Global Environmental Change 95 (2025) 103082

Contents lists available at ScienceDirect

Global Environmental Change

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

Implications of demographic policies on China's food-related environmental footprints amid population ageing

Qingling Wang [a,1], Han Zhang [a,1,*], Kuishuang Feng [b], Pan He [c,*], Richard Wood [d], Peipei Tian [e], Yiming Wang [f], Saige Wang [g,h], Yu Liu [i,j], Huifang Liu [a], Heran Zheng [f,*]

[a] College of Economics and Management, Northwest A&F University, Yangling 712100, China
[b] Department of Geographical Sciences, University of Maryland, College Park, MD 20742, United States
[c] School of Earth and Environmental Sciences, Cardiff University, Cardiff CF10 3AT, the United Kingdom of Great Britain and Northern Ireland
[d] Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway
[e] Institute of Blue and Green Development, Shandong University, Weihai 264209, China
[f] Bartlett School of Sustainable Construction, University College London, London WC1E 6BT, the United Kingdom of Great Britain and Northern Ireland
[g] School of Energy and Environmental Engineering, University of Science & Technology Beijing, Beijing 100083, China
[h] Advancing Systems Analysis (ASA) Program International Institute for Applied Systems Analysis, Laxenburg 2361, Austria
[i] College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
[j] Institute of Carbon Neutrality, Peking University, Beijing 100871, China

A R T I C L E I N F O

Keywords:
Demographic policy
Food system
Environmental footprints
Dietary transition
China

A B S T R A C T

China has implemented a range of demographic policies to address population ageing, which exert significant potential impacts on aggregate food demand and associated environmental effects. However, prior studies have not integrated these policies and age-specific food consumption patterns into environmental impact projections. Here, we quantify China's four food-related environmental footprints under representative demographic policy scenarios by employing a Quadratic Almost Ideal Demand System (QUAIDS) and a multi-regional input–output (MRIO) model. This study is the first attempt to link China's pro-natalist policies with multi-dimensional food-related environmental footprints through an age-cohort demand model. We find older adults (> 60 years) will become the largest contributor to the nation's total food-related footprints (accounting for approximately 37% by 2050), despite having below-average per capita footprints. From 2020 to 2050, total land use footprint is projected to increase, whereas GHG emissions, water consumption, and eutrophication footprints would decline. Reduction in GHG emissions is primarily driven by declining environmental intensities, while changes in other three footprints are mainly due to dynamic population sizes. Relative to the no-policy baseline scenario, China's demographic policies could lead to an approximate 3–18% increase in environmental footprints by 2050, imposing a notable burden on sustainability targets. Land use footprint would emerge as the most policy-sensitive indicator, with its peak year delayed by at least a decade under the most aggressive fertility-boosting policy. By analyzing dietary change scenarios, we find only ambitious transitions (nationwide adoption of plant-rich diets) can fully offset the policy-induced footprint increases, except for water consumption, in which case plant-rich diets would conversely result in higher footprints. Our findings underscore dietary change can help mitigate the additional environmental pressures induced by China's demographic policies, while also highlighting critical trade-offs across different environmental indicators.

1. Introduction

The global food system exerts growing pressures on the natural environment, contributing to approximately one-third of anthropogenic greenhouse gas (GHG) emissions (Crippa et al., 2021); driving substantial land use (Bai et al., 2021), water consumption (Fan et al., 2022), and elevated nitrogen and phosphorus levels in aquatic ecosystems (Bouwman et al., 2024). These environmental impacts stem from human

* Corresponding authors.
E-mail addresses: hanzhang@nwafu.edu.cn (H. Zhang), HeP3@cardiff.ac.uk (P. He), heran.zheng@ucl.ac.uk (H. Zheng).
[1] These authors contributed equally: Qingling Wang and Han Zhang.

https://doi.org/10.1016/j.gloenvcha.2025.103082
Received 25 March 2025; Received in revised form 2 August 2025; Accepted 5 November 2025
Available online 19 November 2025
0959-3780/

food demand, which is profoundly shaped by socioeconomic factors and demographic shifts (Miller et al., 2022; Tian et al., 2024b). Currently, a global demographic transition characterized by shifts in population size, age structure, and cohort composition is in progress (O'Neill et al., 2010; Long et al., 2024). This transition is particularly pronounced in China, which is home to approximately 17% of the global population and the world's largest older adults (United Nations, 2022). By 2040, nearly 30% of its total population would be over 60 years (Chen et al., 2020). To address population ageing challenges, China has implemented a series of age-friendly and pro-natalist policies, such as the two-child policy (Zeng and Hesketh, 2016) and the more recent three-child policy (Tatum, 2021). These policies may induce changes in population size and age structure, which in turn affect food demand and environmental outcomes—a linkage that is implicitly suggested yet not explicitly framed as a core research question. Given China's pivotal role in global food systems, elucidating the net environmental impacts of its demographic policies and associated demand shifts is essential for advancing global sustainability. Nevertheless, this critical issue remains underexplored in the existing literature.

Previous research has revealed relationships between demographic characteristics and food consumption patterns, indicating that older adults exhibit distinct habits relative to younger individuals (Chen et al., 2017; Smed et al., 2022). Notable dietary variations have also been documented across cohorts primarily due to age-related biological factors and socioeconomic conditions (Long et al., 2024; Gustavsen, 2014; Lee et al., 2020). Dietary preferences of older adults exhibit large variability contingent on social contexts. For instance, China's elderly tend to consume greater quantities of cereals and vegetables (Chen et al., 2017), while their counterparts in most Sub-Saharan African countries show a preference for meat and dairy products (Yin et al., 2024). Regarding future food demand, it is projected that China's total demand will continue to rise over the coming decades, particularly for animal-derived foods (Tilman et al., 2011; Yu et al., 2016). However, their projection models often overlook disparities in food consumption patterns across age groups or simply assume static dietary preferences, which is unrealistic for a country experiencing rapid demographic shifts. In terms of food-related environmental impacts, previous findings exhibit inconsistent trends owing to variations in modelling methodologies and parameter assumptions. For example, in the absence of technological advancements, total environmental impacts would increase by approximately 20% between 2011 and 2030 (Hu et al., 2020). In contrast, assuming declining environmental intensities (i.e., technological improvements), other studies indicate that total GHG emissions, cropland use, and nitrogen and phosphorus losses will decrease (Zhao et al., 2021; Ren et al., 2023; Tong et al., 2023). This striking inconsistency underscores that environmental intensity represents a key parameter in footprint prediction. In view of global proactive efforts to advance environmental sustainability, the assumption of constant environmental intensity or static technologies appears inappropriate. So far, only a handful of studies have measured the environmental consequences of China's demographic policies, and these have been limited to carbon emissions (Tang et al., 2024; Yu et al., 2018) while ignoring other indicators closely related to food systems, such as land use, green and blue water consumption, and the eutrophication potential of water bodies. To explore demand-side mitigation strategies, prior studies have endeavoured to assess the potential environmental outcomes of dietary change. For example, adoption of the EAT-Lancet reference diet could substantially reduce GHG emissions and land use (Gatto et al., 2023; Clark et al., 2019), whereas promoting adherence to Chinese official dietary guidelines might increase carbon emissions as well as nitrogen and phosphorus footprints (Wang et al., 2020; Zhu et al., 2023). Overall, in exploring the environmental impacts of China's demographic policies, prior studies have largely overlooked the heterogeneity of dietary preferences across different age cohorts and have failed to propose actionable mitigation measures to enhance the sustainability of food systems amid population ageing.

In this paper, we aim to address two key questions: (1) How will China's ageing and demographic policies alter its food demand and associated GHG emissions, land use, water consumption, and eutrophication footprints by 2050? (2) To what extent can demand-side dietary changes mitigate any increased environmental pressures? The four footprints were selected herein due to their strong association with food systems and their dominant roles within planetary boundaries (Steffen et al., 2015). To identify age- and cohort-specific characteristics in food demand, we employed an econometric demand system, combined with a multi-regional input–output (MRIO) model for environmental accounting (see Methods), which enables us to capture direct and indirect effects throughout whole supply chains (Feng et al., 2013; Tian et al., 2023). For demographic scenarios, we established a business-as-usual (BAU) baseline scenario (assuming no changes in policies) and four alternative scenarios reflecting different types of policies, as detailed in Section 2.3. To explore strategies to mitigate the policy-induced environmental burdens, we conducted a scenario analysis of dietary patterns, incorporating a set of widely recognized healthy diets and plant-rich diets. By integrating population heterogeneity, demographic policies, and dynamic food demand, this study contributes to reconciling projections of China's multi-dimensional food-related environmental footprints. This integration enables policymakers to gain more comprehensive insights into the socioeconomic and environmental trade-offs. Moreover, understanding these trade-offs may hold broader implications for other middle-income countries undergoing similar demographic transitions.

2. Methods

2.1. Identification of dietary preferences

Within an economic framework, dietary preferences are critical in shaping food consumption behaviours (Valin et al., 2014). In this study, income elasticities (describing the responsiveness of demand to income changes) were used to identify dietary preferences and to inform subsequent demand projection models. The individual food consumption data were obtained from four waves (2004, 2006, 2009, and 2011) of the China Health and Nutrition Survey (CHNS), which is a longitudinal study tracking nutritional status across 12 provinces. Although the CHNS was updated in 2019, the most recent publicly available data were from the 2011 wave. Food intake was assessed using three consecutive 24-hour dietary recalls for each participant. As the daily intake of cooking oil was reported based on the household level, we allocated it to each person proportionally to their energy consumption. All food items were coded according to the Chinese Food Composition Table released by the National Institute of Nutrition and Food Safety and were categorized into fourteen food groups for simplicity (see Table S1 for concordances).

To characterize the dietary preferences of different population groups, we distinguished between the age effect and cohort effect but ignored the period effect, as it is difficult to predict and can be considered to average out to zero over the long term (Deaton, 1997; von Lampe et al., 2014; Fujimori et al., 2022). To separate the age and cohort effects, we set "age" as the grouping variable and "cohort" as demographic characteristic variables (i.e., the control variables in the demand function) (Lee et al., 2020; Banks et al., 1997). More specifically, we divided the total population into five age groups: under 20 years old, 20–39 years old, 40–59 years old, 60–69 years old, and 70 years and older. Among them, the groups aged 60–69 and those aged 70 + are collectively named as the "aged group". Based on the birth year of surveyed samples, individuals born before 1940 and those born after 2010 were each assigned to a distinct cohort, with the remaining population divided into cohorts at ten-year intervals. To construct a dataset rich enough for estimating cohort effects, we pooled data from four survey waves.

Quantification of age-specific income elasticity involved three steps: (i) estimate the expenditure elasticity of demand, (ii) characterize the income elasticity of expenditure, and (iii) multiply the expenditure elasticity of demand by the income elasticity of expenditure to yield the income elasticity of demand. In the first stage, we used the Quadratic Almost Ideal Demand System (QUAIDS) model, which allows for flexible Engel curves by integrating a quadratic logarithmic income term to encapsulate non-linear relationships between income and demand (Banks et al., 1997). It has been widely used for characterizing dietary preferences and forecasting food demand (Bjelle et al., 2021; Roosen et al., 2022). The model is derived from a cost function belonging to the general class of "price-independent, generalized logarithmic", expressed as:

$$lnC(p,u) = (1-u)loga(p) + ulogb(p) \tag{1}$$

where p is a vector of prices; u is the utility index; $a(p)$ and $b(p)$ denote the minimum expenditure required by a consumer to satisfy the basic survival demand and maximum utility, respectively. $a(p)$ is the translog price index, given by:

$$lna(p) = \alpha_0 + \sum_{i=1}^{n}\alpha_i lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij} lnp_i lnp_j \tag{2}$$

where p_i is the price of food i; $b(p)$ is the Cobb-Douglas aggregator function of the price vector, taking the following form:

$$lnb(p) = lna(p) + \beta_0\prod_{i=1}^{n} p_i^{\beta_i} \tag{3}$$

Applying Shephard's Lemma to equation (2), for a certain age group, the share equation for food i can be represented as:

$$w_i = \alpha_i + \sum_{j=1}^{n}\gamma_{ij} lnp_j + \beta_i ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left\{ln\left[\frac{m}{a(p)}\right]\right\}^2 \tag{4}$$

where w_i is the expenditure share of food i; α_i is an average budget share in the absence of price and income effects; m is the total food expenditure; α_i, γ_{ij}, β_i, and λ_i are parameters to be estimated. By using the scaling approach, the share equation is written as:

$$w_i = \alpha_i + \phi_h C_h + Z + \sum_{j=1}^{n}\gamma_{ij} lnp_j + \beta_i ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left\{ln\left[\frac{m}{a(p)}\right]\right\}^2 \tag{5}$$

where C_h is birth cohort; Z represents other demographic variables (including survey year, region, gender, and education levels). The share equations need to comply with a series of constraints, including adding-up, homogeneity, and symmetry conditions:

$$\sum_{i=1}^{n}\alpha_i = 1,\ \sum_{i=1}^{n}\beta_i = 0,\ \sum_{j=1}^{n}\gamma_{ij} = 0,\ \sum_{i=1}^{n}\lambda_i = 0 \tag{6a}$$

$$\sum_{i=1}^{n}\gamma_{ij} = 0 \tag{6b}$$

$$\gamma_{ij} = \gamma_{ji},\ \forall i \neq j \tag{6c}$$

By differentiating equation (5) with respect to lnm, the expenditure elasticity of food i can be expressed as:

$$e_i = 1 + \frac{\mu_i}{w_i} = 1 + \frac{\beta_i + \frac{2\lambda_i}{b(p)} ln\left[\frac{m}{a(p)}\right]}{w_i} \tag{7}$$

The seemingly unrelated regression (SUR) was adopted to estimate parameters in the demand system. Given the substantial proportion of zero observations in the survey data, a consistent two-step estimation procedure was also used to avoid potential biases arising from censoring.

In the second stage, we employed a log–log inverse (LLI) demand equation (Gale and Huang, 2007) to estimate the income elasticity of expenditure, which allows the expenditure elasticity to vary with income levels—the most predictable factor related to individual consumption patterns (Gustavsen, 2014; Lee et al., 2020; Valin et al., 2014; Muhammad et al., 2017). This income-dependent elasticity can thus be used to approximate dietary preferences of future generations. Mathematically, the demand equation is given by:

$$lnm = \phi_0 + \phi_1 lny + \frac{\phi_2}{y} \tag{8}$$

where y represents the per capita disposable income level. By differentiating equation (8), the income elasticity of food expenditure can be written as:

$$e_y = \frac{dlnm}{dlny} = \phi_1 - \frac{\phi_2}{y} \tag{9}$$

In the third stage, we combined equations (7) and (9) to yield the dynamic income elasticity of food demand:

$$E_{i,y} = e_i \bullet e_y = \left(1 + \frac{\beta_i + \frac{2\lambda_i}{b(p)} ln\left[\frac{m}{a(p)}\right]}{w_i}\right) \bullet \left(\phi_1 - \frac{\phi_2}{y}\right) \tag{10}$$

2.2. Demand projection and demographic scenarios

To project age-specific demand for particular food commodities, we first used the income elasticity estimated from equation (10) and the forecasted income growth rates to calculate per capita demand. Subsequently, we multiplied the per capita value by each age group's population size to derive the total demand. Since the core objective of this study is to compare the differences in environmental footprints under various demographic policy scenarios, rather than precisely predicting the absolute food demand, in the demand projection model, we focused on income-driven demand changes while disregarding the effect of price volatility (nominal prices are held constant over the period). This assumption is a common practice to simplify model complexity (particularly when the focus of our study is not on price mechanisms), enabling us to isolate the effects of income by eliminating the interference of price volatility on consumer behaviours. Meanwhile, data availability constraints (the lack of long-term forecast data for category-specific food prices) limit more intricate model setups. Mathematically, given an income growth rate from year $T-1$ to year T, changes in per capita demand for food i of a certain age group can be expressed as:

$$\Delta q_i^{T-1,T} = q_i^{T_0} \bullet E_{i,y} \bullet \left(\frac{\Delta y}{y}\right)^{T-1,T} \tag{11}$$

where $q_i^{T_0}$ is the demand for food i of the base year; $\left(\frac{\Delta y}{y}\right)^{T-1,T}$ is the income growth rates. Multiplied by population size (N^T), the total food demand of a certain age group in year T can be obtained by:

$$Q_i^T = (q_i^{T_0} + \Delta q_i^{T_0,T_1} + \cdots + \Delta q_i^{T_{t-1},T_t}) \bullet N^T \tag{12}$$

Therefore, the national total demand for food commodity i in year T can be written as:

$$FD_i^T = Q_i^T(<20) + Q_i^T(20-39) + Q_i^T(40-59) + Q_i^T(60-69) + Q_i^T(70+) \tag{13}$$

Population projection data were sourced from the United Nations 2022 World Population Prospects (WPP), while income projection data were derived from the Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017), which were cross-referenced with scenarios in WPP (see Appendix Methods for detailed matching process). The baseline/BAU population scenario corresponds to the "no change" scenario in WPP. While this selection deviates from conventional practices, it aligns with the core aim of this study: to examine the net environmental impacts of China's demographic policies by comparing discrepancies in food-related footprints between policy-adoption scenarios and a policy-free scenario. The four policy-adoption scenarios retrieved from WPP include: the high fertility, medium fertility, constant fertility, and constant mortality scenarios (see Table S2 for detailed assumptions underlying each scenario).

2.3. Quantification of environmental footprints

We employed an environmentally extended MRIO model to quantify environmental footprints driven by food demand. The MRIO approach is advantageous in tracking environmental spill-over effects and has been widely used in previous studies for calculating agricultural carbon emissions, land-use change, biodiversity loss, and energy footprints (Sun et al., 2022; Tian et al., 2024a; Zhong et al., 2024). Mathematically, the classic Leontief model is expressed as:

$$x = \boldsymbol{A}x + y \tag{14}$$

where x is the total output vector; A denotes the matrix of technical coefficients (which gives the value of inputs required to produce a unit output); y is the final demand vector. Using simple matrix notation, equation (14) can be rewritten as:

$$x = (\boldsymbol{I} - \boldsymbol{A})^{-1}y \tag{15}$$

where I is an identity matrix; $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse matrix. Therefore, food-related environmental footprints can be derived by extending the classic Leontief model with environmental satellites, expressed as:

$$F = f(\boldsymbol{I} - \boldsymbol{A})^{-1}y \tag{16}$$

where f is the vector of environmental impact per unit output (i.e., environmental intensity, reflecting production technologies); F is the environmental footprint driven by final demand y. In our MRIO projection model, we made two assumptions on parameters in equation (16). First, we assumed constant global trade patterns by fixing the Leontief inverse matrix throughout the study period (Sun et al., 2022; Zhong et al., 2024; Liu et al., 2023). This assumption was necessitated by the current lack of reliable models for projecting future supply chains. Second, we assumed that environmental intensities would follow their historical trends. Using a linear extrapolation approach, we projected the rates of decline in four environmental intensities (per decade) as follows: an 8% reduction in greenhouse gas emissions, a 5% reduction in water consumption, a 4% reduction in land use, and a 7% reduction in eutrophication. It is noteworthy that absolute footprint projections depend on the rate of technological progress, which may either stagnate or accelerate in the future. Therefore, the assumptions put forward in this paper represent a simplified case of technological development.

The global MRIO tables were sourced from EXIOBASE (version 3.8.2). This database offers a distinct advantage over other MRIO databases due to its fine granularity in the food sectors. In this study, four environmental accounts were incorporated, with their respective accounting scopes and characterization metrics specified as follows: (i) GHG emissions, measured in carbon dioxide equivalents (CO_2eq), are based on 100-year global warming potentials. (ii) The land use footprint encompasses the aggregated utilization of cropland (including arable land and permanent crops), permanent pasture (including permanent meadows and pastures), and other land (see Table S3 for details). (iii) The water footprint quantifies the consumption of both blue water in agriculture and livestock farming and green water in agriculture. Blue water consumption is defined as water abstracted from surface water and groundwater bodies, and green water consumption refers to precipitation that infiltrates into the soil and is subsequently taken up by plants. (iv) The eutrophication footprint assesses potential impacts on terrestrial and aquatic ecosystems, expressed in terms of phosphate equivalents (PO_4^{3-}eq). All characterization factors were sourced from the descriptive documentation of the EXIOBASE database (Stadler et al., 2018).

2.4. Decomposition of driving factors

To reveal driving factors' contributions to changes in environmental footprints, we employed the logarithmic mean Divisia index (LMDI) method (Ang, 2004; Sun, 1998). In this paper, environmental footprints were determined by population size, food expenditure, expenditure structure, and environmental intensity. Thus, changes in footprints can be decomposed as:

$$F = \sum_i \sum_j P_i \frac{E_i}{P_i} \frac{E_{ij}}{E_i} \frac{F_{ij}}{E_{ij}} = \sum_i \sum_j P_i Q_i S_{ij} I_{ij} \tag{17}$$

where P_i indicates the population size of age group i. E_i and E_{ij} represent the total expenditure by age group i and the detailed expenditure on food j. F_{ij} refers to the environmental footprints generated by age group i for food j. The equation can be separated into four effects: the population effect (P_i), the expenditure effect (Q_i), the expenditure structure effect (S_{ij}), and the intensity effect (I_{ij}). LMDI can be divided into additive decomposition and multiplicative decomposition. Despite the two methods yielding similar outcomes, the additive approach was chosen due to its user-friendliness and ease of interpretation. The basic form of additive decomposition is as follows:

$$\Delta F = F^T - F^0 = \Delta P + \Delta Q + \Delta S + \Delta I \tag{18}$$

where, F^T and F^0 are food-related environmental footprints of period T and 0, respectively. The extent to which each effect contributes to the change in the environmental footprints for a given age group is estimated by the following equation:

$$\Delta P = \sum_i \sum_j \frac{F^T - F^0}{lnF^T - lnF^0} \ln\left(\frac{P^T}{P^0}\right) \tag{19}$$

$$\Delta Q = \sum_i \sum_j \frac{F^T - F^0}{lnF^T - lnF^0} \ln\left(\frac{Q^T}{Q^0}\right) \tag{20}$$

$$\Delta S = \sum_i \sum_j \frac{F^T - F^0}{lnF^T - lnF^0} \ln\left(\frac{S^T}{S^0}\right) \tag{21}$$

$$\Delta I = \sum_i \sum_j \frac{F^T - F^0}{lnF^T - lnF^0} \ln\left(\frac{I^T}{I^0}\right) \tag{22}$$

2.5. Dietary scenarios

In the dietary change scenario analysis, we examined six dietary patterns with globally recognized health and/or environmental benefits, including: the Chinese Dietary Guideline (CDG); the EAT-Lancet reference diet (EAT); the World Health Organization's healthy global diet (HGD); and three plant-rich diets—pescatarian (PESC), vegetarian (VEG), and vegan (VGN). To enhance the realism of these scenarios, we established two adoption modes: a relatively feasible mode (targeting only the younger population, age < 60 years) and a more stringent mode (targeting the entire population). For each scenario, daily food intakes are substituted and unified in grams. Due to differences in energy requirements, we adjusted the recommended quantities of each food type for each age group (Table S7).

3. Results

3.1. China's food-related environmental footprints by age groups under the BAU scenario

Under the BAU population scenario, China's food-related GHG emissions, water consumption, and eutrophication would decrease by around 26%, 13%, and 12%, respectively, while land use would increase by 5% from 2020 to 2050 (Fig. S1). The largest decrease would arise from the youngest group (<20 years), with reductions of 51% in GHG emissions and 41% in water consumption and eutrophication. Conversely, due to population ageing, the aged group (60 +) would roughly double their shares of total environmental impacts. For instance, between 2020 and 2050, their eutrophication footprint would increase by 70% and water consumption by 68% (Table S4). Our estimated simulated growth rates of per capita food demand fall within the ranges reported in a global *meta*-analysis (van Dijk et al., 2021). With technological improvement assumptions, our finding that GHG emissions would decline contrasts with prior work which assumes constant technology (Zhao et al., 2021; Ren, 2023). This suggests that continued yield and efficiency gains are crucial. Without such improvements, China's food-related GHG emissions might rise instead.

The contribution of older adults to total environmental footprints is projected to steadily increase over time, eventually surpassing that of the middle-aged group (40–59 years) and becoming the largest contributor by around 2040 (Fig. 1a, Fig. S2). Throughout the period of 2020–2050, food-related environmental impacts attributed to the aged group would nearly double, the trend consistent in the four environmental indicators. Specifically, the aged group's contribution to total GHG emissions would rise from 19% to 36%, land use from 19% to 37%, water consumption from 19% to 36%, and eutrophication from 18% to 36%. Notably, the oldest group (70 +) is projected to contribute more than those aged 60–69. Their footprint shares in 2050 would be roughly 2.5 times that in 2020. By contrast, the contribution share of the three younger groups (<60 years) would shrink with population ageing. This trend was particularly pronounced in the 20–39 age group, whose contribution would decrease from 31% to 23% average over the period.

However, on a per capita basis, the aged group showed the lowest environmental impact among all adult groups (Fig. 1b). By 2050, the per capita footprint of older adults would reach 794 $kgCO_2eq$ of GHG emissions, 0.4 ha of land use, 916 m^3 of water consumption, and 4.4 $kgPO_4^{3-}eq$ of eutrophication. This is primarily because older individuals generally demand less food compared to younger individuals (Fig. S3), likely due to their low purchasing power and rigid diet preferences. For example, people aged 70 + exhibited smaller expenditure elasticities for meat than those aged 20–39 (Table S5), meaning that the same income growth would result in smaller increases in meat demand for an older adult than a younger one. This result compares well with previous work on China (He et al., 2020; Li et al., 2015), but contrasts with evidence from some developed countries, where the elderly have more environmentally intensive dietary patterns (Smed et al., 2022; Zheng et al., 2022). The discrepancy is likely due to variations in income levels, different stages of the nutrition transition, and diverse food cultures (Popkin and Ng, 2021; Turner et al., 2021). In light of Fig. 1a, this finding also indicates that even with environmentally sustainable dietary habits, the anticipated increase in the size of the older population would still make them the dominant driver of China's future food demand.

Regarding the food sector composition in footprints, Fig. 1c shows that grains and beef are the two main contributors to GHG emissions, accounting for 33% and 24% of the total in 2050. From 2020 to 2050, the contribution share of grains to total GHG emissions would decrease (-6%), while the proportion of beef would increase (+7%), indicating that demographic shifts towards an ageing population could result in altered demand structure. In addition, beef contributes most to the land use footprints, accounting for nearly half (43% in 2020, 49% in 2050) of the national total. Between 2020 and 2050, an additional 42 million hectares (Mha) of land would be needed to meet China's growing beef demand, with the reduced land use from three young groups (10.8 Mha) offset by the increased land use from the two aged groups (53.1 Mha). Regarding water consumption, grains constituted the largest component, making up 61% in 2020 and 58% in 2050. By age group, the projected increases of water consumption from aged groups (9.4 Bm^3) would be offset by the decrease from three young groups (22.9 Bm^3). In terms of eutrophication, poultry, grains, and pork played the most leading roles (representing 28%, 23%, and 22% in 2050). Notably, the grains-related contribution to total eutrophication is likely to decline, while the pork-related contribution will conversely rise over the study period. This diverse trend reflects that the major food components of China's food-related environmental impacts would alter with the ageing population, thus calling for adaptive changes on the production side.

3.2. Driving factors to changes in environmental footprints

For the three declining footprints (GHG emissions, water consumption, and eutrophication), the four driving factors' contributions vary largely among age groups (Figs. 2a, c, d). Population growth was the primary factor driving down the environmental footprints of three young groups (contributing 40–73%), while driving up those of the aged groups (contributing 20–55%). These trends are primarily due to the projected population trajectory under the BAU scenario, characterized by a significant increase in the number of older adults aged 60+ (from 266 million in 2020 to 451 million in 2050, a 70% increase), alongside a substantial decline in young populations (from 1159 million in 2020 to 765 million in 2050, a 34% decrease; Table S6). Technological effects are projected to consistently reduce the three footprints, but with varying contributions for different impacts: 159% for GHG emissions, 77% for eutrophication, and 48% for water consumption. Conversely, rising food expenditure would boost all three footprints, contributing 82% for water consumption, 78% for eutrophication, and 75% for GHG emissions. Notably, the aged groups exhibit a smaller expenditure effect compared to their younger counterparts, which is likely because older people tend to have lower food energy requirements and lower purchasing power than younger ones (Gustavsen, 2014; He et al., 2018).

Interestingly, the expenditure structure effect contributed to increasing GHG emissions and eutrophication (by 17% and 19%) but decreasing water consumption (by 26%). This pattern is probably because Chinese consumers have lower demand elasticity for the most water-intensive foods (such as wheat and rice) than other foods (Table S5), implying that the same income growth would result in smaller increases in the demand for wheat and rice compared to others. When examining by age group, negative preference effect is most pronounced in the 20–39 years youth group (13%), followed by the middle-aged group (12%) and the youngest group (5%). Notably, this effect contributed to an increase in water consumption among the aged groups This outcome can be attributed to age-related differences in food preferences and corresponding changes in the shares of specific foods over time. For instance, the proportion of wheat in personal total food expenditure decreased most significantly among the youth group but least among the eldest group.

China's food-related land use is expected to increase by around 5% over 2020–2050, because the combined positive effects of per capita expenditure and expenditure structure would outweigh the total negative effects of population size and land use intensity (Fig. 2b). Specifically, population size was the dominant factor in reducing total land use, contributing 94% to the decrease, but this effect would be significantly offset by the rising expenditure effect, which contributes 85% in the opposite direction. Interestingly, the technological effect on land use is substantially lower compared to other footprints (18% vs. 48–77%), primarily due to huge challenges associated with further improving land use patterns (Bai et al., 2021; Semenchuk et al., 2022). Notably, the preference effect contributed more to the increase in land use than to

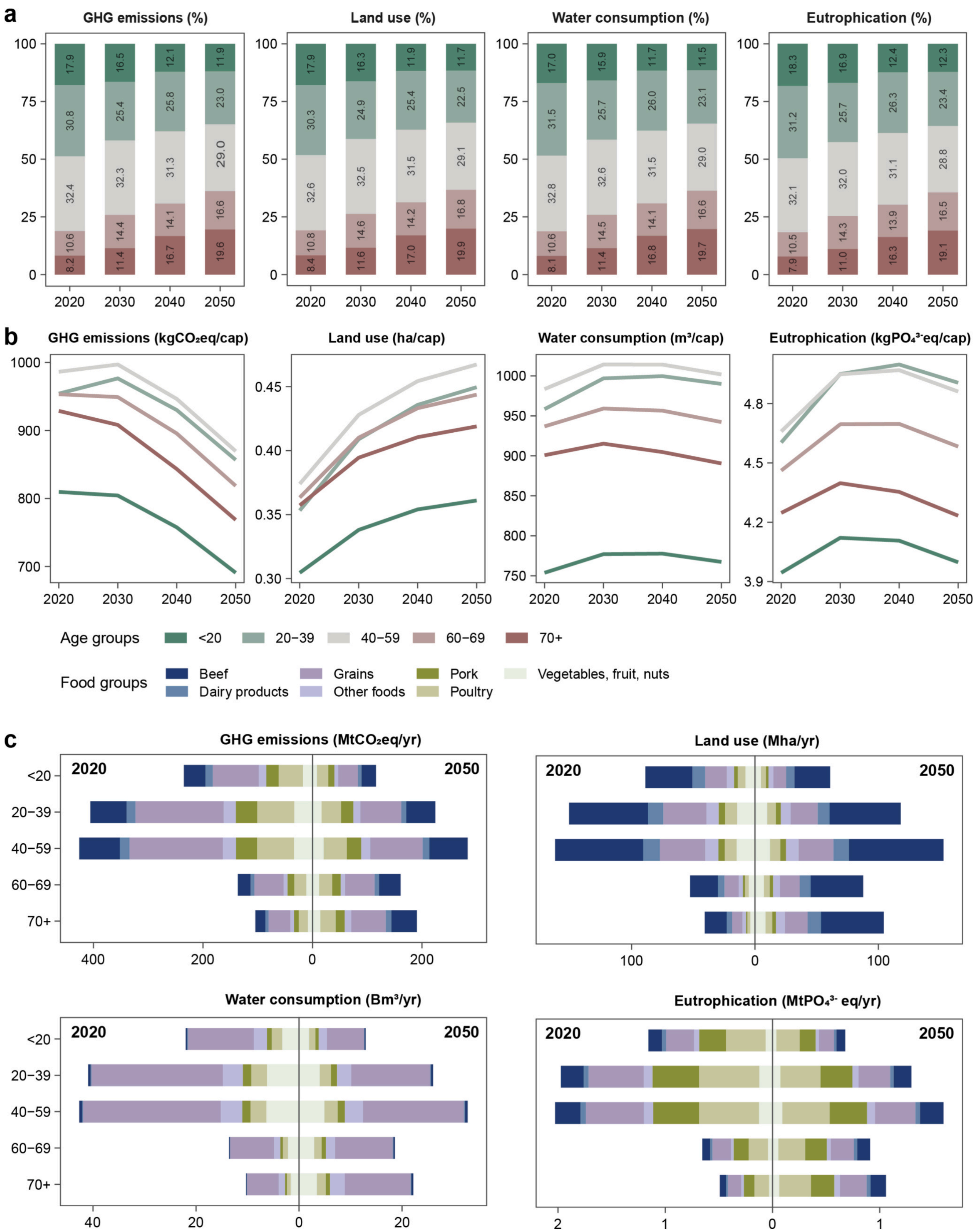

Fig. 1. Historical and projected China's food-related environmental footprints by age group and year. **a,** Contributions of different age groups to the total footprints by year. **b**, Per capita footprint by age group and year. **c**, Composition of food groups in 2020 and 2050. For simplicity, food items were categorized into seven groups (see Table S1 for detailed concordances).

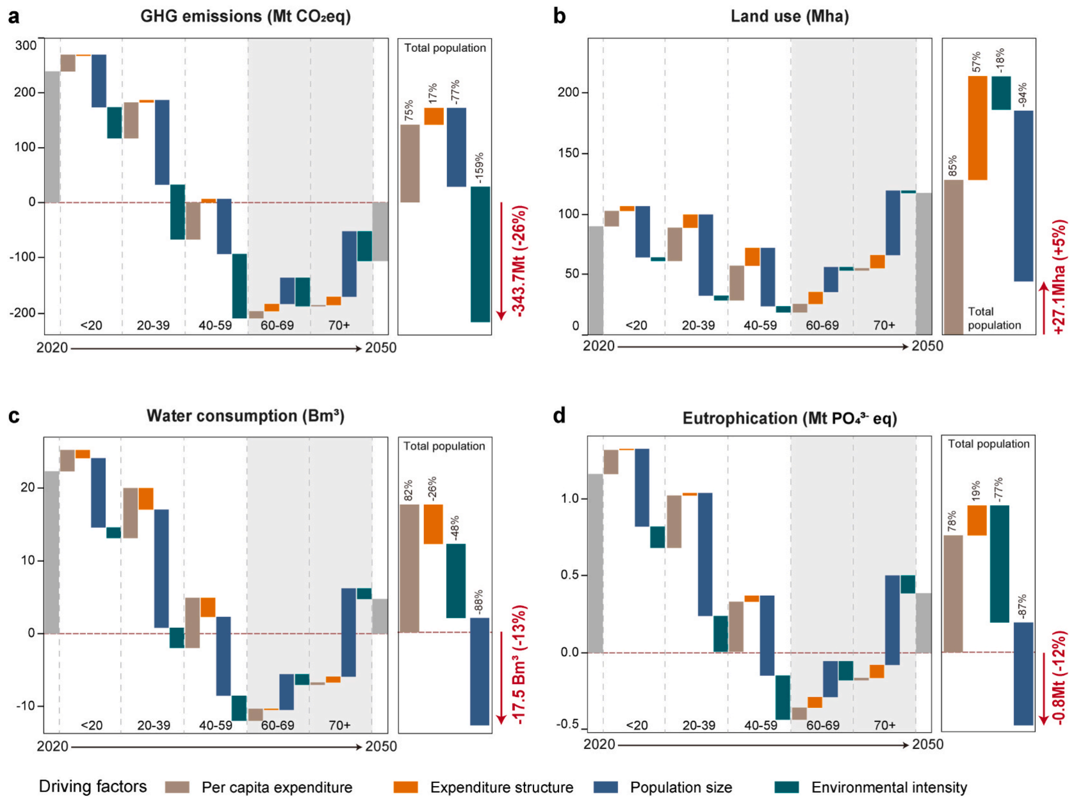

Fig. 2. Contributions of driving factors to changes in China's food-related environmental footprints from 2020 to 2050. The percentages marked in the subplots represent the contribution of each driving factor. Vertical red numbers (and percentages) indicate the total changes (and change rates) in each environmental footprint. Four socioeconomic factors were included: population size, per capita food expenditure, expenditure structure, and environmental intensity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

other footprints (57% vs. 17–26%), largely because its main contributor—beef—has the highest land use intensity (Fig. S4). Beef production systems are traditionally extensive, particularly in China's major beef-exporting regions, such as Argentina and Brazil (Chen et al., 2022; Ermgassen et al., 2020). When examining the effects by age group, our results indicate that the middle-aged group (40–59 years) has the largest positive effect of expenditure structure (17%), followed by the eldest group (13%). This can be attributed to age-related dietary patterns, where China's young adults would consume more beef compared to their older counterparts.

3.3. *Environmental implications under different demographic scenarios*

To address population ageing challenges, Chinese government has introduced a range of demographic policies aimed at increasing fertility rates and enhancing the quality of life for older populations. Policies targeting fertility assumptions were identified as fertility-boosting policies, such as children-related transfers and tax benefits (Zeng and Hesketh, 2016; Jing et al., 2022). Policies targeting mortality assumptions were named as age-friendly policies, such as improving healthcare efficiency and enhancing social pension schemes (Kruk et al., 2018; Winter et al., 2016). Specifically, the high-fertility scenario (HFS) envisions the successful implementation of comprehensive fertility-boosting policies, leading to a total fertility rate (TFR) of 1.89 by 2050. The medium-fertility scenario (MFS) assumes the adoption of moderate fertility-boosting measures, resulting in a TFR of 1.39 in 2050. The constant-fertility scenario (CFS) assumes that the TFR will remain constant at the level of BAU (1.17). The constant-mortality scenario (CMS) shares the same medium fertility assumptions as MFS and the same constant mortality assumptions as BAU.

Fig. 3 shows that, compared to the no-policy baseline projection in 2050, implementing demographic policies would increase China's total food-related environmental footprints by around 3–18%. Among the four policy scenarios, HFS would result in the largest potential increases in total footprints, ranging from 16.4% for water consumption to 17.8% for GHG emissions. This is primarily because the HFS projects the most significant population growth (195 million more than the BAU scenario) and the highest number of expected new births relative to other demographic scenarios, attributable to the successful implementation of comprehensive fertility-boosting policies. In contrast, CMS would lead to the smallest potential increases in overall environmental impacts compared to the no-policy baseline. The growth rates for various impacts under CMS range from 2.5% for water consumption to 2.8% for GHG emissions. This minimal increase is primarily attributed to the lowest projected population growth (32 million) among all scenarios. This outcome stems from the assumption that the CMS employs only modest fertility-boosting policies and does not incorporate age-friendly policies.

Interestingly, land use is the most sensitive environmental indicator to China's demographic policies, with its projected peak year being delayed by at least a decade, shifting from 2040 to 2050 or potentially even later (under the most aggressive policy scenario, HFS). The high sensitivity of land use footprint might be due to increased population's growing demand for livestock meat and dairy products, which exhibit the highest land use intensity among all food types (Fig. S4). In addition, under the assumption of aligning with the current technological development trajectory, implementing the most aggressive fertility-boosting policies (HFS) would drive sustained growth in China's land use footprints beyond 2050. This finding implies the necessity for more stringent land use management strategies in future policy planning, as well as the importance of promoting a transition to lower-meat diets. When synthesizing the temporal trends of the four environmental footprints across

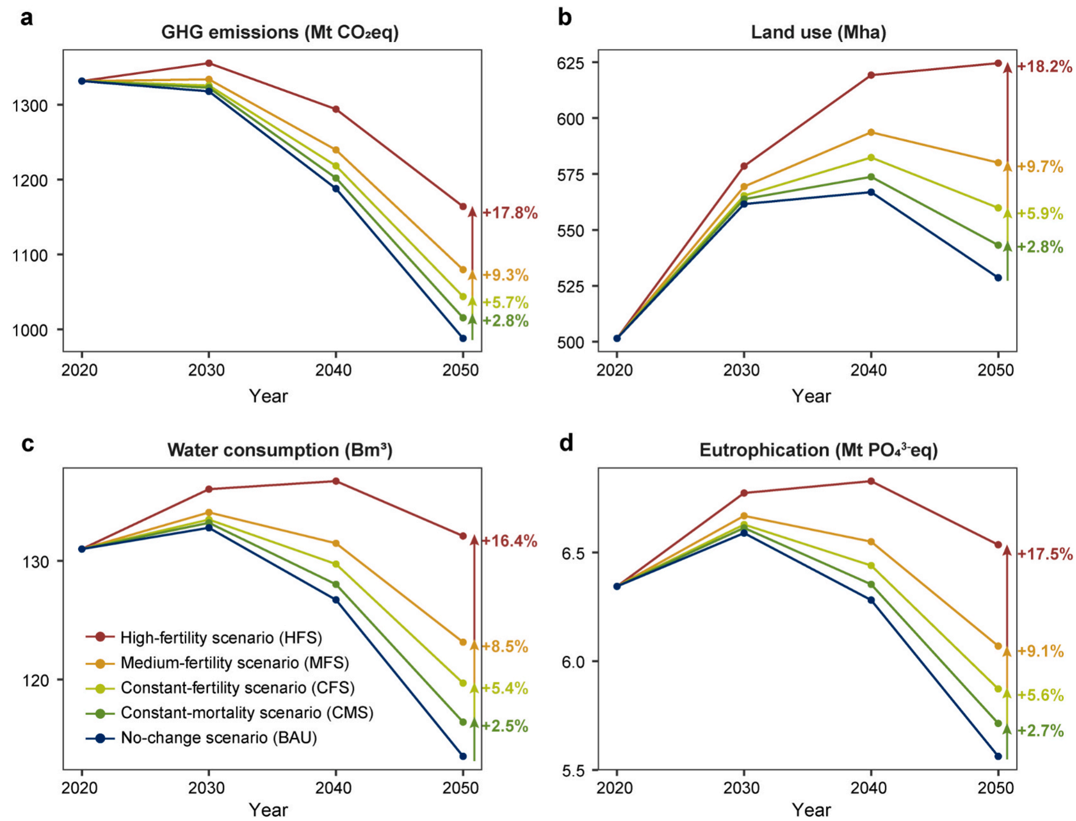

Fig. 3. China's food-related environmental footprint projections across demographic scenarios by 2050. Sensitivity analyses of expenditure elasticities within the 95% confidence interval are shown in Table S8.

all demographic policy scenarios, we found GHG emissions, water consumption, and eutrophication could be effectively mitigated through reductions in intensities (these three impacts still exhibiting a downward trend under HFS before 2050). Conversely, if technological development continues at the current pact, land use would be the most challenging environmental impact to alleviate under the most aggressive policy scenario.

3.4. Dietary changes can partly offset the policy-induced environmental pressures

Overall, transitioning towards alternative diets can largely mitigate but cannot fully offset the policy-induced additional environmental footprints. Fig. 4 shows that, apart from water consumption, the most stringent vegan scenario represents the greatest mitigation potential. If adopted by all residents, it could reduce GHG emissions by 494–648 Mt CO_2eq, land use by 333–354 Mha, and eutrophication by 3.5–3.7 Mt PO_4^{3-}eq. In comparison, the CDG-based scenario yields the smallest mitigation, with potential reductions of 56.3–106.7 Mt for GHG emissions, 2.4–18.2 Mha for land use, and 0.2–0.9 Mt for eutrophication. Notably, under the high- and medium-fertility scenarios, adopting CDG by only young populations is insufficient to reduce the policy-induced increased GHG emissions and land use. Conversely, it would result in an additional 11 Mt of GHG emissions and 10–46 Mha of land, which is consistent with previous studies (Wang et al., 2022; He et al., 2019). This result is largely because the CDG-based diet imposes less stringent restrictions on red meat (e.g., 40–50 g/person/day vs. 14 g/person/day in the EAT (Willett et al., 2019) and simultaneously recommends higher consumption of dairy products (e.g., 300–500 g/person/day vs. 250 g/person/day in the EAT). These findings suggest that more drastic or widespread dietary changes are necessary in China to counterbalance the population-driven increases in future food demand.

Fig. 4 also shows that shifting towards plant-rich diets (i.e., HGD, PESC, VEG, and VGN) would lead to extra water consumption, particularly under high- and medium-fertility scenarios. This is primarily because these plant-heavy diets replace animal-sourced foods (such as meat, fish, eggs, and dairy) with grains, vegetables, and fruits. For example, the vegan diet recommends 510 g of grains per capita per day, compared to only 232 g in EAT. Meanwhile, these plant-based foods are relatively larger contributors to water consumption (Fig. S4). Importantly, having only young populations adhere to these plant-heavy diets would not suffice to offset the increased water footprint resulting from aggressive fertility-boosting policies. Under the high-fertility scenario, for example, shifting young populations' diets to the four plant-heavy options would add 2–8 Bm^3 of water consumption. These results highlight a critical trade-off: engaging the Chinese population in a dietary transition may reduce certain environmental impacts while simultaneously increasing others. This finding echoes previous studies (Wang et al., 2020; Zhu et al., 2023) but deepens our understanding of the interplay between demand-side mitigation strategies (dietary change) and demographic policies in the pursuit of food-system sustainability.

To counterbalance potential environmental burdens resulting from demographic policies, mitigation strategies can also be implemented on the production side to reduce environmental intensities. We established 2050 as a target year and retroactively calculated the required environmental intensities needed to bring the increased footprints back to the BAU baseline (no policy scenario). This approach has identified a set of role models that can guide future technological advancements in the food system. Table 1 reveals that European countries serve as primary role models for China's food-system technological advancements. To neutralize the incremental footprints, a reduction of approximately 2–15% in environmental intensities would be necessary. The most substantial technological improvements are required under the high-fertility scenario, indicating a need for intensity decreases of about

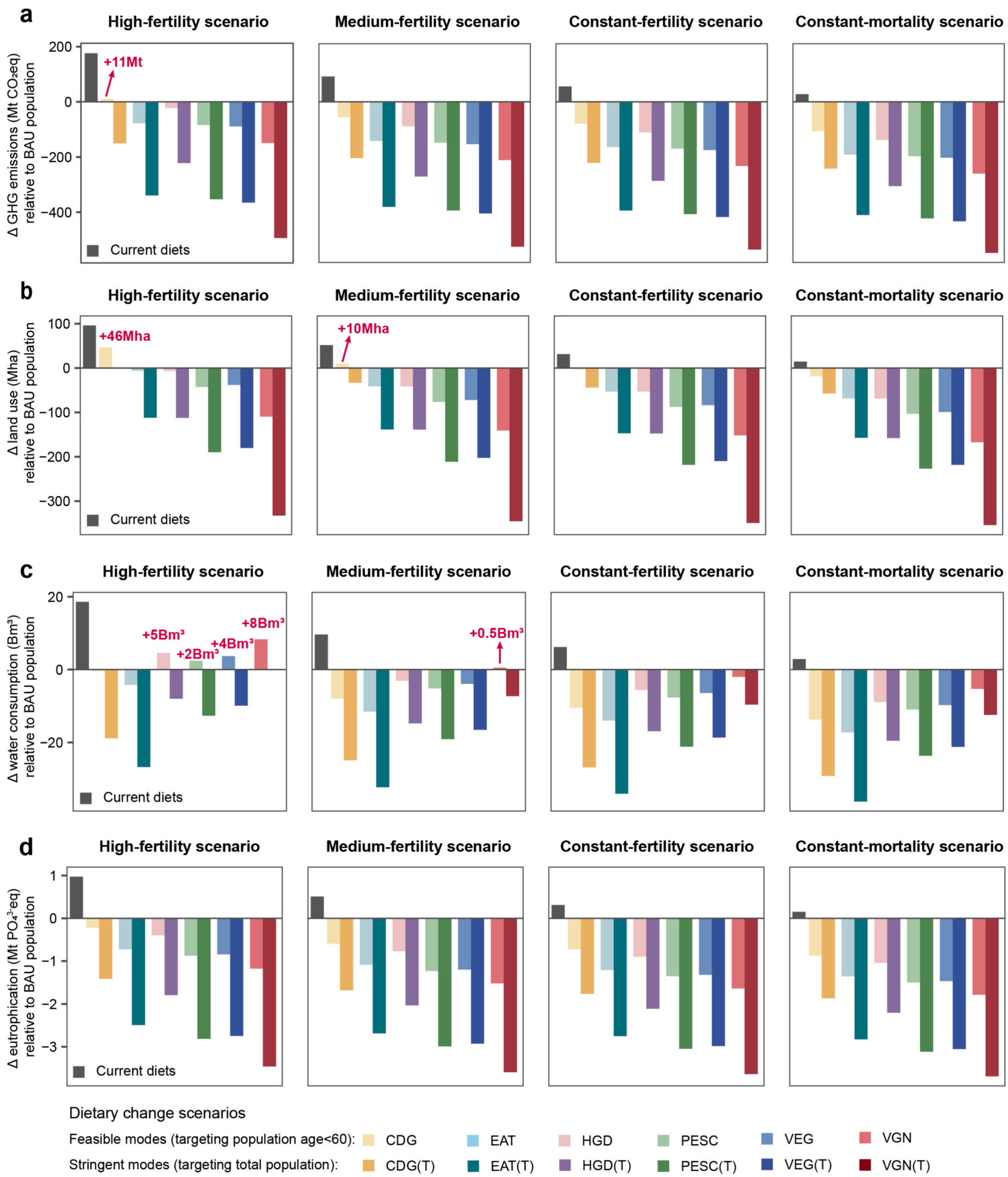

Fig. 4. Simulated environmental footprints under different dietary change scenarios. Twelve scenarios were constructed, based on six diet patterns and two adoption modes (see Methods). CDG = Chinese Dietary Guideline, EAT = EAT-Lancet reference diet, HGD = Healthy Global Diet, PESC = Pescatarian, VEG = Vegetarian, VGN = Vegan. A relatively feasible mode targeting populations under 60 years. A more stringent mode targeting the entire population.

Table 1
Changes in environmental intensities by demographic scenario compared to the BAU scenario in 2050 and the matched role models for future technological advancements.

Scenario	GHG emissions	Land use	Water consumption	Eutrophication
HFS	15.1% [Ireland, 2019]	15.4% [Denmark, 2020]	14.1% [Spain, 2050]	14.9% [EU, 2030]
MFS	8.5% [Ireland, 2018]	8.9% [Denmark, 2017]	7.8% [Spain, 2040]	8.4% [EU, 2017]
CFS	5.3% [Norway, 2016]	5.6% [Denmark, 2016]	5.2% [Spain, 2030]	5.3% [EU, 2013]
CMS	2.7% [Norway, 2020]	2.7% [Denmark, 2015]	2.5% [Spain, 2020]	2.7% [EU, 2011]

Note: Percentages indicate the magnitude of intensity changes for each scenario relative to the BAU scenario; the country/region and years in brackets represent role models for technological advancements in food system production side. HFS = the high-fertility scenario, MFS = the medium-fertility scenario, CFS = the constant-fertility scenario, CMS = the constant-mortality scenario.

14.1–15.4%. In contrast, the constant-mortality scenario demands the least technological progress, necessitating only a 2.5–2.7% reduction in intensities. The identified role models differ based on the environmental indicator: for GHG emissions, benchmarks include Ireland and Norway; land use should use Denmark as a reference; water consumption and eutrophication should be modelled after Spain and the European Union, respectively. These benchmarks provide guidance for China to further reduce environmental impacts through technological improvements.

4. Discussion

This study examines age-related heterogeneity in China's food consumption patterns and their associated environmental impacts within the context of population ageing, while also quantifying potential burdens arising from multiple demographic policies aimed at encouraging higher birth rates and creating supportive environments for the growing older adults. We also test mitigation strategies to counterbalance the policy-driven environmental pressures. Our findings indicate that notable differences exist in consumer preferences between China's older and younger populations, and the older adults would become the largest footprint contributors after 2040. Under different policy scenarios, we find different environmental indicators display varying trajectories: GHG emissions, water consumption, and eutrophication are projected to decrease, whereas land use is likely to initially rise and then decline over the period 2020–2050. Reduction in GHG emissions is primarily driven by declining environmental intensities, while changes in other three footprints are mainly due to dynamic population sizes. Dietary shifts to plant-rich patterns could significantly offset the policy-induced increases in environmental footprints, but it is crucial to be mindful of the potential for higher water consumption—as plant-based foods are water-intensive. These novel findings underscore the necessity of integrating demographic trends into food demand models and suggest that China's demographic policies may pose notable challenges for land use, which warrants heightened attention given its critical role in ensuring food security and preserving biomass diversity (Boakes et al., 2024; Niu et al., 2024; Vanham et al., 2023).

Compared to previous work, this paper presents three major advancements. **Firstly**, we integrated age-specific food consumption preferences into environmental footprint projections, revealing the predominant role of older populations on the overall footprints, despite their lower per capita impact, a detail often overlooked by national-level models. This approach can be applied to other countries undergoing similar demographic shifts, thereby deepening their understanding of age- and generation-specific dietary preferences. **Secondly**, in quantifying the environmental burdens driven by demographic policies, we selected four distinct indicators which are closely associated with food sectors. This represents an improvement compared to prior studies, which conventionally focused on carbon emissions. Notably, we identified significant trade-offs among environmental impacts when advocating for the adoption of alternative healthy diets. **Thirdly**, in addition to elucidating the environmental implications of China's demographic policies, we explored the mitigation effects of both consumption-side and production-side strategies. This offers policymakers precise and practical measures to reconcile population ageing with environmental sustainability. Overall, prior to this study, the magnitude and composition of the environmental impacts of China's demographic policies, as well as the partial mitigating effects of technological advancements and dietary transitions, remained unknown.

In the analysis of demand-side dietary transition scenarios, we found shifting China's current diets towards healthier or more plant-based alternatives could substantially reduce GHG emissions, land use, and eutrophication. Advocating dietary transitions is crucial given their co-benefits for both environmental sustainability and human health (Springmann et al., 2021; Lucas et al., 2023). However, significant challenges remain in achieving these dietary transitions. For example, recommended nutritious foods often cost more than unhealthy options (Semba et al., 2020), which could pose significant barriers to ensuring food affordability for low-income and vulnerable populations. As indicated in previous studies, adopting the CDG-based diet can increase food expenditure by 20–121%, with even greater increases for the EAT diet (Hirvonen et al., 2020). This implies that additional economic subsidies or educational campaigns may be needed to facilitate dietary shifts. Moreover, a diet that is nutritionally or environmentally sustainable does not necessarily align with culturally accepted norms. For instance, pork intake in China significantly exceeds the CDG recommended levels (Wang et al., 2020); however, pork consumption is deeply entrenched in Chinese food culture, implying that any proposed dietary transition will be a gradual process. Therefore, combining moderate dietary adjustments with moderate technological improvements may be a practical strategy.

For production-side strategies, we found China's food system requires an additional 15% improvement in production technology to entirely counterbalance the policy-driven environmental burdens. This progress can be benchmarked against certain European countries, particularly Ireland, Norway, and Denmark. However, there are numerous barriers to both the advancement and adoption of such technologies. For example, implementing novel technologies to improve production practices, such as enhancing manure management or modifying the compositions of feeds, may be costly in practice (Bai et al., 2016; Castonguay et al., 2023; Herrero et al., 2020). Meanwhile, the widespread deployment of these technologies is also contingent upon public infrastructure, improved regulation, and constructive dialogue surrounding food systems (Springmann et al., 2018). Consequently, these practical barriers and challenges underscore the necessity for multifaceted policy strategies to address the additional environmental impacts associated with demographic policies. For instance, this could involve encouraging investment in sustainable agricultural research and development (R&D) to achieve the extra 15% efficiency gain, while simultaneously promoting dietary shifts through public health interventions.

Through global supply chains, China's demographic policies and intended dietary changes would exert an impact not only on its domestic environment but also on those of its trading partners (Figs. S5-S7). By 2050, approximately one-fourth of total land use and one-fifth of GHG emissions are projected to occur outside China's territory. Around 10% of eutrophication and water consumption would be situated in its trading partners. Under the baseline population scenario, China's food-related environmental footprints exhibit varied impacts on different countries/regions from 2020 to 2050 depending on the indicators. For land use, Canada and Indonesia would benefit the most from decreased land use. Regarding GHG emissions, water consumption, and eutrophication, China, Canada, and other Asia-Pacific countries are likely to see reduced environmental impacts. These results show that global supply chains play a significant role in distributing the environmental impacts of food-consuming countries, which implies that shifting existing trade patterns towards areas with lower impact intensities could potentially reduce China's food related environmental burdens. However, such a shift may be challenging, as trade patterns are primarily shaped by political and economic factors as well as resource endowments, rather than environmental considerations. Moreover, although relying on lower-intensity exporters could reduce impacts—provided such capacity exists—it might also have geopolitical or food security ramifications.

5. Limitations

This study has several limitations that necessitate further exploration. **Firstly**, the individual food consumption data we used lags behind China's rapid development. We acknowledge that dietary habits may have evolved over the last decade. For instance, the rise of e-commerce grocery shopping and shifts in urban diets have introduced new consumption patterns. Therefore, future research should verify whether the estimated age-specific income elasticities remain valid with more recent data. **Secondly**, our identification of dietary patterns disregarded the period effect. However, this assumption may not hold under disruptive events, such as pandemics or significant food policy changes, or in the face of unforeseen period-specific shifts, such as economic shocks, which could alter future food demand. In characterizing dietary preferences, we employed income-dependent elasticities for proxying and for demand projection. While this approach may not fully capture intergenerational differences in preferences, it has accounted for the predominant determinant (income levels) of food choices. Sensitivity analysis in Table S8 reveals that variations in expenditure elasticities within the 95% confidence interval have a negligible impact on our core results. **Thirdly,** our projection model focuses on income-driven demand changes under varying demographic policies, without accounting for future food production. We generally assume that future food supply will be well-adapted to shifts in demand. However, climate change and extreme weather events are likely to affect agricultural production and/or food supply chains (Tchonkouang et al., 2024; Malik et al., 2022). Accordingly, future research can build on this work by incorporating production-side factors. **Fourthly**, with respect to the price effect, we assumed food prices remain constant over the projection period. We acknowledge this assumption might be idealized, as prices fluctuate in response to supply and demand dynamics, technological advancements in production, policy changes, and other factors. However, given the limitations in the availability of long-term price forecast data and the capacity of our single-factor prediction model, we are currently unable to incorporate the price-demand feedback mechanism. It should be noted that this study focuses on the direct effects of demographic policies on food demand; incorporating additional variables such as price elasticity may introduce more uncertainties, overcomplicate the model, and hinder the interpretation of underlying mechanisms. **Finally,** regarding the intensity coefficients in the MRIO prediction model, we employed a simplified approach (linear extrapolation) to estimate future environmental intensities. It must be acknowledged that future climate change, improvements in resource use efficiency, and the expansion or shift of irrigation areas could all introduce uncertainties to the environmental intensities and our footprint projections. To assess the robustness of this approach, we compared the projected GHG emissions with estimates from prior studies and found them to be closely aligned (Fig. S8). The uncertainties and limitations outlined above warrant more in-depth investigation in future studies.

CRediT authorship contribution statement

Qingling Wang: Writing – original draft, Visualization, Validation, Software, Methodology, Data curation. **Han Zhang:** Supervision, Resources, Funding acquisition, Conceptualization. **Kuishuang Feng:** Writing – review & editing, Supervision, Conceptualization. **Pan He:** Writing – review & editing, Supervision, Conceptualization. **Richard Wood:** Writing – review & editing. **Peipei Tian:** Writing – review & editing. **Yiming Wang:** Writing – review & editing. **Saige Wang:** Writing – review & editing. **Yu Liu:** Writing – review & editing. **Huifang Liu:** Writing – review & editing. **Heran Zheng:** Writing – review & editing, Software, Methodology, Conceptualization.

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.

Acknowledgements

The authors acknowledge the financial support from the Major Project of National Social Science Foundation of China [grant number 24&ZD108]. This work was supported by High-performance Computing Platform of Peking University. We also thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention, Carolina Population Center, and the University of North Carolina at Chapel Hill for providing the CHNS raw data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2025.103082.

Data availability

Data will be made available on request.

References

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32 (9), 1131–1139. https://doi.org/10.1016/S0301-4215(03)00076-4.

Bai, Z., Ma, L., Jin, S., Ma, W., Velthof, G.L., Oenema, O., Liu, L., Chadwick, D., Zhang, F., 2016. Nitrogen, phosphorus, and potassium flows through the manure management chain in China. Environ. Sci. Technol. 50 (24), 13409–13418. https://doi.org/10.1021/acs.est.6b03348.

Bai, Z., Ma, W., Zhao, H., Guo, M., Oenema, O., Smith, P., Velthof, G., Liu, X., Hu, C., Wang, P., Zhang, N., Liu, L., Guo, S., Fan, X., Winiwarter, W., Ma, L., 2021. Food and feed trade has greatly impacted global land and nitrogen use efficiencies over 1961–2017. Nat. Food 2 (10), 780–791. https://doi.org/10.1038/s43016-021-00351-4.

Banks, J., Blundell, R., Lewbel, A., 1997. Quadratic engel curves and consumer demand. Rev. Econ. Stat. 79 (4), 527–539. https://doi.org/10.1162/003465397557015.

Bjelle, E.L., Wiebe, K.S., Többen, J., Tisserant, A., Ivanova, D., Vita, G., Wood, R., 2021. Future changes in consumption: The income effect on greenhouse gas emissions. Energy Econ. 95. https://doi.org/10.1016/j.eneco.2021.105114.

Boakes, E.H., Dalin, C., Etard, A., Newbold, T., 2024. Impacts of the global food system on terrestrial biodiversity from land use and climate change. Nat. Commun. 15 (1), 5750. https://doi.org/10.1038/s41467-024-49999-z.

Bouwman, A.F., Beusen, A.H.W., Doelman, J.C., Stehfest, E., Westhoek, H., 2024. Impact of lifestyle, human diet and nutrient use efficiency in food production on eutrophication of global aquifers and surface waters. Glob. Environ. Chang. 87, 102874. https://doi.org/10.1016/j.gloenvcha.2024.102874.

Castonguay, A.C., Polasky, S., Holden, H.M., Herrero, M., Mason-D'Croz, D., Godde, C., Chang, J., Gerber, J., Witt, G.B., Game, E.T., Bryan, A.B., Wintle, B., Lee, K., Bal, P., McDonald-Madden, E., 2023. Navigating sustainability trade-offs in global beef production. Nat. Sustainability 6 (3), 284–294. https://doi.org/10.1038/s41893-022-01017-0.

Chen, K., Huang, T., Zhang, X., Liu, X., Jian, X., Zhugu, R., Wang, L., Tao, S., Liu, J., Gao, H., Liu, Y., Zhao, Y., Ma, J., 2022. Drivers of global methane emissions embodied in international beef trade. Environ. Sci. Technol. 56 (16), 11256–11265. https://doi.org/10.1021/acs.est.2c03509.

Chen, Q.H., Deng, T.H., Bai, J.F., He, X.R., 2017. Understanding the retirement-consumption puzzle through the lens of food consumption-fuzzy regression-discontinuity evidence from urban China. Food Policy 73, 45–61. https://doi.org/10.1016/j.foodpol.2017.09.006.

Chen, Y., Guo, F., Wang, J., Cai, W., Wang, C., Wang, K., 2020. Provincial and gridded population projection for China under shared socioeconomic pathways from 2010 to 2100. Sci. Data 7 (1), 83. https://doi.org/10.1038/s41597-020-0421-y.

Clark, M.A., Springmann, M., Hill, J., Tilman, D., 2019. Multiple health and environmental impacts of foods. Proceed. National Academy of Sci. United States of America 116 (46), 23357–23362. https://doi.org/10.1073/pnas.1906908116.

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F.N., Leip, A., 2021. Food systems are responsible for a third of global anthropogenic GHG emissions. Nat. Food 2 (3), 198–209. https://doi.org/10.1038/s43016-021-00225-9.

Deaton, A., 1997. The analysis of household surveys : A microeconometric approach to development policy (English). The World Bank, Washington, D.C.

Ermgassen, E.K.H.J.Z., Godar, J., Lathuilliere, M.J., Lfgren, P., Meyfroidt, P., 2020. The origin, supply chain, and deforestation risk of Brazil's beef exports. Proc. Natl. Acad. Sci. 17 (50), 31770–31779. https://doi.org/10.1073/pnas.2003270117.

Fan, J., Feng, X., Dong, Y., Zhang, X., 2022. A global comparison of carbon-water-food nexus based on dietary consumption. Glob. Environ. Chang. 73, 102489. https://doi.org/10.1016/j.gloenvcha.2022.102489.

Feng, K., Davis, S.J., Sun, L., Li, X., Guan, D., Liu, W., Liu, Z., Hubacek, K., 2013. Outsourcing CO2 within China. Proc. Natl. Acad. Sci. 110 (28), 11654–11659. https://doi.org/10.1073/pnas.1219918110.

Fujimori, S., Wu, W., Doelman, J., Frank, S., Hristov, J., Kyle, P., Sands, R., Van Zeist, W.-J., Havlik, P., Domínguez, I.P., 2022. Land-based climate change mitigation measures can affect agricultural markets and food security. Nat. Food 3 (2), 110–121. https://doi.org/10.1038/s43016-022-00464-4.

Gale, F., Huang, K., 2007. Demand for Food Quantity and Quality in China. https://doi.org/10.22004/ag.econ.7252.

Gatto, A., Kuiper, M., van Meijl, H., 2023. Economic, social and environmental spillovers decrease the benefits of a global dietary shift. Nat. Food 4, 496–507. https://doi.org/10.1038/s43016-023-00769-y.

Gustavsen, G.W., 2014. Consumer cohorts and demand elasticities. Eur. Rev. Agric. Econ. 42 (2), 217–237. https://doi.org/10.1093/erae/jbu020.

He, P., Baiocchi, G., Feng, K., Hubacek, K., Yu, Y., 2019. Environmental impacts of dietary quality improvement in China. J. Environ. Manage. 240, 518–526. https://doi.org/10.1016/j.jenvman.2019.03.106.

He, P., Baiocchi, G., Hubacek, K., Feng, K., Yu, Y., 2018. The environmental impacts of rapidly changing diets and their nutritional quality in China. Nat. Sustainability 1 (3), 122–127. https://doi.org/10.1038/s41893-018-0035-y.

He, P., Cai, B., Baiocchi, G., Liu, Z., 2020. Drivers of GHG emissions from dietary transition patterns in China: Supply versus demand options. J. Ind. Ecol. 25 (3), 707–719. https://doi.org/10.1111/jiec.13086.

Herrero, M., Thornton, P.K., Mason-D'Croz, D., Palmer, J., Benton, T.G., Bodirsky, B.L., Bogard, J.R., Hall, A., Lee, B., Nyborg, K., Pradhan, P., Bonnett, G.D., Bryan, B.A., Campbell, B.M., Christensen, S., Clark, M., Cook, M.T., de Boer, I.J.M., Downs, C., Dizyee, K., Folberth, C., Godde, C.M., Gerber, J.S., Grundy, M., Havlik, P., Jarvis, A., King, R., Loboguerrero, A.M., Lopes, M.A., McIntyre, C.L., Naylor, R., Navarro, J., Obersteiner, M., Parodi, A., Peoples, M.B., Pikaar, I., Popp, A., Rockström, J., Robertson, M.J., Smith, P., Stehfest, E., Swain, S.M., Valin, H., van Wijk, M., van Zanten, H.H.E., Vermeulen, S., Vervoort, J., West, P.C., 2020. Innovation can accelerate the transition towards a sustainable food system. Nat. Food 1 (5), 266–272. https://doi.org/10.1038/s43016-020-0074-1.

Hirvonen, K., Bai, Y., Headey, D., Masters, W.A., 2020. Affordability of the EAT-Lancet reference diet: A global analysis. Lancet Global Health 8 (1), e59–e66. https://doi.org/10.1016/S2214-109X(19)30447-4.

Hu, Y., Su, M., Wang, Y., Cui, S., Meng, F., Yue, W., Liu, Y., Xu, C., Yang, Z., 2020. Food production in China requires intensified measures to be consistent with national and provincial environmental boundaries. Nat. Food 1 (9), 572–582. https://doi.org/10.1038/s43016-020-00143-2.

Jing, W., Liu, J., Ma, Q., Zhang, S., Li, Y., Liu, M., 2022. Fertility intentions to have a second or third child under China's three-child policy: a national cross-sectional study [Article]. Hum. Reprod. 37 (8), 1907–1918. https://doi.org/10.1093/humrep/deac101.

Kruk, M.E., Gage, A.D., Joseph, N.T., Danaei, G., Garcia-Saiso, S., Salomon, J.A., 2018. Mortality due to low-quality health systems in the universal health coverage era: A systematic analysis of amenable deaths in 137 countries [Article]. Lancet 392 (10160), 2203–2212. https://doi.org/10.1016/s0140-6736(18)31668-4.

Lee, J., Qian, Y., Gustavsen, G., Nayga, R., Rickertsen, K., 2020. Effects of consumer cohorts and age on meat expenditures in the United States. Agric. Econ. 51. https://doi.org/10.1111/agec.12568.

Li, H., Shi, X., Wu, B., 2015. The retirement consumption puzzle in China [Article; Proceedings Paper]. Am. Econ. Rev. 105 (5), 437–441. https://doi.org/10.1257/aer.p20151007.

Liu, G., Zhang, F., Deng, X., 2023. Half of the greenhouse gas emissions from China's food system occur during food production. Commun. Earth Environ. 4 (1), 161. https://doi.org/10.1038/s43247-023-00809-2.

Long, Y., Yoshida, Y., Huang, L., Chen, P., Wu, Y., Gasparatos, A., 2024. Demographic transitions hinder climate change mitigation for Japan's shrinking and aging households. Cell Reports Sustainability 1 (3), 100053. https://doi.org/10.1016/j.crsus.2024.100053.

Lucas, E., Guo, M., Guillen-Gosalbez, G., 2023. Low-carbon diets can reduce global ecological and health costs. Nat. Food 4 (5), 394–406. https://doi.org/10.1038/s43016-023-00749-2.

Malik, A., Li, M., Lenzen, M., Fry, J., Liyanapathirana, N., Beyer, K., Boylan, S., Lee, A., Raubenheimer, D., Geschke, A., Prokopenko, M., 2022. Impacts of climate change and extreme weather on food supply chains cascade across sectors and regions in Australia. Nat. Food 3 (8), 631–643. https://doi.org/10.1038/s43016-022-00570-3.

Miller, V., Webb, P., Cudhea, F., Al, E., 2022. Global dietary quality in 185 countries from 1990 to 2018 show wide differences by nation, age, education, and urbanicity. Nat. Food 3, 694–702. https://doi.org/10.1038/s43016-022-00594-9.

Muhammad, A., D'Souza, A., Meade, B., Micha, R., & Mozaffarian, D. 2017. The Influence of Income and Prices on Global Dietary Patterns by Country, Age, and Gender, ERR-225, U.S. Department of Agriculture, Economic Research Service, February 2017. doi:10.22004/ag.econ.256711.

Niu, K., Li, M., Lenzen, M., Wiedmann, T., Han, X., Jin, S., Malik, A., Gu, B., 2024. Impacts of global trade on cropland soil-phosphorus depletion and food security. Nat. Sustainability 7 (9), 1128–1140. https://doi.org/10.1038/s41893-024-01385-9.

O'Neill, B.C., Dalton, M., Fuchs, R., Jiang, L., Pachauri, S., Zigova, K., 2010. Global demographic trends and future carbon emissions. Proc. Natl. Acad. Sci. 107 (41), 17521–17526. https://doi.org/10.1073/pnas.1004581107.

Popkin, B.M., Ng, S.W., 2021. The nutrition transition to a stage of high obesity and noncommunicable disease prevalence dominated by ultra-processed foods is not inevitable. Obes. Rev. 23 (1), e13366. https://doi.org/10.1111/obr.13366.

Ren, M., Huang, C., Wu, Y., Deppermann, A., Frank, S., Havlík, P., Zhu, Y., Fang, C., Ma, X., Liu, Y., Zhao, H., Chang, J., Ma, L., Bai, Z., Xu, S., Dai, H., 2023. Enhanced food system efficiency is the key to China's 2060 carbon neutrality target. Nat. Food 4 (7), 552–564. https://doi.org/10.1038/s43016-023-00790-1.

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Chang. 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Roosen, J., Staudigel, M., Rahbauer, S., 2022. Demand elasticities for fresh meat and welfare effects of meat taxes in Germany. Food Policy 106. https://doi.org/10.1016/j.foodpol.2021.102194.

Semba, R.D., de Pee, S., Kim, B., McKenzie, S., Nachman, K., Bloem, M.W., 2020. Adoption of the 'planetary health diet' has different impacts on countries' greenhouse gas emissions. Nat. Food 1 (8), 481–484. https://doi.org/10.1038/s43016-020-0128-4.

Semenchuk, P., Plutzar, C., Kastner, T., Matej, S., Bidoglio, G., Erb, K.-H., Essl, F., Haberl, H., Wessely, J., Krausmann, F., Dullinger, S., 2022. Relative effects of land conversion and land-use intensity on terrestrial vertebrate diversity. Nat. Commun. 13 (1), 615. https://doi.org/10.1038/s41467-022-28245-4.

Smed, S., Ronnow, H.N., Tetens, I., 2022. The retirement (food)-consumption puzzle revisited - A panel data study from Denmark [Article]. Food Policy 112. https://doi.org/10.1016/j.foodpol.2022.102330.

Springmann, M., Clark, M.A., Rayner, M., Scarborough, P., Webb, P., 2021. The global and regional costs of healthy and sustainable dietary patterns: a modelling study. Lancet Planet. Heath 5 (11), e797–e807. https://doi.org/10.1016/S2542-5196(21)00251-5.

Springmann, M., Clark, M., Mason-D'Croz, D., Al, E., 2018. Options for keeping the food system within environmental limits. Nature 562 (7728), 519–525. https://doi.org/10.1038/s41586-018-0594-0.

Stadler, K., Wood, R., Bulavskaya, T., Södersten, E.A., 2018. EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. J. Ind. Ecol. 22 (3), 502–515. https://doi.org/10.1111/jiec.12715.

Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., Folke, C., Gerten, D., Heinke, J., Mace, G.M., Persson, L.M., Ramanathan, V., Reyers, B., Sörlin, S., 2015. Planetary boundaries: Guiding human development on a changing planet. Science 347 (6223), 1259855. https://doi.org/10.1126/science.1259855.

Sun, J.W., 1998. Changes in energy consumption and energy intensity: A complete decomposition model. Energy Econ. 20 (1), 85–100. https://doi.org/10.1016/S0140-9883(97)00012-1.

Sun, Z., Scherer, L., Tukker, A., Spawn-Lee, S.A., Bruckner, M., Gibbs, H.K., Behrens, P., 2022. Dietary change in high-income nations alone can lead to substantial double climate dividend. Nat. Food 3 (1), 29–37. https://doi.org/10.1038/s43016-021-00431-5.

Tang, L., Yang, J., Zheng, J., Sun, X., Cheng, L., He, K., Li, L., Li, J., Cai, W., Wang, S., Drummond, P., Mi, Z., 2024. Assessing the impacts of fertility and retirement policies on China's carbon emissions. Nat. Clim. Chang. 14 (12), 1261–1267. https://doi.org/10.1038/s41558-024-02162-4.

Tatum, M., 2021. China's three-child policy [Editorial Material]. Lancet 397 (10291), 2238. https://doi.org/10.1016/S0140-6736(21)01295-2.

Tchonkouang, R.D., Onyeaka, H., Nkoutchou, H., 2024. Assessing the vulnerability of food supply chains to climate change-induced disruptions. Sci. Total Environ. 920, 171047. https://doi.org/10.1016/j.scitotenv.2024.171047.

Tian, P., Feng, K., Sun, L., Hubacek, K., Malerba, D., Zhong, H., Zheng, H., Li, D., Zhang, N., Li, J., 2024a. Higher total energy costs strain the elderly, especially low-income, across 31 developed countries. Proc. Natl. Acad. Sci. 121 (12), e2306771121. https://doi.org/10.1073/pnas.2306771121.

Tian, P., Zhong, H., Chen, X., Feng, K., Sun, L., Zhang, N., Shao, X., Liu, Y., Hubacek, K., 2024b. Keeping the global consumption within the planetary boundaries. Nature 635 (8039), 625–630. https://doi.org/10.1038/s41586-024-08154-w.

Tian, P., Feng, K., Zheng, H., Hubacek, K., Li, J., Zhong, H., Chen, X., Sun, L., 2023. Implementation of carbon pricing in an aging world calls for targeted protection schemes. PNAS Nexus 2 (7). https://doi.org/10.1093/pnasnexus/pgad209.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. 108 (50), 20260–20264. https://doi.org/10.1073/pnas.1116437108.

Tong, B., Zhang, L., Hou, Y., Oenema, O., Long, W., Velthof, G., Ma, W., Zhang, F., 2023. Lower pork consumption and technological change in feed production can reduce the pork supply chain environmental footprint in China. Nat. Food 4 (1), 74–83. https://doi.org/10.1038/s43016-022-00640-6.

Turner, M.D., Teague, M., Ayantunde, A., 2021. Eating groups within households: Differentiation in food consumption by age, gender, and genealogical position in rural Burkina Faso. Food Policy 101. https://doi.org/10.1016/j.foodpol.2021.102093.

United Nations. 2022. World Population Prospects. https://population.un.org/wpp.

Valin, H., Sands, R., van der Mensbrugghe, D., Nelson, G., Ahammad, H., Blanc, E., Bodirsky, B., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Mason-D'Croz, D., Paltsev, S., Rolinski, S., Tabeau, A., van Meijl, H., von Lampe, M., Willenbockel, D., 2014. The future of food demand: understanding differences in global economic models. Agric. Econ. 45 (1), 51–67. https://doi.org/10.1111/agec.12089.

van Dijk, M., Morley, T., Rau, M.L., Saghai, Y., 2021. A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. Nat. Food 2, 494–501. https://doi.org/10.1038/s43016-021-00322-9.

Vanham, D., Bruckner, M., Schwarzmueller, F., Schyns, J., Kastner, T., 2023. Multi-model assessment identifies livestock grazing as a major contributor to variation in European Union land and water footprints. Nat. Food 4 (7), 575–584. https://doi.org/10.1038/s43016-023-00797-8.

von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., Mason d'Croz, D., Nelson, G.C., Sands, R.D., Schmitz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., van Meijl, H., 2014. Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison. Agric. Econ. 45 (1), 3–20. https://doi.org/10.1111/agec.12086.

Wang, L., Gao, B., Hu, Y., Huang, W., Cui, S., 2020. Environmental effects of sustainability-oriented diet transition in China. Resour. Conserv. Recycl. 158, 104802. https://doi.org/10.1016/j.resconrec.2020.104802.

Wang, X., Bodirsky, B.L., Müller, C., Chen, K.Z., Yuan, C., 2022. The triple benefits of slimming and greening the Chinese food system. Nat. Food 3 (9), 686–693. https://doi.org/10.1038/s43016-022-00580-1.

Willett, W., Rockstrom, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., Jonell, M., Clark, M., Gordon, L.J., Fanzo, J., Hawkes, C., Zurayk, R., Rivera, J.A., De Vries, W., Sibanda, L.M., Afshin, A., Chaudhary, A., Herrero, M., Agustina, R., Branca, F., Lartey, A., Fan, S., Crona, B., Fox, E., Bignet, V., Troell, M., Lindahl, T., Singh, S., Cornell, S.E., Reddy, K.S., Narain, S., Nishtar, S., Murray, C.J.L., 2019. Food in the anthropocene: The EAT-Lancet commission on healthy diets from sustainable food systems. Lancet 393 (10170), 447–492. https://doi.org/10.1016/s0140-6736(18)31788-4.

Winter, S., Diamond, M., Green, J., Karasic, D., Reed, T., Whittle, S., Wylie, K., 2016. Transgender people: Health at the margins of society [Article]. Lancet 388 (10042), 390–400. https://doi.org/10.1016/s0140-6736(16)00683-8.

Yin, K., Zhao, X., Liu, Y., Zhu, J., Fei, X., 2024. Aging increases global annual food greenhouse gas emissions up to 300 million tonnes by 2100. Environ. Sci. Technol. 58 (13), 5784–5795. https://doi.org/10.1021/acs.est.3c06268.

Yu, B., Wei, Y., Gomi, K., Matsuoka, Y., 2018. Future scenarios for energy consumption and carbon emissions due to demographic transitions in Chinese households. Nat. Energy 3 (2), 109–118. https://doi.org/10.1038/s41560-017-0053-4.

Yu, Y., Feng, K., Hubacek, K., Sun, L., 2016. Global implications of China's future food consumption. J. Ind. Ecol. 20 (3), 593–602. https://doi.org/10.1111/jiec.12392.

Zeng, Y., Hesketh, T., 2016. The effects of China's universal two-child policy [Review]. Lancet 388 (10054), 1930–1938. https://doi.org/10.1016/S0140-6736(16)31405-2.

Zhao, H., Chang, J., Havlík, P., van Dijk, M., Valin, H., Janssens, C., Ma, L., Bai, Z., Herrero, M., Smith, P.C., Obersteiner, M., 2021. China's future food demand and its implications for trade and environment. Nat. Sustainability 4, 1042–1051. https://doi.org/10.1038/s41893-021-00784-6.

Zheng, H.R., Long, Y., Wood, R., Moran, D., Zhang, Z.K., Meng, J., Feng, K.K., Hertwich, E., Guan, D.B., 2022. Ageing society in developed countries challenges carbon mitigation. Nat. Clim. Chang. 12 (3), 241–248. https://doi.org/10.1038/s41558-022-01302-y.

Zhong, H., Li, Y., Ding, J., Bruckner, B., Feng, K., Sun, L., Prell, C., Shan, Y., Hubacek, K., 2024. Global spillover effects of the European green deal and plausible mitigation options. Nat. Sustainability. https://doi.org/10.1038/s41893-024-01428-1.

Zhu, Y., Zhang, Y., Zhu, X., 2023. The evolution process, characteristics and adjustment of Chinese dietary guidelines: A global perspective. Resour. Conserv. Recycl. 193, 106964. https://doi.org/10.1016/j.resconrec.2023.106964.