

A modelled estimate of food access within countries shows that inequality within countries has increased despite rising equality between countries

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ARTICLE INFO

Keywords:

Food security
Inequality
Food access
Global model

ABSTRACT

Global food calorie supply per person is more than 2900 kcal per day on average, but we have failed to ensure equitable access to these calories. Yet how uneven food access is within countries has remained poorly understood, as has the progress made over the past five decades on closing the access gap. Using publicly available data, we developed a theoretically-grounded statistical model to estimate the cross-national relationship between average per capita expenditure and per capita food availability and used this to estimate within-country access to food for income deciles in 135 countries. We find that, from 1961 to 2013, despite between-country inequality declining by 48% (decline in Gini coefficient from 0.15 to 0.078), within-country inequality in food access increased by 25% for the countries in our study sample (Gini coefficient increased from 0.088 to 0.111). Furthermore, we find that the poorest 10% of the population in the majority of countries in South Asia, South East Asia and Africa—home to the majority of the world's food insecure—continue to access their calories primarily from staple foods and have extremely limited access to nutrient-dense foods, resulting in inequality in access to nutrient-dense foods that is even greater than inequality in access to total calories (within-country Gini coefficient of 0.2). These results strongly support continued investments in social safety nets targeted at the poorest half of the income distribution to swiftly reduce inequality in food access, and proactive programs that help vulnerable households build assets to sustain themselves through future food crises.

1. Introduction

The eradication of hunger and food insecurity depends on sufficient production of food, sufficient and stable access to it, and adequate utilization of nutrients within food (World Food Summit, 1996). The Food and Agriculture Organization of the United Nations (FAO) estimates that the average amount of calories supplied per person globally has increased from 2196 kcal per person per day in 1961 to 2963 kcal per person per day in 2019 (FAO, 2022). Similarly, the prevalence of undernourishment has declined over time from 18.9% in 1990 (FAO IFAD & WFP, 2013) to 8.4% in 2019 (FAO et al., 2021). Even applying the conservative caloric requirement of 2500 kcal per capita per day, the world has already been producing enough dietary energy for everyone since 1981.

These global numbers, however, mask wide disparities in

improvements between countries, which has been a key focus of studies examining inequality in food access across the world (Bell et al., 2021; D'Odorico et al., 2019; Hasegawa et al., 2019; Wood et al., 2018). The latest FAO estimates suggest the rate of progress in global hunger eradication has not only stalled, but progress has been reversed. Since 2015 there has been an increase in the absolute number of undernourished despite the continued growth in food availability; a pattern driven mostly by the increased number of undernourished in Sub-Saharan Africa (FAO et al., 2021). This trend has recently been further exacerbated by the Covid-19 pandemic (FAO et al., 2021; Laborde et al., 2020).

So, while there has been great progress in increasing caloric supply globally, not all countries have seen similar improvements. In addition, we have little understanding of disparities *within* nations, where access to food is shaped by variations in income and expenditure, market integration, food prices (Muhammad et al., 2017), as well as social

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factors (e.g. gender, age, membership in a minoritized group). In other words, national accounts of agricultural production, trade and calorie supply commonly used in food insecurity metrics and analyses (reported by FAO as Food Balance Sheets, FBS) mask *within-country* differences in access to dietary energy. Improved estimates of differential food accessibility across income groups within countries will allow for a better understanding of how the situation has changed for low-income populations, i.e., the people in greatest need of improved food security.

Here, using a readily reproducible approach, we develop a statistical model to estimate food access by income decile for 135 countries (see **Materials and Methods** for full description). We first use publicly available data between 1961 and 2013 to estimate the *cross-national* statistical relationship between national average per capita expenditure¹ and per capita food availability for 9 different food categories, building on past demand system analyses (Gouel and Guimbard, 2019; Verma et al., 2011). We then apply this model to total monetary *expenditure deciles* within countries to estimate access to food for these income groups for the study countries between 1961 and 2013. We calculate Gini coefficients of inequality in access to food between and within countries. We complement this popular metric of inequality by comparing access to food for the richest and poorest 10% in every country in the sample. Our estimates of access to food are presented in two forms: total calories, and calories from nutrient dense foods, a critical metric for improved nutrition outcomes.

2. Materials and Methods

2.1. Modelling framework

The overall modelling framework is as follows (see [Figure S1](#) for a flowchart). We first use national-average data on per-capita expenditure and per-capita food availability and develop a model to establish the relationships between them. We then validate this model using household survey data from FAO. The validation exercise reveals that our model has a bias; we therefore apply a bias correction term to our model. Then, we use this bias-corrected model (which was developed based on the cross-national relationship) to disaggregate national food availability into the income deciles within each nation.

2.2. Data

2.2.1. Food availability

The national average food availability data for our analysis was sourced from FAOSTAT Food Balance Sheets, spanning 1961 to 2013 (FAO, 2022). This food availability data from FAO is sometimes called food demand in other papers (Gouel and Guimbard, 2019) (Table 1 summarizes the use of food security terms throughout this paper). According to FAO, Food Balance Sheet (FBS) data are calculated based on national accounts and reported by each country's statistical office (FAO, 2001). They represent domestic food supplies available for human consumption at the national level after accounting for international trade, changes in stocks, and losses arising during storage and transportation. In instances where countries are the unit of study, one can assume that FBS represent food demand at the country level, or what the country can access based on income. At the same time, it is the food available to final consumers.

2.2.2. Food groups

Similar to Gouel and Guimbard (2019), we aggregated 17 FAO FBS food categories into 9 food groups that behave similarly across countries in terms of nutritional value or role in culinary traditions ([Fig. 1](#)). For

¹ The term income is used interchangeably with total expenditure throughout the other sections of the paper, i.e. we used total expenditure as a proxy for income (See Materials and Methods).

Table 1
Food security components' definitions and respective data sources used.

Concept	Definition	Data source
Food availability	The total food available based on national accounts. It is also usually expressed on a per capita basis and common units are weight or energy (calories). This availability can also be thought of as national food demand — a response to the nations' purchasing power, the food the country can access through its means of production and trade.	FAOSTAT, Food Balance Sheets based on national accounts
Food access (ed)	The food that is accessible physically and economically by the household or the individual. Economic access is the focus of this paper.	Estimated in this paper
Food consumed (acquired)	The food that the household or individual actually acquires of the food accessible to them through a combination of purchases, gifts, and self-production. In household surveys and economic literature the term food consumption is commonly used. But consumption can mean dietary intake to nutritionists. In this paper the term food consumption is used in the economic sense, and does not refer to dietary intake.	Household Surveys, FAO
Food intake	The food that is actually ingested by the individual once acquired. This term is often used interchangeably with consumption, but is not the same as economic consumption (see above). In this paper we refer explicitly to food intake and any use of the term consumption refers to food purchased/acquired.	Usually Food Diaries and other individual recall methods. Not the focus of this paper

example, one of the categories includes all of the starchy carbohydrate rich foods such as cereals, roots, tubers, and plantains (see supplementary material for treatment of plantain and bananas). Our categories of choice are slightly different from Gouel and Guimbard (2019) and from FAO FBS, e.g. we decided not to aggregate treenuts with pulses as done by Gouel and Guimbard (2019), because treenuts are usually expensive foods consumed in moderation whose demand one expects to increase in response to income, whereas pulses are mostly inexpensive protein-rich foods ("inferior protein") that sometimes replace animal proteins in many vegetarian cultures or in low income households, and whose demand decreases with income. These expected patterns of correlation between treenuts and pulses with income are confirmed in [Fig. 1](#). FAO FBS have 21 categories. However, we ignore 4 – *Alcoholic Beverages, Spices, Stimulants, and Miscellaneous*. The *Grand Total* food grouping was thus recalculated as the sum of the other 17 categories we worked with.

We also report calories and proportion of calories for 3 aggregations. First, nutrient dense foods comprised of: Fruits, Vegetables, Pulses and Oilseeds, Meat and Seafood, Dairy and Eggs, and Treenuts. Second, staples comprised of Starches – itself an aggregation of cereal, tubers, roots and plantain. And third, empty calorie foods comprised of: Oils and Fats, and Sugars and Sweeteners, following Tilman and Clark (2014); note that this is comprised of the FAO FBS categories of refined products containing either the pure sugars or pure fats, i.e., processed.

2.2.3. Minimum dietary energy requirements (MDER)

The MDER of an individual is defined as the minimum caloric intake an individual would have to consume to attain a minimum acceptable

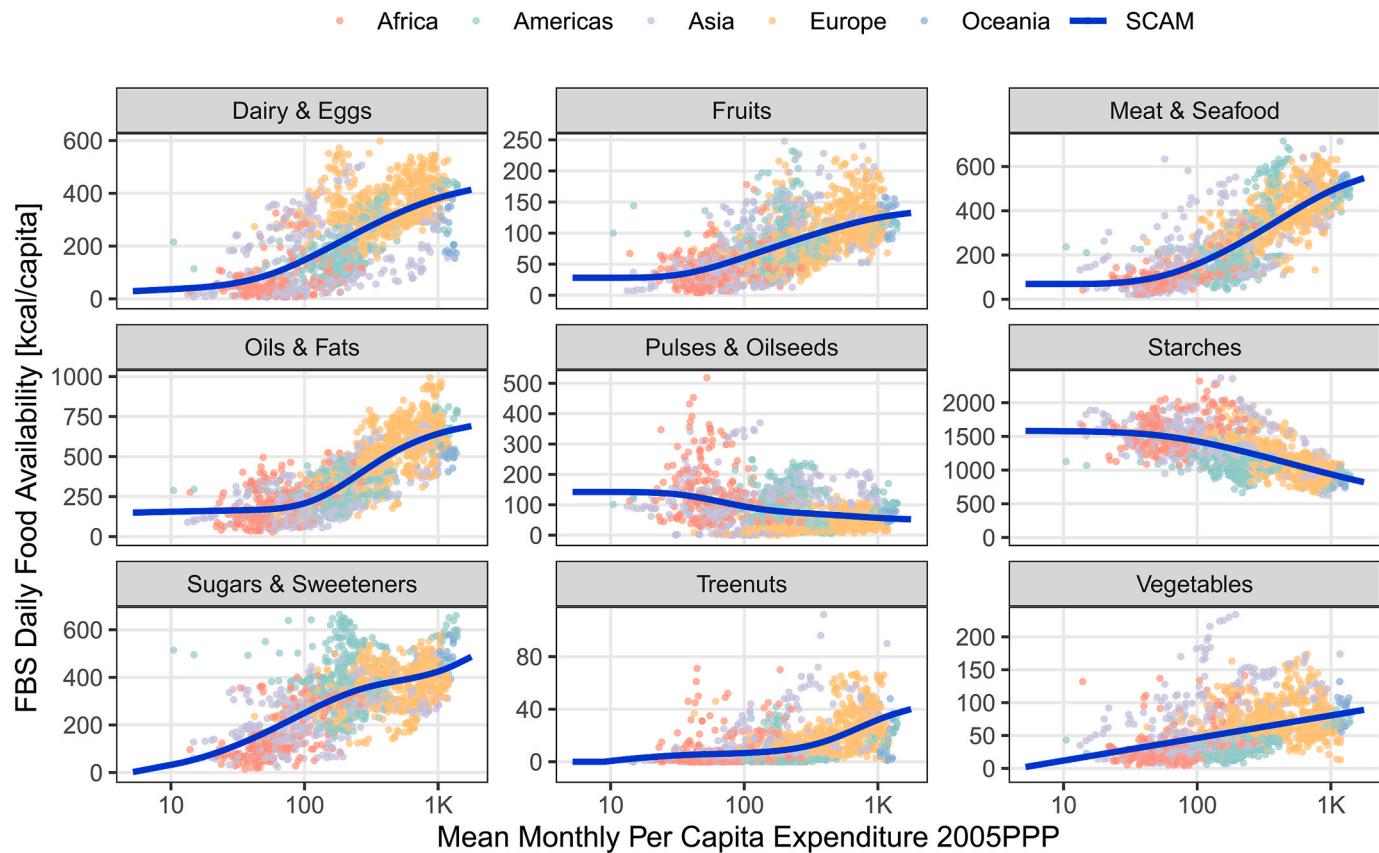


Fig. 1. Empirically estimated relationship between mean monthly per capita expenditure and national per capita food availability from the FAO Food Balance Sheets for 9 food categories. Each panel has an independent y-axis and shows the data points used for estimating a shape constrained additive model (SCAM) fit shown as the continuous line (Figure S2 extends to include out of bounds predictions and all the data points including those used for prediction).

weight for height (FAO & WHO, 2001). Population structure by sex and age from the UN Department of Economic and Social Affairs (DESA) Population Prospects was utilized to determine the population composition and calculate an MDER for each country in each year based on weighted averages of the minimums of the energy requirement ranges of each sex and age class, using the population size in each class as weights and an assumption of median physical activity levels (FAO & WHO, 2001; FAO et al., 2021; United Nations, Department of Economic and Social Affairs, 2019).

2.2.4. Income, expenditure and corresponding shares

Even though we use the term income throughout the other sections of the paper, the model uses consumption expenditure as the explanatory variable. This is because consumption expenditure is more accurately measured and is a more stable variable (ILO, 2003). The mean expenditure data was sourced from the global consumption and income project (GCIP)—a comprehensive database of both expenditure and income. The share of expenditure held by each decile was also sourced from GCIP. This data was used to disaggregate national food availability based on expenditure group as explained in the *Model Development* section. The GCIP dataset, based on underlying household surveys, presents yearly estimates (1960–2014) of real expenditure and income for deciles in more than 160 countries in 2005 PPP dollars per month (Lahoti et al., 2016).

2.2.5. Countries

To estimate the relationship between expenditure and food demand we included all countries that have complete data on mean expenditure per capita, expenditure shares, and per capita food availability. In the GCIP database only 22.6% of the country-years have an actual survey

underlying the income by decile estimates (the rest are imputed) — we only included those country-years with actual surveys in the estimation database. The FBS database on food availability describes all values as estimated and thus we don't make exclusions there. We excluded countries whose population in a given year was below 0.015% of the global population (roughly 1 million people in 2010). This excludes most small island states and partly solves the problem of countries with very particular diets (e.g. Maldives) affecting the estimation procedure. After applying these criteria, the model estimation database has 1757 country-years out of the 8569 country-years in the prediction database. The number of countries in our estimation database ranges from 3 in 1977 to 76 in 2010 (median 24, mean 32). The annual average expenditure ranged from 10 to 1395 \$2005PPP per month and the range of total caloric consumption was 1548 to 3695 kcal/capita/day. We disaggregated the FBS data for those countries included in the model estimation, i.e., those with both expenditure and FBS data for at least one year. The resulting prediction database has a total number of countries ranging from 114 (in 1990) to 135 (from 2006 to 2013) covering between 97% (in 1994) to 98.1% (in 1961) of the global population. The number of countries changes over time because there is not a perfect match between the two datasets; in addition, there were several country dissolutions during this period.

2.2.6. Food consumed

For model validation purposes we used FAO's Indicators from Household Surveys (HSS) dataset (FAO, 2014). These surveys report mean household total consumption (expenditure), and mean food purchases (consumption) in local currency units and calories by national expenditure terciles. For some countries, data on more than one year is available. There is a total of 37 distinct countries and 43 distinct

country-years in this validation data set. After converting monetary units from local currency to \$2005PPP and removing countries that underwent currency denomination changes or abrupt inflation we had a final validation dataset with 24 distinct countries and 29 distinct country-years (see Table S1 for final list of country-years).

2.3. Model development

To estimate the cross-country and cross-temporal (1961–2013) relationship between expenditure per capita and food availability for each of the 9 food groups we specified a shape constrained generalized additive model (SCAM (Pya and Wood, 2015)). A SCAM is an adaptation of generalized additive models (GAM) to introduce shape constraints. And GAMs are an adaptation of generalized linear models (such as linear regression) that allows one to model non-linear relationships (Pya and Wood, 2015). So the SCAM allows us to model potential non-linear relationships between per-capita expenditure and food availability, while introducing the shape constraints that the relationships are either monotonically increasing or decreasing.

Our SCAM takes the following form:

$$FAV_{i,g} = \alpha_0 + \sum_{l=1}^q \beta_{il} b_{il}(\log_e(Income_i)) + \zeta_{j[l]} + \varepsilon_i$$

$$\zeta_j = N(0, \sigma_{\zeta}^2)$$

$$\varepsilon_i = N(0, \sigma^2)$$

Where, $FAV_{i,g}$ is Food availability, for each country-year observation i and food group g , α_0 is an intercept, b_{il} are the l th of q monotonically increasing P-spline basis functions for $\log_e(Income)$, β_{il} are the spline coefficients, ζ are random effects for j th country-specific intercepts (to account for non-independence of observations within countries) and ε is residual error. Splines are used to model smooth functions of interest including non-linear effects as we did (Perperoglou et al., 2019); P-splines in particular penalize wigginess (Wood 2017). This model was run separately for each food group with monotonic increasing P-splines for all food groups except Pulses and Starchy food, for which monotonic decreasing P-splines were used, as these are inferior goods (in the economic sense) whose demand decreases with income. Our modelled relationships are consistent with previous theoretical and empirical expectations (Gouel and Guimbard, 2019; Timmer et al., 1983), including Engel's law (that the proportion spent on food decreases with increasing income) and Bennet's law (the decreasing demand for inferior goods with increasing income) (Bennett, 1941). We did not impose a saturation of demand as did Gouel and Guimbard (2019) (See Figure S7 and SI Text for details).

We did consider (and reject) alternate model specifications. A simple approach might have been to model each country (or maybe groups of countries) separately (i.e., a time-series regression, as done by Tilman and Clark (2014)). But such a specification would not have permitted us to make predictions for countries without estimation (training) data. As described in the earlier 'countries' section, the estimation data had only 3 countries in 1977 and 76 in 2010, while the prediction data was much larger (114 in 1990 to 135 from 2006 to 2013). Alternately, we could have developed a separate cross-sectional model for each year. Again, estimation-database limitations would have meant that we would have far less data for model training in earlier years. So the choice of a panel model, with random effects for country (allowing for unexplained variations such as cultural differences, between countries) allowed us the most flexibility for including all available data for model estimation and application of the model to prediction for countries and years that were not part of the estimation data.

2.4. Model prediction and rescaling with FAO Food Balance Sheets mean

An important modelling assumption is that the cross-national and cross-temporal relationships between income and food availability also hold within each country, as a reasonable approximation (Verma et al., 2011). Accordingly, we use our model, together with income by decile data for each country, to estimate the access to food for each decile within each of the 135 countries. But as the regression model's predictions are not exact, the sum of decile predicted values for each country will not exactly match that country's national food availability reported in FAO FBS. Therefore, for each country, we scaled the predicted results for deciles so that their sum matches the national food availability reported in the FAO FBS, keeping total national predicted food access by food group consistent with FAO FBS food availability, as follows:

$$FA_{i,d,g}' = FA_{i,d,g} * \frac{TFAV_{FAO,i,g}}{\sum_{d=1}^{10} FA_{i,d,g}}$$

Where, $FA_{i,d,g}'$ is the scaled Food Access, for each country-year observation i , decile d and food group g , and $TFAV_{FAO,i,g}$ is the Total Food Availability as per FAO' FBS for that country-year and food group g . Another way to think about this is that, we only used our model to disaggregate national FAO FBS data into deciles, not to predict the national values themselves.

2.5. Validation

To validate the model we use the household survey data from 24 countries that are broken down by income terciles available from the FAO HSS (FAO, 2014) as our test data. We use the model developed above (including the rescaling step) to predict total caloric access for the income reported in the surveys and compare that to the household food consumption reported in the HSS. This comparison (Figure S3) shows that our model-predicted food access is less responsive to income compared to the household survey data (this mismatch is not altogether surprising, see Salois et al. (2012)). A comparison of *national* food availability from FAO FBS to *national* mean consumption from FAO HHS also shows a similar mismatch (in absence of our modeling), with FBS mostly overestimating food purchases based on representative HHS (Figure S4). The mismatch is likely a direct logical consequence of the two data sources measuring different points of the food supply chain, i.e. the difference likely being food wasted between retail and household. Another possible explanation is that HHS are not perfect means of capturing food accessed (Fiedler, 2013). Consequently, bottom-up (HHS) vs top-down (FBS) approaches are not expected to match perfectly, and we accordingly apply a bias correction to our model predictions as explained next.

2.6. Bias correction

As noted above, the validation exercise showed that our model under predicts the response of caloric food access to income; we corrected this by applying a bias correction as follows. First, because there were differences between the FAO FBS and FAO HSS national means (Figure S4), we normalized both our model predictions and HHS data sets by their respective country means. Thus, our normalized data only showed variations due to changes in food access in response to income (Figure S5). From a comparison of these normalized data, we calculated the difference in slope between our model predictions and HHS data, and used this to bias correct our model predictions (Figure S6). As this bias correction was based just on the total calories, the calories for individual food groups did not sum up to match the original FAO FBS; so these needed to be rescaled again, maintaining their relative proportions to the total. Then we iteratively applied the bias correction and adjusted

the individual food group calories until they converged to a solution (see the mathematical details in SI Text).

3. Results and discussion

Total calorie demand rises with per-capita income for all food groups except starches, and pulses and oilseeds.

Most food groups show increasing national demand as per capita national incomes rise (Fig. 1); the two exceptions—starches as well as pulses and oilseeds—show decreasing trends, as has been extensively described in the food demand literature (Bennett, 1941; Gouel and Guimbard, 2019; Timmer et al., 1983). Model comparison to the demand-system model of Gouel and Guimbard (2019) found no differences in trends except for the Sugars and Sweeteners food group. Furthermore, we calculated a Prevalence of Undernourishment (PoU) indicator as a quasi-validation to compare to FAO's PoU indicator and found that 10.9% of the population would not meet the Minimum Dietary Energy Requirement (MDER, see Materials and Methods for definition and calculation) in 2013, whereas FAO estimates between 9 and 11.3% (FAO et al., 2021; FAO IFAD & WFP, 2013) for the year 2013. Although our approach is different from FAO's,² our estimate of global PoU is very close to FAO's.

3.1. Within-country access to food has become more unequal over time

With this empirical food demand system in hand, we are in a position to assess global, international and intranational inequality in food access. We find that, between 1961 and 2013, global inequality declined by 35% from 0.176 to 0.13. Overall, this is good news. However, global inequality is a combination of *between-country* inequality and *within-country* inequality, and therefore its patterns are driven by whichever one dominates. Examining these two terms separately, we find that *within-country* inequality in food access increased on average by 25% for the countries in our study sample (Gini coefficient increased from 0.088 to 0.111; Fig. 2), while *between-country* inequality decreased by 48% (Gini coefficient decrease from 0.15 to 0.078³). This global and cross-national pattern in food access inequality is, not surprisingly, consistent with what has been observed for global incomes in this time period (Chancel and Piketty, 2021). A few large countries with a substantial share of global population such as China and India have become wealthier contributing to declines in between-country and global inequality. Our analysis shows that excluding China from the inequality time trend analysis (Figure S8) attenuates the trend of within-country inequality increase and between-country inequality decrease but the final values are very close. Despite the decline in global inequality, rising within-country inequality is worrisome because comparison of oneself to peers in the local context generates anxiety and a feeling of unfairness more easily than the abstract comparison to those living in other countries (Nygård et al., 2017). On the flip side, within-country inequality is more readily influenced by national policies whereas

² FAO's PoU is calculated using a probability distribution model that estimates the dietary energy intake levels of an average representative individual in the population. The model uses a lognormal distribution consisting of two parameters for each country – the national average dietary energy consumption and its coefficient of variation. The model is then used to calculate the likelihood that the caloric consumption of a random individual is below the MDER (FAO et al., 2021).

³ These Gini coefficients (as the chosen measure of inequality) are low compared to the more commonly known Gini ranges in income or wealth inequality. This is expected because the subsistence requirements of caloric intake require the lowest values to be higher than would be the case for wealth or income, which can be very close to zero and the highest values of caloric intake are bound by physiology (compared to wealth and income which over the last decades have seen unbounded increases). The shorter range and larger lower limit make the Gini coefficient for food access smaller by construction.

global redistribution of income (or entitlements to access food) is much more difficult to achieve.

Inequality in access to nutrient-dense foods is larger than for total calories for all three measures, with between- and within-country inequality converging to similar levels by 2013 (Fig. 2). This result is consistent with past food demand literature, as it is at higher incomes that demand for nutrient-dense foods materializes and demand for staple calories saturates or declines (Bennet 1941). Similar to the finding for total calories, excluding China reduces the overall steepness of decline for between-country inequality but the final values are very close. However, it is likely that our results are an underestimate of how unequal access to nutrient-dense foods is. Our model was corrected for a revealed bias in total calories using household surveys (see Methods and Materials - Bias Correction). But it was not possible to assess with household surveys whether the food group level predictions were underestimating the responsiveness to increases in income (income elasticity by food group).

3.2. There are vast disparities in food access inequality between countries

We show a wide disparity in national average per capita food availability between countries (see representative country means in Fig. 3) but also a wide range of within-country inequalities in access to food (distance between poorest and richest 10% in Fig. 3). For example, South Africa has the largest difference in access to calories between the richest and poorest deciles (5040 kcal and 1658 kcal respectively), while Taiwan has the smallest difference (3315 kcal and 2515 kcal respectively). Belgium's poorest 10% has the largest calorie access (2966 kcal) of all the lowest deciles in the world, more than 3 times that of the poorest 10% in Central African Republic who access the lowest amount of calories (926 kcal). The richest 10% in the Egypt, access the largest amount of calories globally (5363 kcal), roughly two times more calories than the richest 10% of the population in Afghanistan who have the least access to calories (2765 kcal) of all the top deciles of the world. These stark inequalities are almost invisible in national per capita estimates of food access, such as the FAO's Food Balance Sheets.

3.3. There is large variation in access to nutritious foods between and within countries

Major differences between countries. In general, when comparing the richest or poorest income deciles between nations, African nations and some South Asian (SA) and South East Asian (SEA) nations show a heavy reliance on starchy staple foods for their calories compared to the rest of the world. Consequently, there is also a low reliance on nutrient-dense foods to access calories in these nations. The Americas (in particular North America) and Europe show the highest share of accessed calories coming from empty calories (Fig. 4).

Major differences within countries. There are also stark differences in access to calories from nutrient-dense foods (NDF) between the richest and poorest 10% within the majority of African countries as well as the Andean countries, Central America and the Caribbean, SA, and SEA (Fig. 4). South Africa has the largest difference in share of calories accessed from NDF and Australia has the lowest. South Africa's poorest 10% access just 9% of their calories from NDF. Even worse, Liberia's, Lesotho's and Bangladesh's poorest 10% access less than 4% of their calories from NDF and access at least 77%, 61%, and 56% fewer calories from NDF than South Africa's poorest 10%, while their richest 10% access at least 16% of calories from NDF. In contrast, in The Netherlands, Finland, Albania, and Hong Kong, both the richest and poorest 10% access at least 40% of their calories from NDF, with small differences between the richest and the poorest.

The biggest difference between richest and poorest 10% in terms of calories accessed from empty calories is Botswana. But the share of calories accessed from empty calories by the richest 10% is very high in the US and Canada, as well as central European countries (Fig. 4).

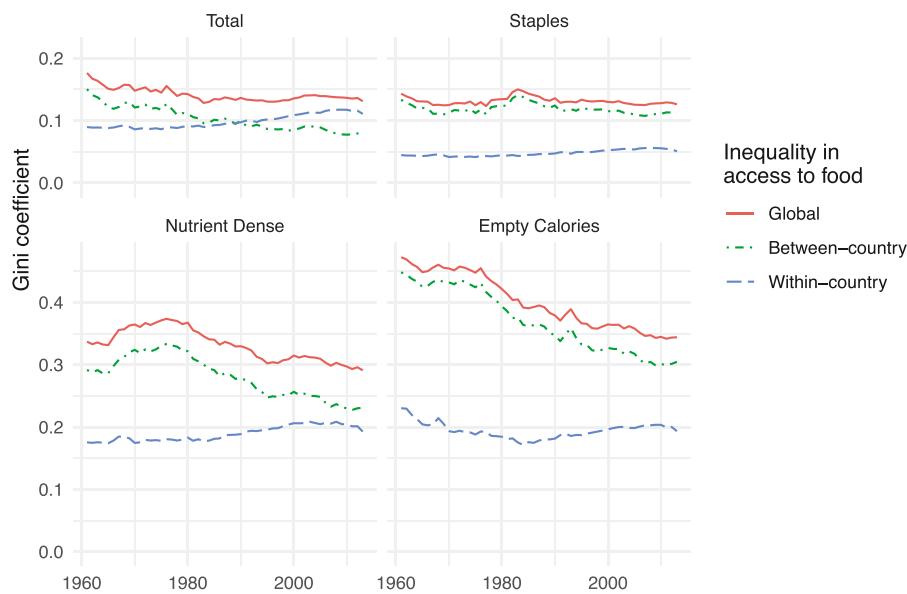


Fig. 2. Inequality in access to food measured by the Gini coefficient. A value of one represents absolute inequality, a value of zero represents perfect equality, i.e. everyone has access to same number of calories from the designated food group. Between-country inequality in access to food is a population weighted Gini of daily per capita calorie availability according to FAO Food Balance Sheets. Within-country inequality is a population weighted average of the within country Gini coefficients in food access for the 10 deciles for which food access was estimated. Global inequality is a population weighted Gini coefficient of all the country deciles we estimated food access for. Nutrient-dense foods include: dairy, eggs, fruits, vegetables, pulses, seeds, tree nuts, meat, and seafood; staples include: cereals, roots, tubers and plantain; and empty calorie foods include: oils and sugars. See [Figure S8](#) for a replica of this figure where China is excluded.

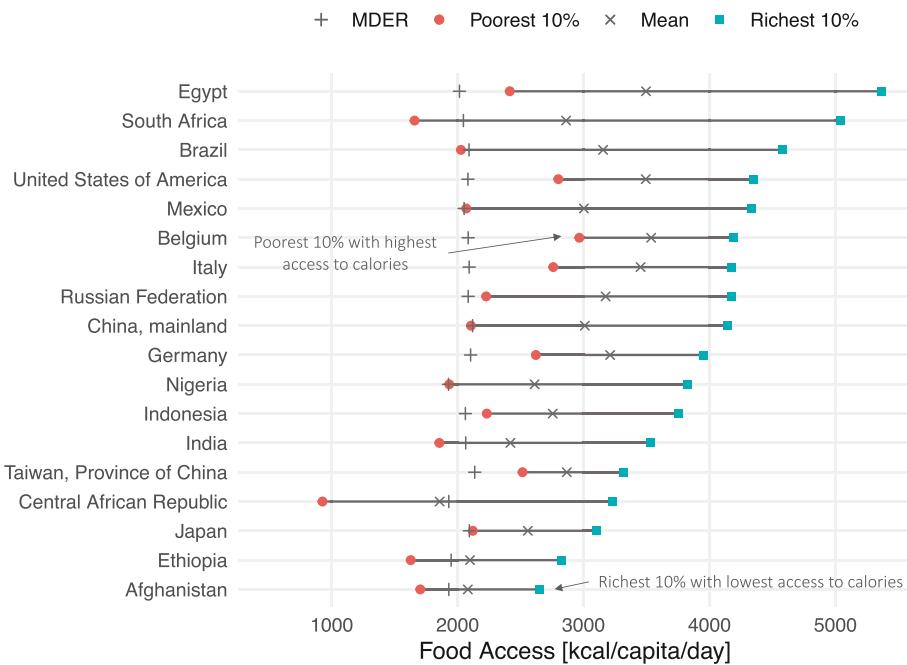


Fig. 3. Estimated food access for richest and poorest income decile for select countries in 2013. To visualize global inequality in access to food this figure shows the richest 10% and the poorest 10% of a selection of highly populated countries of different world regions (representing 65% of global population), as well as the country with the decile accessing the least calories (Central African Republic), the country with the richest 10% with least access to calories (Afghanistan), the country with the poorest 10% with greatest access to calories (Belgium), the country with the richest 10% with greatest access to calories (Egypt), and the territory with the smallest gap between richest and poorest deciles (Taiwan, 800 kcal/capita/day). MDER = minimum dietary energy requirement (See [Figure S9](#) for the progress from 1961 to 2013 for the same selection of countries).

Estimating that the richest 10% access more calories from empty-calorie foods than the poorest 10% in the richest countries might seem contradictory to the opposite pattern found on markers such as obesity and overweight rates by socio economic groups or results from food diaries and questionnaires. These estimates are nonetheless consistent with the

food access definition, and the obesity-income relationship across countries that cannot systematically be reversed for within country predictions (See Materials and Methods, [Table 1](#) and [SI Text](#) for detailed discussion).

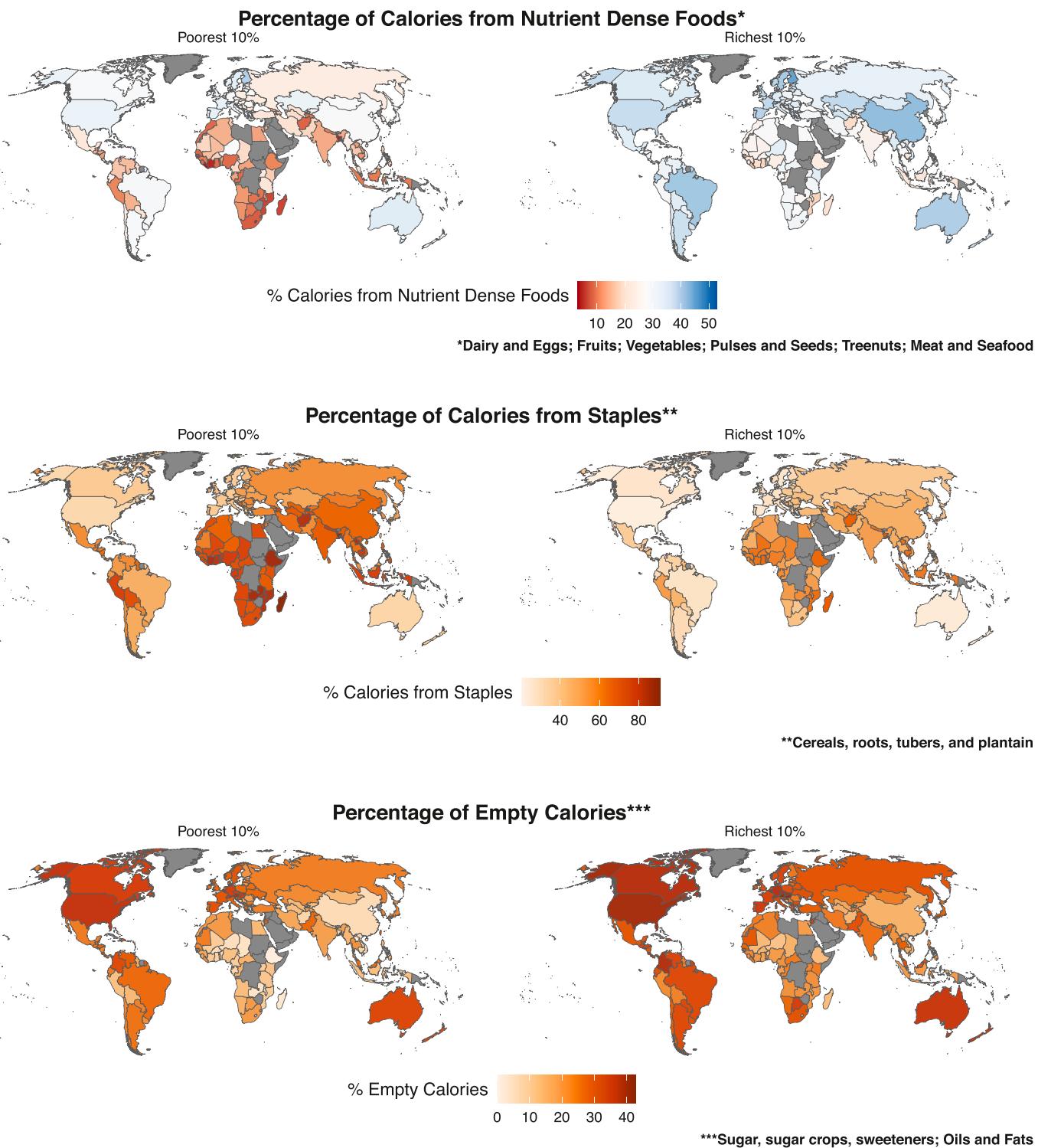


Fig. 4. Composition of food calories for the poorest (left) and richest (right) income deciles by country in 2013. The maps disaggregate the total calorie access into three sources: top: nutrient dense foods (comprised of dairy, eggs, fruits, vegetables, pulses, seeds, tree nuts, meat, and seafood); middle: staples (comprised of cereals, roots, tubers and plantain); and bottom: empty calorie foods (oils and sugars). The three categories add up to total caloric access.

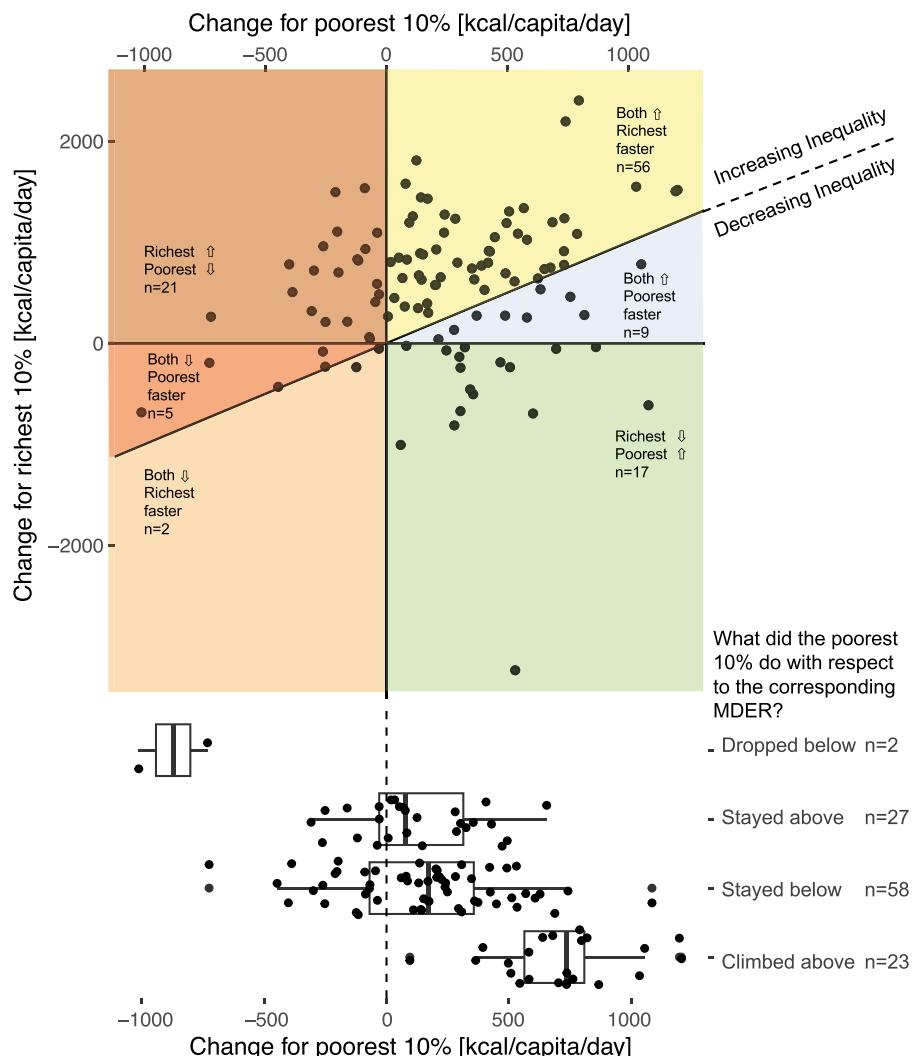


Fig. 5. Change from 1961–2013 in access to calories for richest and poorest 10% of the population by country with respect to the change in MDER from 1961–2013. Taking into account the change in MDER from 1961 to 2013 means that the poorest decile in a country might have seen an increase in *absolute* total calories accessed but if the increase in MDER for such country were bigger, then the change in total calories *relative* to the change in MDER would be negative. The black diagonal line is the $x = y$ line, the closer a country observation is to the line the more equal the change in access to calories was for richest and poorest decile. Countries above that diagonal saw an increase in inequality in access to food between richest and poorest 10%, countries below the diagonal saw a decrease. The total number of countries in this figure is 110 (out of 135) because only countries with data from 1961 to 2013 are included, those countries that underwent dissolutions were excluded.

3.4. Progress in food access has been slower for the poorest

A majority of countries ($n = 65$; top-right quadrant of Fig. 5) saw an increase in access to calories for both the poorest and richest income deciles from 1961 to 2013. But the gains for the richest income decile have been larger than for the poorest ($n = 56$; more countries lie above the diagonal in the top-right quadrant of Fig. 5) — China, India and the USA all fall within this group. In many countries ($n = 60$; bar charts at bottom of Fig. 5), the poorest income deciles have failed to rise above their MDER (e.g. China, India, Brazil, Mexico, and South Africa), and in most such cases ($n = 44$; not shown) the richest income decile actually saw increases in access to food. In those countries where the poorest income decile was already above its MDER in 1961 ($n = 27$), food access for the richest income decile increased even faster for the majority (21 out of 27 countries), signaling excess calorie access beyond needs that could partly be explained by increased food waste or overconsumption; almost every high-income country falls into this group, e.g. USA, UK,

Germany, etc.⁴ A worrisome observation is that in 58 countries where the poorest income decile stayed below MDER, 18 countries are estimated to have experienced a decrease in access to calories, and 8 of the 58 saw decreases in mean access to calories. On the positive, in 28 countries (bottom bar chart of Fig. 5) the poorest 10% rose above the MDER and in 7 of those the poorest 10% actually increased access to calories faster than the richest 10%, signaling efficient and focused growth on the poorest.

4. Conclusion

Analysis of food access based on national per capita figures provided by the FAO Food Balance Sheets indicates that inequality in access to

⁴ Some of the increase in food access by the richest income decile can be attributed to increase in food waste (Lopez Barrera and Hertel, 2021).

calories has been declining. However, these national averages mask a much more nuanced, and in many cases worrisome, trend in food access inequality within countries. By estimating a food demand model that permits prediction of food access across deciles within countries, we have been able to shed light on these hidden trends. Most worrisome is the limited progress for the poorest income deciles with respect to the national MDER.

This analysis has focused on access to calories as the bare minimum requirement of energy needs that food provides. By examining the proportion of these calories coming from the nutrient-dense food group we also evaluate the inequality in access to key micro and macro nutrients. Our results show that inequality in access to nutrient-dense foods is even greater than inequality in access to total calories. This has important implications for implementation of dietary guidelines and public health programming around improved nutrition, including development programs that aim to concentrate income growth in the poorest half of the income distribution. This work can also be extended to model income-driven inequality in access to different macro and micronutrients within countries, and for evaluation of the impacts of inequality on hidden hunger.

Our analysis has many limitations. First, it relies on the FAO Food Balance Sheets (FBS) as the metric of food availability and later a proxy for food accessed (See Materials and Methods for details). There are known caveats with the use of this data, and for this study in particular, that are important to mention. For instance, subsistence farming food, primarily in the least developed economies, are not captured in FBS. The proportion of calories from subsistence farming is expected to be highest in lower income groups, and thus underestimation of total caloric access and calories from nutrient dense foods for low income groups within poor countries cannot be ruled out. Second, it's likely that our model is not as good at predicting demand at higher incomes, an issue also noted by [Gouel and Guimbard \(2019\)](#). Our model validation and bias correction relies on the FAO HSS dataset, which is limited to 24 countries, and therefore does not capture the full spectrum of incomes seen across the world. Future iterations of this work should focus on compiling a more complete model training and validation data set. It should be noted that our model ignores many important aspects of food access including population age structure, sex, physical activity, etc. Finally, those familiar with demand systems modelling and economic literature might find the omission of prices in our model problematic. We intentionally used PPP adjusted incomes to account for the omission of prices because the most recent literature on the affordability of healthy diets suggests that the cost of a healthy diet is very similar across different country income levels in PPP dollars ([Bai et al., 2021](#)). Additionally, the most recent of such demand system models to our knowledge is that of [Gouel and Guimbard \(2019\)](#) and as mentioned previously—with a simpler implementation that excludes prices—our statistical approach yields very similar estimates by food group compared to their demand system estimated using prices ([Figure S7](#)).

Our work is in line with recent literature that concludes that food access is quite responsive to income particularly at low levels of income—i.e. bigger increases in food demand or caloric intake as incomes increase when the starting income is low ([Colen et al., 2018](#); [Ogundari and Abdulai, 2013](#); [Salois et al., 2012](#)). Our study underscores the need for targeting the poorest 10–50% of the populations with programs that boost incomes and improve food access and calls for policy instruments that effectively reduce inequality in access to food. The results emphasize that there is still a sizeable gap to bridge in access to calories and an even larger gap in access to calories from nutrient dense foods. Any effort to end hunger by 2030 will necessarily need to revisit the entitlement theory of Amartya [Sen \(1981\)](#) and focus primarily on the food access of the world's poorest populations.

Policymakers around the world need to plan and execute future development scenarios in which income growth is concentrated in the poorest half of the income distribution to swiftly reduce inequality in access to food with concomitant positive outcomes in terms of under-

over nutrition. This need is further exacerbated by the recent disproportionate negative impact that the COVID-19 pandemic likely had on lower income families and individuals around the world ([Darvas, 2021](#); [World Bank, 2020](#)). The surge in social safety net programs in low-income countries over the last four years is a promising development. However, these programs were reactionary responses to the COVID-19 pandemic and heavily reliant on international donor support—ensuring their persistence into the future, coupled with proactive programs that help vulnerable households build assets which can sustain them through future crises, is key to reducing global hunger ([Headey, 2014](#); [Hertel et al., 2021](#); [Hertel, 2016](#)).

Funding sources

This research was funded through the University of British Columbia 4 Year Doctoral Fellowship, Natural Sciences and Engineering Research Council of Canada (NSERC) grants RGPIN-2017-04648, RGPIN-2023-05236, and the Canada Research Chairs Program award AWD-002767 UBCARTS 2016. The funding sources had no role in data collection or analysis.

CRedit authorship contribution statement

Juan Diego Martinez: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Funding acquisition. **Navin Ramankutty:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Funding acquisition. **Zia Mehrabi:** Methodology, Writing – review & editing, Supervision. **Thomas W. Hertel:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

We would like to thank Monica Verma and Paul V. Preckel for input during the early stages of the ideation phase, Milind Kandlikar for valuable feedback on final manuscript, Julie Fortin for proofreading, and two anonymous reviewers for valuable feedback on the initial submission. This work contributes to the Global Land Programme (<https://glp.earth>).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.gfs.2024.100774>.

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