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Income inequality reduction as a pathway to sustainable and healthy dietary transitions in Brazil

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Abstract

Middle-income countries face challenges in achieving diets that are both nutritionally adequate and environmentally sustainable, while income-related dietary heterogeneity adds uncertainty to population-wide dietary transitions. Here we investigate how income inequality shapes long-term dietary transitions from nutritional and environmental perspectives. We project Brazilian dietary patterns from 2020 to 2100 in scenario-based income pathways by integrating national-representative survey data with nutritional and environmental databases. We find that reducing income inequality improves dietary nutritional quality by 5.7%, and avoids 40-50% of the increase in dietary environmental impacts projected under income-inequality-increasing scenarios by 2100. However, inequality reduction is associated with a short-term worsening of dietary environmental impacts, with an average deterioration of 2.2% relative to the baseline scenario. These results highlight a trade-off between short-term environmental pressures and long-term nutrition and sustainability benefits, underscoring that income inequality reduction alone is insufficient and should be complemented by broader policy packages to promote dietary transitions.

Keywords: Middle-income country; Dietary shift; Income inequality; Double burden; Nutritional quality; Environmental impacts.

Introduction

Dietary changes are causing critical nutritional and environmental issues, particularly in middle-income countries, challenging the achievement of multiple Sustainable Development Goals (SDG), including zero hunger (SDG 2), good health and well-being (SDG 3), and climate change mitigation (SDG 13)[1,2]. Rapid socio-economic development has increased demand for high-calorie and animal-sourced foods, thereby intensifying the environmental pressures of agri-food systems[2,3]. Combined with population growth, this ongoing shift towards resource-intensive diets has contributed to a rapid rise in food-system greenhouse gas (GHG) emissions in middle-income countries by about 25.4% since 1990 compared with a global average increase of 14.3%[4]. From a health perspective, many middle-income countries face undernutrition and overnutrition simultaneously, resulting in a severe double burden of malnutrition[2]. In Brazil, China and India, for example, about 2.2%, 3.4%, and 43.5% of the population remain undernourished, while 52.8%, 25%, and 11.2% are overweight, respectively[5]. A shift in individual diets towards improved nutrition and environmental sustainability is thus urgently needed in these countries[1,6].

Dietary heterogeneity associated with income inequality can obscure prospects for population-wide shifts toward healthy and sustainable diets[6–9]. Income growth fundamentally alters dietary pattern by changing food affordability, availability, and preferences, but these changes do not occur uniformly across the population[1,10]. As incomes rise, low-income groups often increase consumption of animal-sourced and other resource-intensive foods, while higher-income groups may eventually shift toward diets with lower shares of such foods and improved nutritional quality[11,12]. Income inequality shapes how quickly and for whom these transitions occur, thereby influencing the population-wide balance between nutritional benefits and environmental costs[11,12]. As a result, future dietary outcomes depend not only on average income growth but also on how income gains are distributed across society[1,13]. Particularly in middle-income countries, such as Brazil, rapid development coupled with income inequality can exacerbate such heterogeneity substantially, strongly amplifying uncertainty about the long-term health and environmental consequences of dietary transitions[14–17].

As one of the world's largest middle-income countries, Brazil has a food system with substantial environmental impacts at both national and global scales, shaped by dietary patterns and marked by pronounced income inequality[17,18,19]. Brazil ranks first in global beef exports and among the top countries in per-capita beef consumption, making animal-sourced foods a dominant contributor to dietary environmental impacts[4]. Brazil thus accounts for a substantial share of global environmental impacts and ecological degradation, not only driven by deforestation, land conversion to croplands or cattle pastures in the Amazon, but also by broader agri-food supply chain, including livestock production, feed and fertilizer use, processing, and logistics[20–22]. At the same time, pronounced income disparities and heterogeneous diets across population groups mean that future dietary transitions may unfold very differently across society[17,19]. Although existing studies have examined links between income, dietary quality, and environmental pressures and highlighted the potential of dietary shifts in Brazil to improve nutrition and reduce environmental impacts[2,23,24], most rely on static or short-term analyses and treat income inequality as an observed correlate rather than a policy-relevant driver. Consequently, how alternative income distribution pathways shape long-term, population-wide dietary transitions and their nutritional and environmental outcomes remains poorly understood, even though such pathways may fundamentally alter macro-level environmental trajectories through the aggregation of heterogeneous dietary patterns across socio-economic groups at different stages of dietary transition[2,25].

In this paper, we examine how income inequality shapes long-term dietary transitions in Brazil from both nutritional and environmental perspectives. We develop a scenario-based framework that combines five alternative income distribution pathways (Equality Scenario, ES), representing varying degrees of inequality reduction or exacerbation, with five reference Shared Socioeconomic Pathways (SSPs) that quantitatively describe potential future developments under different GHG emission intensity conditions (Supplementary Table 3)[26], generating 25 plausible scenarios spanning 2020-2100. Using individual-level relationships between dietary patterns and socio-economic characteristics, we project future dietary patterns under each scenario. The nutritional quality is assessed using the Alternative Healthy Eating Index (AHEI)[27], while environmental impacts including GHG emissions, acidification, eutrophication, land use, and freshwater withdrawals are estimated using a multi-indicator life cycle assessment (LCA) database[3]. Projected dietary patterns are further compared with the EAT-Lancet Planetary Health Diet to evaluate alignment with recommended healthy and sustainable consumption patterns[1]. This study examines the role of income inequality in shaping dietary transitions and their nutritional and environmental outcomes in Brazil. By integrating individual-level dietary data with nutritional and environmental metrics, it offers insights relevant for designing policies that jointly address inequality, dietary quality, and sustainability in middle-income countries.

Results

Effects of income inequality on dietary nutritional quality and environmental impacts. Reducing income inequality would improve dietary nutritional quality and would limit long-term growth in dietary environmental impacts, while being associated with a short-term worsening of population-wide dietary environmental impacts. Across scenarios, pre-capita dietary nutritional quality, measured by the AHEI score, improves steadily from approximately 52 in 2020 to around 54-55 by 2100, corresponding to an increase of about 4-6% (Figure 1a; Supplementary Figure 7a). Income-inequality-reducing scenarios (SSP-Ref-ES75, SSP-Ref-ES62.5) consistently achieve slightly higher pre-capita AHEI levels over time than income-inequality-increasing scenarios (SSP-Ref-ES75, SSP-Ref-ES62.5). In addition, although per-capita dietary environmental impacts generally increase over time (Figure 1b-f; Supplementary Figure 6), these changes remain relatively modest compared with current levels, amounting to approximately 5-8% for GHG emissions, 4-7% for acidifying emissions, 3-6% for eutrophying emissions, 3-5% for land-use requirements, and 3-6% for freshwater withdrawals by 2100.

Furthermore, the effects of reducing or exacerbating income inequality on dietary environmental impacts differ remarkably over time (Figure 1). Income-inequality-reducing scenarios mitigate dietary environmental impacts only in the long term, while exacerbating them in the short term. By contrast, under income-inequality-increasing scenarios (SSP-Ref-ES37.5, SSP-Ref-ES25), the dietary environmental impacts are generally curbed in the short term but increase in the long term, reflecting a non-linear temporal pattern. This pattern is more clearly illustrated by comparisons with income-inequality-constant baseline scenario (SSP-Ref-ES50; Supplementary Figure 7b-f). The differences between SSP-Ref-ES75 or SSP-Ref-ES62.5 and SSP-Ref-ES50 are generally positive in the short term but negative in the long term, whereas the differences between SSP-Ref-ES37.5 or SSP-Ref-ES25 and SSP-Ref-ES50 show the opposite pattern, being generally negative in the short term but positive in the long term (Supplementary Figure 7b-f). By 2100, income-inequality-reducing scenarios are associated with a substantially smaller increase in dietary environmental impacts than income-inequality-increasing scenarios, with long-term growth reduced by approximately 40-50%. In contrast, during the mid-century period these scenarios may temporarily intensify population-wide dietary environmental impacts, reaching an average deterioration of about 2.2% relative to the baseline scenario (SSP-Ref-ES50).

The nutritional quality and environmental impacts of dietary shifts may either improve or deteriorate, depending on individuals' starting dietary patterns, which differ remarkably across income groups (Figure 2). The distribution of AHEI score across income deciles remains stable, with higher income consistently associated with higher AHEI score, indicating better dietary nutritional quality (Figure 2a). In contrast, the distributions of dietary environmental impacts across income deciles vary substantially (Figure 2b-f). In 2030, the income-decile distributions of dietary environmental impacts are broadly consistent with those observed in the 2008-09 and 2017-18 survey data (Supplementary Figure 1). In both 2050 and 2100, higher income levels are generally associated with lower dietary environmental impacts. However, the distribution of high impacts across income groups differs over time and across scenarios. In 2050, under income-inequality-reducing scenarios (SSP-Ref-ES75 and SSP-Ref-ES62.5), the highest dietary environmental impacts are relatively higher among low-income populations. By 2100, this pattern persists but shifts to income-inequality-increasing scenarios (SSP-Ref-ES37.5 and SSP-Ref-ES25). This shift reflects differences in the time scale of dietary transitions across scenarios, characterized by an inverted U-shaped relationship between income and the consumption of resource-intensive foods (see *The mechanism of dietary transitions*). Under income-inequality-reducing scenarios, faster income growth among low-income groups brings this peak forward to the mid-term, whereas under income-inequality-increasing scenarios, slower income growth shifts it to later in the century. Generally, from a temporal perspective, dietary environmental impacts decline among high-income populations, while continuing to increase among low-income populations (Figure 2b-f).

The changes in dietary pattern and associated GHG emissions. Although dietary patterns are shifting toward healthier and more sustainable diets, a substantial gap remains compared to the EAT-Lancet Planetary Health Diet recommendations (Figure 3)[1,28]. We show the dietary patterns measured by GHG emissions (kg CO_2 equivalent/capita/day) for 3 time points: 2030, 2050, and 2100. In Brazilian diets, the animal protein food has the greatest environmental impacts (Figure 4a) and therefore largely drives the distribution of total dietary GHG emissions across income decile (Figure 2b, Figure 3a). The high-income populations will reduce animal protein food consumption, while the low-income populations will increase consumption (Figure 3a). Similar patterns are also observed for other high-calorie food groups defined by EAT-Lancet framework, such as those high in added fats and added sugars (Figure 3h,3i). Besides, income growth is associated with increased consumption of plant-based foods across scenarios; however, the magnitude of this increase varies substantially across income groups (Figure 3b-d). While plant-based food intake rises more remarkably among high-income populations, low-income groups tend to exhibit more modest increases or near-maintenance relative to their baseline levels. Notably, under income-inequality-reducing scenarios, these disparities between income groups are considerably smaller, resulting in a more even distribution of dietary environmental burdens (Figure 3).

The mechanism of dietary transitions. The key mechanism underlying our results is the inverted U-shaped relationship between income and red meat consumption, where meat intake initially increases with rising income but declines at higher income levels (Figure 4b). This pattern is consistent with the well-established concept of the nutrition transition[29], and the subsequent second nutrition transition emphasizing increased meat consumption during early stages of economic development[30]. While similar income-diet relationships have been documented in previous cross-national studies[11], their environmental consequences are particularly pronounced in Brazil due to its high levels of animal protein consumption, with red meat being the dominant contributor to dietary environmental impacts (Figure 4a). Under income-inequality-reducing scenarios (SSP-Ref-ES75, SSP-Ref-ES62.5), income among low-income populations grow faster than those of high-income populations. As a result, increases in red meat intake among low-income populations generally outweigh the concurrent declines observed among high-income populations, leading to a net rise in dietary environmental impacts in the short term. Over time, however, red meat intake in both high- and low-income populations passes its peak and begins to decline, which explains the reduction in dietary environmental impacts in the long term. In contrast, under income-inequality-increasing scenarios (SSP-Ref-ES37.5, SSP-Ref-ES25), the growth of dietary environmental impacts is temporarily curbed relative to the baseline, but accelerates remarkably in the long term. Differences in income growth rates across scenarios, especially the pace of income growth among low-income populations, shape the time scale of dietary transitions and thereby generate the observed differences in dietary environmental impacts across scenarios. Consistent with this mechanism, a more pronounced decline in per-capita dietary environmental impacts can be expected under income-inequality-reducing scenarios beyond 2100. By contrast, under income-inequality-increasing scenarios, environmental impacts may eventually decrease as incomes of low-income populations gradually slowly rise; however, such a turning point is not projected to occur within the visible time horizon up to 2100 (Figure 1).

Discussion

This study shows that reducing income inequality improves dietary nutritional quality and limits the long-term growth of dietary environmental impacts despite potentially aggravating environmental pressures in the short term. This dynamic pattern reflects the non-linear relationship between income growth, dietary transitions, and environmental outcomes. Under income-inequality-reducing scenarios, faster income growth among low-income populations initially leads to increased consumption of resource-intensive high-calorie foods (e.g. animal protein foods, added fats, and added sugars), resulting in a temporary rise in population-wide environmental impacts. Over time, however, dietary patterns move past this peak as preferences gradually shift toward healthier diets with lower environmental footprints. As a result, inequality-reducing pathways ultimately outperform inequality-increasing ones in the long run, highlighting the importance of time scale in evaluating the sustainability consequences of income redistribution. This mechanism is consistent with the well-documented inverted U-shaped relationship between income and the consumption of resource-intensive foods, such as red meat[11,29,30]. At the population level, this turning point corresponds to a monthly income of roughly 2,200 Brazilian reais (adjusted by purchasing power at constant 2015) in the 2017-18 survey, but this value should be interpreted only as a contextual order-of-magnitude reference rather than a threshold, as it is sensitive to price levels, inflation, economic conditions, and substantial heterogeneity in individual dietary preferences. Consistent with this interpretation, recent studies suggest that affluent Brazilians exhibit stronger intentions to reduce unhealthy dietary components, such as ultra-processed foods[12] and sweeteners or sugar additives[31]. The magnitude of our estimates, such as the per-capita dietary GHG emissions on the order of 6 kgCO_2eq/day or 3.8 gCO_2eq/kcal, are broadly consistent with existing empirical studies or statistics[4,22,32], adding to the robustness of the overall trends identified. Nevertheless, our results also indicate that even under income-inequality-reducing scenarios, the projected improvements in dietary environmental impacts remain far from sufficient to close the gap between prevailing Brazilian diets and sustainability benchmarks such as the EAT-Lancet Planetary Health Diet, even by 2100.

This persistent gap indicates that reducing income inequality alone is insufficient to steer dietary transitions toward healthy and sustainable diets and may intensify short-term pressures as consumption expands among previously constrained populations, underscoring the need for coordinated policy packages. On the demand side, fiscal instruments such as taxes on unhealthy or ultra-processed foods, coupled with subsidies for healthier options, can help influence consumption patterns while generating revenues to support redistribution[2,11,33,35]. Nutrition education, dietary guidelines, and food waste reduction policies can further reinforce shifts toward healthier and lower-impact diets[1,33,34,36]. On the supply side, technological progress, particularly reductions in emission intensity within livestock production sectors, and broader investments in sustainable food systems are essential for limiting environmental pressures during dietary transitions[35,37]. At the same time, the studies caution against relying on single-sided interventions, for example, supply-side efficiency gains alone may induce rebound effects where lower prices stimulate higher consumption and offset environmental benefits[38]. This concern is particularly relevant in Brazil, where consumption and exports of animal-sourced foods are already high[4], suggesting that demand-side management, and in some cases selective restraint on resource-intensive foods, may be necessary alongside efficiency improvements. This underscores the need for integrated strategies that align supply- and demand-side interventions with social objectives and manage short-term trade-offs in pursuit of long-term nutrition and environmental sustainability.

Our findings are likely to have broader relevance beyond Brazil. Globally, wealth has continued to grow but has become increasingly unevenly distributed, a trend that is particularly pronounced in many middle-income countries such as India and South Africa, where income inequality remains substantially higher than in high-income economies with uncertain future trajectories[39]. Under the inverted U-shaped relationship between income and the consumption of resource-intensive foods, rapid widening of income gaps may delay or distort population-wide transitions toward healthier and more sustainable diets. Historical experience in high-income countries suggests that dietary environmental impacts often rose sharply during earlier phases of economic development, implying that middle-income countries may follow similar trajectories and risk short-term environmental overshoots as incomes grow[29,30]. While several high-income European countries, such as France, Denmark and Portugal, have experimented with fiscal instruments such as food or carbon-related taxes to reshape dietary patterns and reduce consumption of resource-intensive foods, evidence on their effectiveness remains mixed[40,41]. The policy challenge is arguably more complex in middle-income countries, where larger income disparities coexist with a pronounced double burden of malnutrition, with underconsumption persisting alongside excessive intake among wealthier groups[5]. In such settings, broad consumption-reduction or degrowth-oriented strategies may disproportionately burden low-income populations and risk undermining basic nutritional needs[2,42]. These considerations point to the need for more nuanced policy packages that combine inequality reduction and poverty alleviation with food-related measures, such as investments in clean production technologies, sustainable land use, and climate finance, to limit short-term environmental pressures while enabling long-term improvements in dietary sustainability in middle-income countries[2,11,33,36]. Future research should explore how redistributive policies interact with supply- and demand-side interventions across different food cultures and development contexts. Comparative analyses spanning regions in Latin America, Asia, and Africa would be particularly valuable for assessing the generalizability of this framework and informing context-specific strategies for equitable and sustainable dietary transitions.

Several limitations should be acknowledged. Firstly, our analysis relies on Brazilian Household Budget Surveys from 2008-09 and 2017-18, which constrains the temporal resolution of individual-level dietary and socio-economic data. Secondly, dietary environmental impacts are likely to be conservative estimates, particularly for animal-sourced foods, given that deforestation-related emissions in Brazil may not be fully captured by the global LCA database employed. Finally, scenario construction necessarily involves simplifications due to data availability, which may affect projections of future socioeconomic trajectories. A detailed discussion of these methodological limitations is provided in the Methods section.

Overall, our findings highlight a fundamental trade-off in inequality-driven dietary transitions: while reducing income inequality can deliver clear long-term benefits for nutrition and environmental sustainability, it may entail short-term environmental costs as previously constrained populations increase consumption. This implies that redistribution alone is unlikely to be sufficient, and that complementary policy packages, such as targeted food taxes and subsidies, nutrition education, and investments in sustainable food production, are needed to steer dietary change while managing short-term pressures. These insights are particularly relevant for middle-income countries beyond Brazil, where rapid economic growth, large income disparities, and the coexistence of under- and overconsumption create complex challenges for sustainable food system transformation. By treating income inequality as a policy-relevant driver and embedding it within a long-term, individual-level scenario framework, this study extends existing income-diet literature beyond static associations and provides evidence on how distributional pathways shape the time scale and population-wide outcomes of dietary transitions.

Methods

Evaluation on nutritional quality of individual diet and associated environmental impacts. We used individual diets data (1. Code of the type of food consumed and 2. Amount in grams consumed for each food) from Brazilian Household Budget Surveys for examining the daily diet of Brazilians. All of the individual-level data (food intake and socio-economic factors) come from Brazilian Household Budget Surveys (2008-09, 2017-18)[31]. This survey is carried out by the Brazilian Institute of Geography and Statistics (IBGE) and available at IBGE's Automatic Recovery System (SIDRA)[31]. Totally, 34,003 and 46,164 individual-level samples are available for 2008-09 and 2017-18 respectively[43]. The calculation of dietary nutritional quality using AHEI-2010 requires information on servings of multiple food groups, which are defined within the Food Patterns Equivalents Database (FPED), the Food Patterns Equivalents Ingredients Database (FPID), and the Food and Nutrient Database for Dietary Studies (FNDDS) developed by the U.S. Department of Agriculture (USDA). Because a large share of foods reported in the Brazilian Household Budget Surveys are mixed dishes, and food-group-level information is required for AHEI construction, nutrient data alone from the Brazilian food composition tables are insufficient for this analysis. We mapped food items reported in the Brazilian Household Budget Surveys to the closest corresponding items in USDA's FNDDS, with mixed dishes further disaggregated into ingredient- and food-group components using FPID and FPED. Mappings were manually reviewed with support from native Portuguese-speaking researchers to ensure consistency in food definitions, primary ingredients, and preparation methods. And then we can obtain the components required by calculating AHEI and diets associated environmental impacts. Please see our previous study[44] and Supplementary Figure 3 for more details about matching method, please see Supplementary Figure 2 for framework of this study.

We calculate the AHEI-2010 for individual daily diet. The AHEI scoring index model, considering 11 nutrient components of food, gives scores on individual diets based on foods and nutrients predictive of chronic disease risk[27]. Higher AHEI score means lower possibility to have disease led by food intake, which indicates a better nutritional quality or a healthier diet[27]. A higher AHEI can be achieved by either a higher intake level of components of adequacy (vegetables, fruit, whole grains, nuts and legumes, and long-chain fats), a better dietary structure (fatty acid, polyunsaturated fats, sodium, and alcohol) or a lower intake level of unwanted components (sugar-sweetened beverages, red or processed meat)[27]. The AHEI-2010 is an update version of HEI and AHEI-2005 and has been shown to be strongly associated with major chronic disease such as coronary heart disease and diabetes[27]. Unlike HEI-2015, which is explicitly designed to assess adherence to U.S. Dietary Guidelines, AHEI-2010 is based on general, evidence-based relationships between dietary components and health risks, making it more suitable for cross-country applications[27,45]. Although several population-specific variants exist (e.g. AHEI-Pregnancy[46]), AHEI-2010 remains the most general and widely applied index for assessing dietary transitions across diverse settings[47–49]. We therefore adopt AHEI-2010 as a dietary quality indicator that is grounded in stable diet-health relationships and is suitable for long-term, scenario-based analyses of dietary transitions. Please see Chiuve et al. (2012)[27] for more details about AHEI-2010 calculation.

We calculate environmental impacts associated with individual diets in relation to 1) GHG emissions, 2) acidifying emissions, 3) eutrophying emissions, 4) land use, 5) freshwater withdrawals, with a food-environment database obtained from Poore and Nemecek (2018)[3]. Because, this database records environmental impacts covering each stage of the supply chain from producer to consumer[3]. This database is formed by LCA researches, derived data from a comprehensive meta-analysis, identifying 1530 LCA studies for potential inclusion[3]. Please see Poore and Nemecek (2018)[3] for more details. We do robustness check using alternative local LCA database by calculating the individual diets associated carbon footprint, water footprint, and ecological footprint as reference (Supplementary Figure 8)[50]. Although there are slight differences, the distributions between AHEI and environmental impacts are similar with our current results (Supplementary Figure 9).

The regression model. We project individual dietary patterns under different socio-economic scenarios, based on hypothesis that individual dietary choices are shaped by socio-economic characteristics. Simulations are conducted for 15 EAT-Lancet food groups, including grains, starchy vegetables, vegetables, fruits, dairy, beef, lamb, pork, poultry, eggs, fish, legumes, tree nuts, added fats, and added sugars. To capture potentially non-linear relationships between diet and socio-economic factors, we employ random forest regression to simulate Brazilian dietary patterns under different scenarios. Random forest is an ensemble learning method that constructs multiple decision trees independently and aggregates their predictions, improving robustness and reducing the risk of overfitting and sensitivity to noise[51]. Compared with traditional statistical approaches, random forest regression is well suited to handling complex interactions and non-linear responses and is insensitive to monotonic transformations of variables[52,53].

In this study, the data is analyzed using Python (version 3.8) and implemented using several different packages[52,54,55]. We divide 10% data randomly at one time using as a testing set for 10-fold Cross-Validation to avoid overfitting. With reference to Jiao et al. (2018)[56], significance of random forest regression is calculated with 1000 permutations of the response variable by using the 'A3' package from R (version 4.2.1)[57]. Determination coefficients (R^2), Explained Variance Score (EVS), Absolute Deviation (AD), and Root Mean Square Error (RMSE) are provided to measure the quality of random forest regression, please see Supplementary Table 1 for results of these 4 evaluation indicators. Based on well-trained random forest regression, 2 interpretation methods, relative influence and partial dependence plots[51,53], are introduced to analyze role of determinant drivers underlying dietary pattern change. Please see and follow our previous study[52,55] for more details about establishment of random forest regression, interpretation methods, and calculation of evaluation indicators.

Considering data availability and accessibility, totally we considered 7 socio-economic factors for each individual as follows: 1) Income, 2) Age, 3) Years of Education, 4) Sex, 5) Race, 6) Household Size, and 7) Urbanization. The Income records individual monthly income adjusted by purchasing power at constant 2015 Brazilian reais. The Age identifies the resident's age in full years. The Years of Education identifies the number of years of education of the resident. The Sex identifies the physiological gender of the resident (male or female). The Race identifies the color or race declared by the resident (white, black, yellow, mixed, indigenous, and no statement). The Household Size identifies the total number of residents in the household. The Residence Location records general urbanization level of the location that resident lives at (municipality of capital, rest of metropolitan region, rest of urban area, and rural area). These 7 socio-economic factors can explain 84-88% dietary pattern change and the random forest models exhibit strong performance across food categories, with 10-fold cross-validated determination coefficients (R^2) values ranging from 0.84 to 0.88. Additional evaluation metrics, including root mean square error and absolute deviation for each food group, are reported in Supplementary Table 1. All of the individual-level socio-economic data is obtained from Brazilian Household Budget Surveys[31].

Scenarios set. We combine five Shared Socio-economic Pathways (SSPs) with five Equality Scenarios (ESs), describing alternative income distribution pathways, generating a total of 25 scenarios that span diverse development and inequality conditions. These scenario-specific socio-economic inputs are then fed into the trained regression models to project individual-level dietary patterns under each scenario. An overview of the scenario framework is provided in Supplementary Figure 4. The SSPs describe a wide range of plausible socioeconomic development trajectories at five-year intervals from 2020 to 2100[58]. They are structured using a scenario matrix architecture that spans two dimensions: challenges to socioeconomic development and challenges to climate mitigation (please see O'Neill et al. (2017)[26] for scenario matrix architecture details). This data is obtained from SSP Database-Version 2.0, hosted by the International Institute for Applied Systems Analysis (IIASA, https://tntcat.iiasa.ac.at/SspDb/). The five ESs are constructed using per-capita information derived from the SSPs. Specifically, the SSPs provide projections of per-capita GDP with scenario-specific growth rates over 2020-2100, and we assume that individual income growth follows the corresponding GDP growth trajectory. Using individual-level samples from the 2017-18 Brazilian Household Budget Surveys as the baseline, we allocate 75%, 62.5%, 50%, 37.5%, or 25% of incremental income growth in each projection period to the lower half of the income distribution, thereby constructing alternative income-inequality-reducing or income-inequality-increasing scenarios, please see Supplementary Figure 5 for details. For reference, the implied Gini coefficients diverge substantially across Equality Scenarios over time. By 2050, Gini coefficients range from approximately 0.08-0.21 under ES75, 0.19-0.26 under ES62.5, 0.18-0.32 under ES50, 0.28-0.37 under ES37.5, and 0.39-0.43 under ES25 across SSP pathways. These differences further widen by 2100, with Gini coefficients spanning approximately 0.09-0.11 under ES75 and 0.35-0.39 under ES25. Because these values depend jointly on the redistribution rule and SSP-specific income growth trajectories, the scenarios are intended to represent relative inequality pathways rather than to target specific future Gini coefficients. The individual income is calculated as follows:

$$Per\_capita\_Income^{st} = \frac{GDP^{st}}{GDP^{s(t-5)}} \times Per\_capita\_Income^{s(t-5)} \quad (1)$$

$$Income_i^{st} = Income_i^{s(t-5)} + (Per\_capita\_income^{st} - Per\_capita\_income^{s(t-5)}) \times Ratio_i^s \quad (2)$$

Where i is the independent individual sample, s is the scenario, t is the year. For example, $Income_i^{st}$ is the individual income for sample i in year t under scenario s; and $Ratio_i^s$ is the ratio of individual income increase to per-capita increase for sample i under scenario s. Subsequently, based on generated 5 individual income scenarios and 5 SSPs, we adjust 1) Urbanization, 2) Age, and 3) Years of Education with the baseline obtained from2017-18 Brazilian Household Budget Surveys to further present equality scenarios as:

1) Urbanization. The SSPs show increasing national urbanization rates during 2020-2100. We calculate the number of samples whose urbanization parameter need to be adjusted as follows:

$$Number^{st} = (\frac{Urbanization\_Rate^{st}}{Urbanization\_Rate^{s(t-5)}} - 1) \times Urban\_Population^{s(t-5)} \quad (3)$$

Where $Number^{st}$ is number of samples that need to be adjusted in year t under scenario s. $Urban\_Population^{s(t-5)}$ is the number of samples that living in urban regions in year $t-5$ under scenario s. And then, samples need to be adjusted are selected randomly in rural population. The selection probability assigned to each sample i in year t under scenario s is calculated as follows:

$$Possibility_i^{st} = \frac{Income_i^{st}}{\sum_{i=1}^{Rural\_Population^{st}} Income_i^{st}} \quad (4)$$

Where $Rural\_Population^{st}$ is the sum of samples that living in rural regions in year $t-5$ under scenario s. Based on correlation analysis in Brazil (Supplementary Table 2), this equation reflects that the sample with higher income have higher possibility to live in urban regions. Each selected sample is randomly assigned a new urbanization parameter from municipality of capital, rest of metropolitan region, and rest of urban area. Although Brazil exhibits substantial regional heterogeneity in diets and food systems, region-specific dietary trajectories are not explicitly modelled in the scenario simulations, as SSP projections are only available at the national level. Exploratory checks including region-urbanization interactions at the estimation stage indicate that their omission does not materially affect model fit or the relative importance of key drivers, suggesting that urbanization captures much of the structural variation relevant for dietary transitions (Supplementary Table 4 and 5).

2) Age. The SSPs provide population for each 5-year age group from aged 0-4 to aged 100+ and divided by gender (male and female). We calculate the number of samples whose age parameter need to be adjusted as follows:

$$Number_{ag}^{st} = \left|\frac{Population_{ag}^{st}}{Total\_Population^{st}} \times Total\_Population^{s(t-5)} - Population_{ag}^{s(t-5)}\right| \quad (5)$$

Where $Number_{ag}^{st}$ is number of samples that need to be adjusted both in age group a, in gender group g, in year t, and under scenario s. $Population_{ag}^{st}$ is the population both in age group a, in gender group g, in year t, and under scenario s. $Total\_Population^{st}$ is the total population in year t under scenario s. The selection probability assigned to each sample i both in age group a, in gender group g, in year t, and under scenario s is calculated as follows:

$$Possibility_{iag}^{st} = \frac{Income_{iag}^{st}}{\sum_{i=1}^{Population_{ag}^{st}} Income_{iag}^{st}} \quad (6)$$

Based on correlation analysis in Brazil (Supplementary Table 2), this equation reflects that higher income levels are generally associated with older age. Each selected sample is randomly assigned to a new age parameter within the scope of its new age group.

3) Years of Education. The SSPs provide population for 4 education groups (No Education, Primary Education, Secondary Education, and Tertiary Education), divided by gender (male and female) and age (each 5-year age group from aged 0-4 to aged 100+). Firstly, we define the years of education for these 4 education groups according to Brazilian education system. For example, No Education indicates that a residence has not finish elementary education (Ensino Fundamental I, 5 years), thus perhaps has 0-4 years of education. Primary Education indicates that a residence has finished elementary education but has not finish secondary education (Ensino Fundamental II, 3 years; and High school, 3 years), thus perhaps has 5-11 years of education. Secondary Education indicates that a residence has finished secondary education but has not finish higher education (Ensino Superior, at least 4 years), thus perhaps has 12-15 years of education. Tertiary Education indicates that a residence has finished higher education, thus perhaps has 16+ years of education. Subsequently, we calculate the number of samples whose education parameter need to be adjusted as follows:

$$Number_{age}^{st} = \left| \frac{Population_{age}^{st}}{Total\_Population^{st}} \times Total\_Population^{s(t-5)} - Population_{age}^{s(t-5)} \right| \tag{7}$$

Where $Number_{age}^{st}$ is number of samples that need to be adjusted both in education group e, in age group a, in gender group g, in year t, and under scenario s. $Population_{age}^{st}$ is the population both in education group e, in age group a, in gender group g, in year t, and under scenario s. $Total\_Population^{st}$ is the total population in year t under scenario s. The selection probability assigned to each sample i both in education group e, in age group a, in gender group g, in year t, and under scenario s is calculated as follows:

$$Possibility_{iag}^{st} = \frac{Income_{iage}^{st}}{\sum_{i=1}^{Population_{age}^{st}} Income_{iage}^{st}} \tag{8}$$

Based on correlation analysis in Brazil (Supplementary Table 2), this equation reflects that higher income levels are generally associated with longer years of education. Each selected sample is randomly assigned to a new Years of Education parameter within the scope of its new education group.

Finally, we totally set 25 scenarios from combining 5 SSPs with 5 ESs, and the ESs are indicated by the share of total income increase distributed to poorer group as: SSP1-Ref-ES75, SSP1-Ref-ES62.5, SSP1-Ref-ES50, SSP1-Ref-ES37.5, SSP1-Ref-ES25; SSP2-Ref-ES75, SSP2-Ref-ES62.5, SSP2-Ref-ES50, SSP2-Ref-ES37.5, SSP2-Ref-ES25; SSP3-Ref-ES75, SSP3-Ref-ES62.5, SSP3-Ref-ES50, SSP3-Ref-ES37.5, SSP3-Ref-ES25; SSP4-Ref-ES75, SSP4-Ref-ES62.5, SSP4-Ref-ES50, SSP4-Ref-ES37.5, SSP4-Ref-ES25; SSP5-Ref-ES75, SSP5-Ref-ES62.5, SSP5-Ref-ES50, SSP5-Ref-ES37.5, SSP5-Ref-ES25. The reduction or increase in income inequality is represented by ESs with average of SSPs, for example, the SSP-Ref-ES75 is the average of SSP1-Ref-ES75, SSP2-Ref-ES75, SSP3-Ref-ES75, SSP4-Ref-ES75, and SSP5-Ref-ES75. The SSP-Ref-ES75 and SSP-Ref-ES62.5 indicate that income gap is narrowing to varying degrees. The SSP-Ref-ES37.5 and SSP-Ref-ES25 indicate that income gap is widening to varying degrees. The SSP-Ref-ES50 indicates the constant income gap.

Limitations. Several limitations should be acknowledged. Firstly, our analysis relies on Brazilian Household Budget Surveys from 2008-09 and 2017-18, as these are the only nationally representative datasets that provide dietary information at the individual level together with corresponding socio-economic characteristics. Secondly, linking food items reported in Brazilian Household Budget Surveys to the USDA's FNDDS, FPID, and FPED is not absolutely perfect, as these systems were developed for different national contexts. For some food items, particularly mixed dishes, exact one-to-one matches are not available, requiring approximate mapping to similar items. In such cases, mapping decisions were based primarily on similarity in underlying ingredients and food-group composition rather than on culinary names. To minimize potential bias, all mappings were carefully reviewed with support from native Portuguese-speaking researchers familiar with Brazilian foods and culinary practices. Thirdly, dietary environmental impacts, particularly for animal-sourced foods, are likely to be conservative estimates. A substantial share of Brazil's extensive livestock production is directly linked to deforestation in the Amazon, whereas the LCA data employed here reflect globally integrated production systems and may not fully capture deforestation-related emissions. However, existing Brazilian LCA databases do not allow for systematic disaggregation of mixed dishes (e.g. pizza, sandwich, mixed stew) into their constituent food groups (e.g. vegetable, grain, fruit, pork), which further motivates the use of internationally harmonized databases. Besides, these existing databases are structured based on data from regions such as the United States, China, and European countries[50], which potentially affects its representativeness for Brazil; the development of a comprehensive, Brazil-specific LCA database would help address these limitations in future work. Fourthly, scenario construction necessarily involves simplifications due to data availability. We adjust only those socio-economic variables explicitly represented in the SSP framework, while other individual characteristics are held constant at their 2017-18 values. Besides, future socio-economic relationships are assumed to follow current income-related patterns, because, for example, potential counter-urbanization in Brazil remain highly uncertain. Finally, despite these limitations, this study provides insights into how income inequality, treated as a policy-relevant driver, shapes long-term dietary transitions and their nutritional and environmental consequences in Brazil.

Data availability

All data that support the findings of this study are publicly available and are included within the article (and any supplementary files). The Brazilian Household Budget Surveys can be retrieved from https://www.ibge.gov.br/en/statistics/social/population/25610-pof-2017-2018-pof-en.html. The USDA's FPID, FPED and FNDDS databases are available at https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/. The SSP Database-Version 2.0 is available at https://tntcat.iiasa.ac.at/SspDb/. The source data is available at https://doi.org/10.5281/zenodo.19220625.

Code availability

The data were processed using Microsoft Excel and R studio (version 4.2.1). The random forest algorithm was conducted using Python (version 3.8) and R studio (version 4.2.1). The code is available at https://doi.org/10.5281/zenodo.19220625.

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This study received no external funding.

Author contributions

J.J. conceived the study, developed the methodology, performed the analysis and wrote the original draft. X.W., P.H. and A.I. contributed to study design, analysis and manuscript revision. P.H. and A.I. supervised the research. All authors discussed the results and approved the final manuscript.

Competing interests

The authors declare no competing interests.

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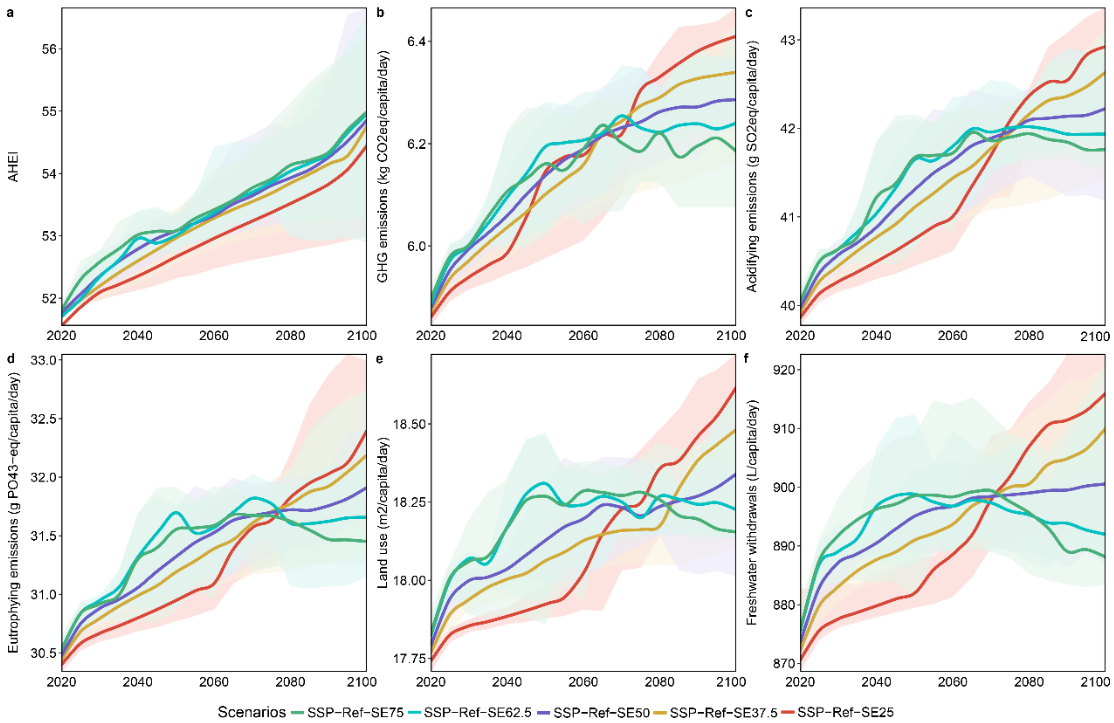

Figure 1. The Effects of income inequality on dietary nutritional quality and environmental impacts over 2020-2100. **a**-**f**, AHEI score (**a**), GHG emissions (**b**), acidifying emissions (**c**), eutrophying emissions (**d**), land use (**e**), and freshwater withdrawals (**f**). The **a**-**f** illustrate the AHEI score and environmental impacts of food intake per-capita per-day. The GHG emissions are measured with CO_2 equivalent (CO_2eq), the acidifying emissions are measured with SO_2 equivalent (SO_2eq), and eutrophying emissions are measured with PO_4^{3-} equivalent (PO_4^{3-}eq). The solid line represents each ES with average of SSPs, for example, the SSP-Ref-ES75 is the average of SSP1-Ref-ES75, SSP2-Ref-ES75, SSP3-Ref-ES75, SSP4-Ref-ES75, and SSP5-Ref-ES75. The shadow is the possible range of each scenario listed in legend.

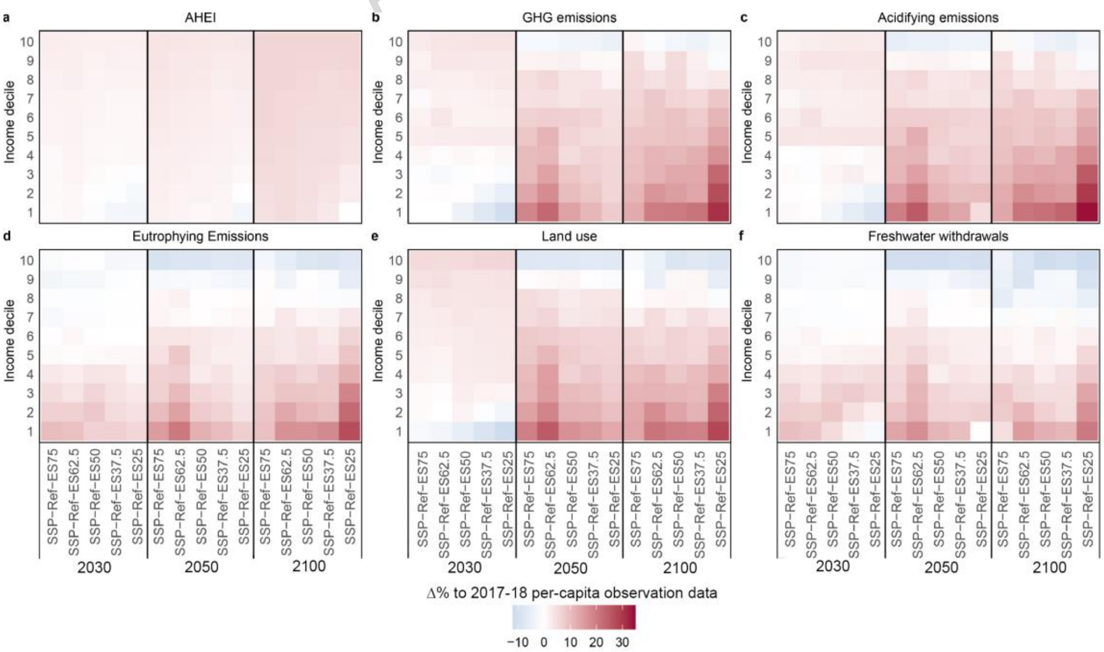

Figure 2. The distributions of dietary nutritional quality and environmental impacts across income decile in 2030, 2050, and 2100. a-f, AHEI score (**a**), GHG emissions (**b**), acidifying emissions (**c**), eutrophying emissions (**d**), land use (**e**), and freshwater withdrawals (**f**). The results for each Equality Scenario are the average of 5 SSPs scenarios, for example, the SSP-Ref-ES75 is the average of SSP1-Ref-ES75, SSP2-Ref-ES75, SSP3-Ref-ES75, SSP4-Ref-ES75, and SSP5-Ref-ES75. The color represents percentage difference to 2017-18 per-capita observation data.

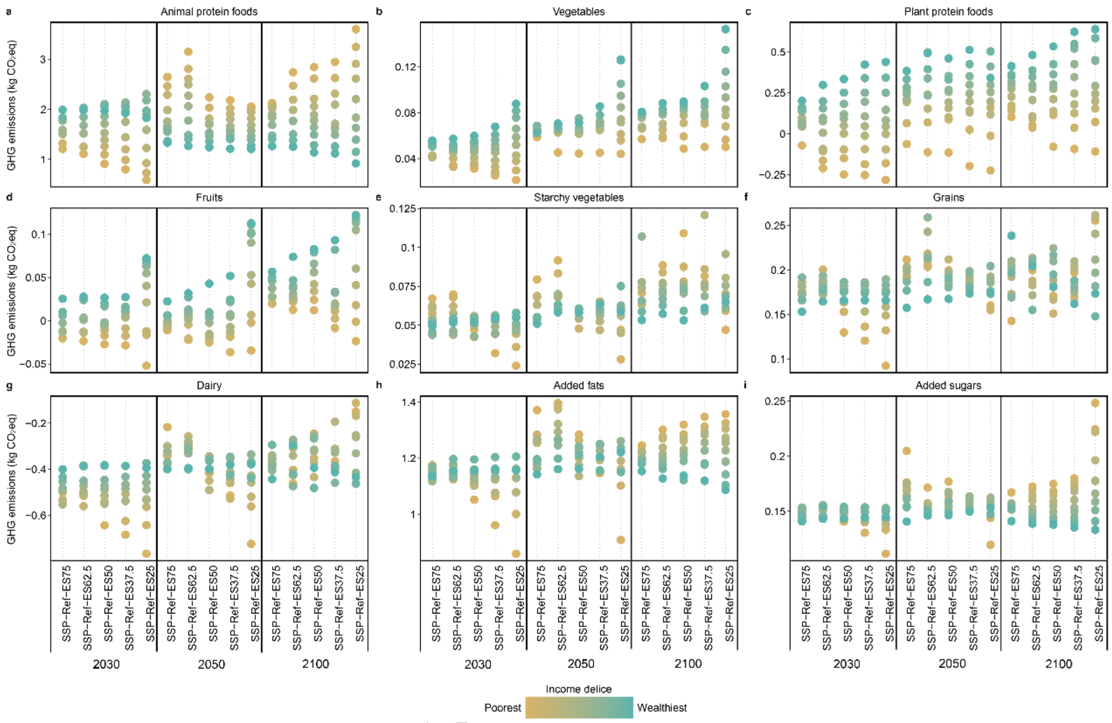

Figure 3. The GHG emissions of dietary pattern and the gap to EAT-Lancet diet in 2030, 2050, and 2100. a-i, animal protein foods (**a**), vegetables (**b**), plant protein foods (**c**), fruits (**d**), starchy vegetables (**e**), grains (**f**), dairy (**g**), added fats (**h**), and added sugars (**i**). The food group is defined by EAT-Lancet commission, please see Willett et al. (2019)[1] and Vaidyanathan (2021)[28] for more details about definition. The per-capita per-day food intake is accounted by associated GHG emissions measured with CO_2 equivalent (CO_2eq). The y-axis presents the GHG emissions difference between projected dietary patterns and EAT-Lancet Planetary Health Diet standard[1]. The carbon footprint values of EAT-Lancet diet are approximately: animal protein foods (1.52 kg), vegetables (0.22 kg), plant protein foods (0.73 kg), fruits (0.48 kg), starchy vegetables (0.05 kg), grains (0.59 kg), dairy (1.38 kg), added fats (0.49 kg), and added sugars (0.08 kg), all expressed as CO_2eq per-capita per-day. The showed results for each Equality Scenario (ES) are the average of SSPs scenarios, for example, the SSP-Ref-ES75 is the average of SSP1-Ref-ES75, SSP2-Ref-ES75, SSP3-Ref-ES75, SSP4-Ref-ES75, and SSP5-Ref-ES75.

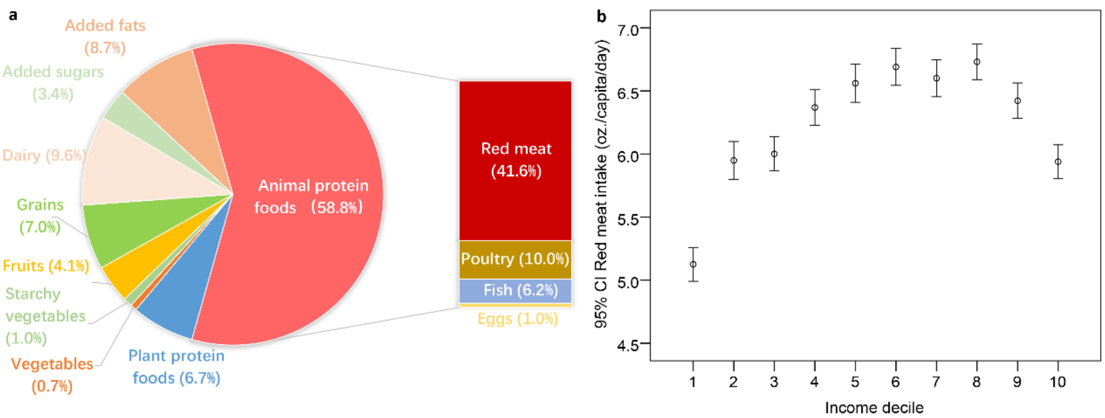

Figure 4. Brazil dietary pattern and the inverted U-shaped curve of red meat intake along with increasing income. a, GHG emissions share of Brazilian dietary pattern; **b**, relationship between red meat intake and income. The per-capita per-day diet is measured by corresponding GHG emission and the GHG emission is measured with CO_2 equivalent (CO_2eq). The data is obtained from Brazilian Household Budget Surveys 2008-09 and 2017–18[31].

Editorial summary:

In Brazil, reducing income inequality is projected to improve nutritional quality and limits long-term environmental impacts, despite a short-term rise in environmental pressures, according to an analysis that uses individual dietary data and scenario modeling.

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