrition planning, and model outputs, and should encourage broader application of sensitivity analysis in the field.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s12571-025-01598-6>.

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Data availability Data sources are sufficiently detailed in the methodology, and the results refer sufficiently to the supplementary material.

Declarations

Conflict of interest The authors declare no conflict of interest.

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