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ANALYSIS

The UK's middle-income dietary trap: High emissions, low nutrition

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A R T I C L E I N F O

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A B S T R A C T

Dietary transitions driven by income disparity increasingly impose a dual burden on health and the climate. This study integrates the Nutrient Rich Food ($NRF_{9.3}$) index and Global Warming Potential (GWP) to evaluate the nutrition-carbon trade-off in UK household food purchases in 2013. Our analysis reveals a "middle-income dietary trap". Across Deciles 4–8, households increase their overall food purchases as income rises, but this expansion is dominated by carbon-intensive, nutrient-poor foods such as meats, dairy, sugars, and vegetable oils. As a consequence, calorie intake peaks while improvements in diet quality lag behind, and carbon emissions reach their highest levels among all income groups. This misalignment reflects a stage in which rising food quantity precedes nutritional gains, generating a dual burden of high-carbon, low-nutrition diets. In contrast, high-income groups (Deciles 9–10) achieve modest improvements in both nutrition and carbon efficiency, associated with higher consumption of nutrient-dense, low-GWP foods such as vegetables, fruits, and seafood. These findings highlight a non-linear income-emission relationship, consistent with the Environmental Kuznets Curve hypothesis. Our decomposition analysis identifies two mechanisms shaping dietary carbon efficiency: a static opposition between expenditure and energy density, and a dynamic trade-off between nutrient density and the carbon intensity of nutrients. Policy interventions should adopt stage-specific strategies targeting middle-income households, where the dietary trap is driven by expenditure–structure imbalance, by steering substitution toward nutrient-dense, lower-carbon foods and accelerating structural dietary change.

1. Introduction

Dietary patterns are increasingly recognized as a critical nexus between human health and environmental sustainability (Zhang and Chai, 2022; Tilman and Clark, 2014). In the UK, diet-related risks constitute a major public health burden (Yusuf et al., 2020), while food systems are also a huge source of greenhouse gas emissions (Crippa et al., 2021). Understanding how dietary behaviors across different socioeconomic groups shape both nutritional outcomes and carbon emissions is therefore essential for designing sustainable food policies.

Socioeconomic status, particularly income, is a key determinant of dietary transition (French et al., 2019; Mullie et al., 2010). Lower-income groups tend to consume energy-dense but nutrient-poor diets due to economic and social constraints (Drewnowski et al., 2020; Laraia et al., 2017). As income rises, diets change, but not necessarily toward simultaneous health and environmental gains. Income growth, a key driver of nutrition transition, is associated with increased calorie intake and a tendency among lower socioeconomic groups to prioritize energy-dense but nutritionally poor foods (Nelson et al., 2018; Mayén et al., 2014; Darmon and Drewnowski, 2008). Meanwhile, the nutrition transition typically involves more intake of animal-sourced foods, which are more expensive and carbon-intensive (Lucas et al., 2023; Frey and Bruckner, 2021). This creates a potential tension between improving nutritional quality and reducing carbon emissions.

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Existing evidence shows a clear socio-economic gradient in the UK dietary pattern: low-income groups consume fewer fruits, vegetables, and whole grains, and rely more on processed and energy-dense foods (Aceves-Martins et al., 2023; Patel et al., 2020; Reynolds et al., 2019b; Mackenbach et al., 2015; Maguire and Monsivais, 2015). Although definitions of income or socio-economic groups vary across studies[1], UK evidence suggests that high-income groups tend to have nutritionally superior diets but higher diet-related carbon emissions, largely due to greater consumption of animal-based and high-value foods (Reynolds et al., 2019b). Similar patterns have been observed in Chile, Japan, the US, the Netherlands, India, and global assessments (Li et al., 2024; Franco et al., 2022; Fujie et al., 2022; He et al., 2021; Van Dooren et al., 2018; Rao et al., 2018; Chaudhary et al., 2018). Single-dimension studies also align with this pattern: higher socioeconomic status is associated with greater dietary emissions in Korea and Sweden (Hong and Kim, 2025; Hjorth et al., 2020), while higher income is associated with better diet quality but persistent dietary inequalities in the US (Conrad et al., 2024). However, evidence from Germany and Mexico complicates this pattern, showing that lower emissions may reflect reduced meat intake or staple-based diets rather than uniformly healthier diets (Grabow et al., 2026; López-Olmedo et al., 2022). These findings highlight substantial heterogeneity in how dietary quality and environmental impacts evolve across income groups, suggesting context-specific and potentially non-linear dietary transitions. Meanwhile, optimisation-based studies from the Netherlands and Finland show that healthier and more sustainable diets can be achieved across socio-economic groups under nutritional and environmental constraints, often via more plant-based foods (Vellinga et al., 2025; Irz et al., 2024). Evidence from the UK and the Netherlands further shows that dietary transitions can follow different pathways shaped by income constraints and preference (Reynolds et al., 2019b; Van Dooren et al., 2018).

Despite these insights, the mechanisms underlying such heterogeneous transitions remain insufficiently understood. In particular, it is unclear how dietary patterns evolve across the income distribution, whether structural upgrading lags emerge during middle-income range, and how food expenditure growth interacts with dietary structural shifts to shape both nutritional outcomes and carbon emissions. The middle-income stage, linking basic consumption and structural upgrading, therefore remains insufficiently characterized, limiting understanding of the nutrition–environment trade-off and the design of targeted policy interventions.

This study hypothesizes the existence of a "middle-income dietary trap", defined as a transitional stage where rising food quantity precedes improvements in dietary quality, while driving emissions to their highest levels. This extends the nutrition transition framework by integrating an environmental efficiency perspective and highlighting a misalignment between nutritional and environmental outcomes. Here, "middle-income" refers to the relative position within the national income distribution.

To address this gap, this study analyzes micro-level dietary data from the 2013 UK Living Costs and Food Survey (LCFS) (UKGov, 2024; ONS, 2024a), covering over 250 food items across income deciles. Nutritional quality is assessed using the Nutrient Rich Food ($NRF_{9.3}$) index. Carbon emission data are derived from the Food and Agriculture Biomass Input-Output (FABIO) database, measured as Global Warming Potential (GWP) (Pinero et al., 2022; Bruckner et al., 2019). The Logarithmic Mean Divisia Index (LMDI) decomposition method is applied to identify key drivers of dietary GWP and dietary GWP intensity, including impact intensity, nutrition density, energy density, spending structure across food groups, and total food spending. Dietary GWP intensity is defined as dietary GWP standardized per 2000 kcal of energy purchased, enabling comparisons across income groups independently of total caloric purchase. The 2000 kcal benchmark reflects the UK government's recommended adult female daily energy intake (PHE, 2016). The analysis combines income-based comparisons with food-level evaluation of nutrition–carbon trade-offs.

This study offers three key contributions. Methodologically, it integrates nutritional quality and carbon emissions within a unified decomposition framework, firstly extending LMDI to dietary GWP intensity. Theoretically, it introduces the concept of a "middle-income dietary trap", identifying a transitional stage where rising income leads to greater food purchases, calorie peaks, lagging nutritional gains, and the highest carbon emissions. It also refines the nutrition transition theory (Darmon and Drewnowski, 2008; Popkin, 2003; Popkin, 1993), by empirically validating the "quantity-before-quality" pathway from the socioeconomic-gradient perspective. This dynamic resonates with an Environmental Kuznets Curve (EKC)-like pattern, suggesting that improvements in both diet quality and carbon efficiency emerge only after a certain income threshold. Empirically, it provides evidence on income-stratified diet–environment interactions in the UK and offers policy-relevant insights for targeted dietary transitions.

2. Methodology

2.1. Nutritional quality

A Nutrient Rich Food (NRF) index, proposed by Drewnowski (2009), comprises two indices: nutrients to encourage (NR_n) and nutrients to avoid or limit (LIM). The NRF family is flexible in the number of nutrients included and can be tailored to specific population groups using corresponding Nutrient Reference Values (NRVs). An NRF index is commonly calculated as the difference between NR_n and LIM.

The $NRF_{9.3}$ index includes nine nutrients to encourage (protein, fibre, calcium, iron, magnesium, potassium, and vitamins A, C, and E) and three nutrients to limit (added sugar, saturated fat, and sodium). It is the most widely used and validated NRF index. Although $NRF_{9.3}$ does not capture the full spectrum of nutritional value, particularly for foods with specific or unique properties, it remains a robust indicator of overall nutrient quality. Fulgoni et al. (2009) systematically evaluated alternative NRF permutations and found $NRF_{9.3}$ to perform best, explaining the highest proportion of variance in the Healthy Eating Index (HEI) when calculated per reference amount customarily consumed and per 100 kcal. Due to data limitations, this study uses total sugar as a proxy for added sugar. Although this substitution modestly reduces explanatory power by 3–5 R^2 units because of naturally occurring sugars in fruit and dairy products, Fulgoni et al. (2009) considered it reasonable when added sugar data are unavailable. Therefore, this study adopts $NRF_{9.3}$ as a suitable proxy for nutritional quality. The nutrients in $NRF_{9.3}$ and their NRVs are shown in Table 1, where $Nutrient_i$ and $Nutrient_j$ are content of qualifying and limiting nutrient. NRV_i and NRV_j are the nutrient reference value of qualifying and limiting nutrient.

$$NR_9 = \frac{1}{9}\sum_{i=1}^{9}\left(\frac{Nutrient_i}{NRV_i}\right) \tag{1}$$

$$LIM = \frac{1}{3}\sum_{j=1}^{3}\left(\frac{Nutrient_j}{NRV_j}\right) \tag{2}$$

$$NRF_{9.3} = NR_9 - LIM \tag{3}$$

Higher values of $NRF_{9.3}$ mean more nutritious food items, due to their high positive nutrients to encourage (NR_9) and comparably few nutrients to limit (LIM).

[1] Definitions of socio-economic groups vary across studies, such as equivalised household income quartiles (Patel et al., 2020), income quintiles (Reynolds et al., 2019b), broader socio-economic position indicators combining income with education or occupation (Mackenbach et al., 2015; Maguire and Monsivais, 2015), and area-level composite deprivation measures such as the Index of Multiple Deprivation (IMD) (Aceves-Martins et al., 2023).

Table 1
Nutrients in the $NRF_{9.3}$ index.

Category	Nutrient	NRV	NRV unit (per person per day)	NRV reference
Macronutrients	Dietary fibre	30	g	TSO (2015)
	Protein	55.5	g	PHE (2016)
Minerals	Calcium	700	mg	PHE (2016)
	Iron	8.7	mg	PHE (2016)
	Magnesium	300	mg	PHE (2016)
	Potassium	3500	mg	PHE (2016)
Vitamins	Vitamin C	40	mg	PHE (2016)
	Vitamin A	700	µg	PHE (2016)
	Vitamin E	4	mg	SACN (2021)
Nutrients to limit	Total sugar	90	g	NHS (2023)
	Saturated fat	25	g	SACN (2019)
	Sodium	2400	mg	PHE (2016)

We calculate the $NRF_{9.3}$ index without applying nutrient capping, while a capped specification is provided in the **Appendix S1** for sensitivity analysis.

2.2. Global warming potential

Our analysis combines UK household food purchase data from the Family Food Module of the Living Costs and Food Survey (LCFS) (UKGov, 2024; ONS, 2024a) with carbon footprint factors in kg of CO_2e per kg of food product supplied, distinguishing between domestic and imported fractions. These factors are obtained from the Food and Agriculture Biomass Input-Output (FABIO) database applying techniques of environmentally extended input-output (EEIO) analysis (Pinero et al., 2022; Bruckner et al., 2019). FABIO offers a global multi-regional input-output framework covering 123 food items and 187 countries, with flows measured in physical units (tonnes or 1000 Head). Pinero et al. (2022) linked FABIO with FAOSTAT, the Land Use Harmonization database and other sources to estimate domestic and foreign fractions of 100-year Global Warming Potential (GWP100) for food products. We use 2013 factors to align with the LCFS data, and GWP factors for the main GHGs follow United Nations guidelines (UNEP, 2016).

The 123 FABIO categories were first matched with the FoodEx2 classification system (Tereza da Silva et al., 2025; Reynolds et al., 2022; Reynolds et al., 2021; Reynolds et al., 2019a), and then to the 337 LCFS food items consumed at home during 2022–2023[2] using recipe-based mappings from Reynolds et al. (2019b). Composite foods (e.g., pizzas, sandwiches, and ready meals) are proportionally disaggregated into their constituent components and allocated across multiple FABIO food items using standardized composition shares, avoiding assignment to a single sector. The full LCFS–FABIO correspondence matrix is provided in **Supplementary Data Sheet 1**. The 316 out-of-home food items were excluded, because their composition and portion sizes could not be reliably standardized or decomposed into ingredient-level components compatible with FABIO.

The LCFS is a nationally representative survey that records detailed UK household food and drink purchases. Households record all purchases over a two-week period, including foods eaten at home and out of home. For each item, LCFS provides individual-level data on weekly purchase weight (grams) and expenditure (£).

Because FABIO represents physical food supply for final purchase, the analysis reflects food supply and purchases rather than actual intake, and thus implicitly includes household-level food waste. Food loss and waste are not explicitly accounted for because disaggregated data by income group are unavailable. If higher-income households waste more food, as suggested by previous studies (Yu and Jaenicke, 2020; Szabó-Bódi et al., 2018), the actual environmental disparities across income groups may be greater than estimated.

The estimation of carbon footprint factors using the EEIO approach enables consistent quantification of GWP across all food items, applying a uniform system boundary. This allows for a systematic evaluation of GWP embodied in the entire food supply chain, from production to consumption. In the EEIO model, total output is the sum of intermediate and final demand, which can be used to derive environmentally relevant indicators such as carbon footprints. The balance of an EEIO model is as following:

$$\varnothing = \varphi' \bullet L \bullet Q \tag{4}$$

where $\varnothing$ is the GWP of food supply in $kgCO_2e$. φ' is the direct GWP per product output. L is the Leontief inverse obtained by $L = (I - A)^{-1}$, where I is the identity matrix. A describes the input requirements per unit of product output in the economy, that is, technological relations in production, and is obtained following $A = Z \bullet X^{-1}$, where Z is the transactions matrix, which shows exchange of intermediate products in a given year in kg, and X is the product output vector in kg. The final demand matrix Q comprises six final demand categories for each country: 1) balancing, 2) food, 3) other (i.e. non-food), 4) stock_addition, 5) tourist, 6) unspecified. This study focuses on GWP which is related to food supplied of each commodity, obtained from the "food" category under final demand, in order to avoid negative values caused by changes of stock. To obtain UK's food supplied, we extracted the related column in Q, which is represented by c.

GWP generated to satisfy the UK's food purchase r can be expressed as described in Eq.5, where $\widehat{c}$ represents the diagonalization of vector c:

$$r' = \varphi' \bullet L \bullet \widehat{c} \tag{5}$$

Then, we conveniently re-arrange GWP generated by the UK's food supplied by converting vector r into a matrix R where for each element r_{ij} subindex i denotes country of origin, and subindex j the food product to satisfy the food supplied of UK. Therefore, we define r^d as total food supplied which is produced at home to satisfy UK's domestic food purchase in kg when i is the UK, while the GWP associated to the imported products is $r^m = \sum_{i \neq UK} R$. Logically, $r = r^d + r^m$. Using the same method, we can re-arrange and aggregate UK's food supplied to obtain UK's food consumption c^d and c^m, for domestically produced and imported food products, respectively. Then, the carbon footprint factors or GWP multipliers, providing a ratio or emission intensity in $kgCO_2e/kg$, to estimate total GWP generated in the income decile are obtained as detailed in Eq. 6.

$$\delta^s = r^s \left(\widehat{c^s}\right)^{-1}, s \in \{d, m\} \tag{6}$$

2.3. LMDI decomposition analysis

We examine how GWP associated with food purchase differs across income groups in the UK using the Logarithmic Mean Divisia Index (LMDI) method. Originally developed by Ang et al. (1998), the LMDI approach enables the decomposition of total changes into additive contributions from multiple driving factors, without residuals. In this study, we apply two decompositions to isolate the influence of structural and behavioral changes on the differences in dietary emissions across income groups.

The first model decomposes differences in total GWP between

[2] For the "Roots" category, which had a carbon intensity of 0 tCO_2e/t, we substituted the estimate for yams (0.054 tCO_2e/t). This value was selected as it represents a conservative, non-zero GWP estimate for staple root crops. The "Oil" category was disaggregated according to domestic final food demand shares in FABIO 2013: Soyabean Oil (17%), Sunflowerseed Oil (12%), Rape and Mustard Oil (36%), Palmkernel Oil (1%), Palm Oil (3%), Olive Oil (4%), Maize Germ Oil (2%), and Other Oilcrops Oil (25%).

income groups into five factors: (1) impact intensity, (2) nutrition density, (3) energy density, (4) spending structure, and (5) total food spending.

The second model uses a dietary GWP intensity metric, expressed as GWP per 2000 kcal. It decomposes into six factors: (1) impact intensity, (2) nutrition level, (3) inversed energy level, (4) energy density, (5) spending structure, and (6) total spending.

Together, these two decompositions offer complementary perspectives: one captures the absolute difference in emissions, while the other isolates differences in emission intensity per unit of energy purchased.

These factor structures are summarized in Table 2. The fundamental variables used to construct each factor, including their data sources, dimensions, and definitions, are further detailed in **Appendix S2**, to ensure transparency and consistency across the linked datasets.

2.3.1. GWP decomposition

We decompose the GWP changes between income groups into contributions of 5 factors: (1) total spending ($SP = spending$), (2) spending structure ($SS_j = \frac{spending_j}{spending}$), (3) energy density ($ED_j = \frac{calories_j}{spending_j}$), (4) nutrition density $ND_{ij} = \frac{nutrient_i}{calories_j}$), and (5) environmental impact per weight equivalent of components $IF_{ij} = \frac{impact_j}{nutrient_i}$).

$$E = \sum_j impact_j$$
$$= \frac{1}{I}\sum_j\sum_i spending \times \frac{spending_j}{spending} \times \frac{calories_j}{spending_j} \times \frac{nutrient_i}{calories_j} \times \frac{impact_j}{nutrient_i}$$
$$= \frac{1}{I}\sum_j\sum_i SP \times SS_j \times ED_j \times ND_{ij} \times IF_{ij} \tag{7}$$

where j denotes the food group, and i denotes the nutrient component with the number of i in total. $spending$ is the total monetary spending on food. $spending_j$ is the money spent on the food group j. $calories_j$ is calories of the food group j. $impact_j$ is per capita environmental impact of the food group j. $nutrient_i$ is the per capita intake of nutrient component i in weight equivalent.

We adopted LMDI to decompose the difference in GWP between two income groups into the contribution of changes in five factors:

Table 2
Decomposition factors used in the two LMDI models for food-related GWP.

Factor Name	Symbol and Formula	GWP	Dietary GWP intensity	Description
Impact intensity	$IF_{ij} = \frac{impact_j}{nutrient_i}$	✓	✓	Environmental impact per unit of nutrient with impact derived from EEIO-based accounting
Nutrition density	$ND_{ij} = \frac{nutrient_i}{calories_j}$	✓		Nutrient intake per unit of energy intake
Nutrition level	$EL_i = \frac{nutrient_i}{2000}$		✓	Nutrient intake normalized to the 2000 kcal reference
Energy level (inverse)	$NL_j = \frac{2000}{calories_j}$		✓	Inverse of energy intake relative to the 2000 kcal reference
Energy density	$ED_j = \frac{calories_j}{spending_j}$	✓	✓	Energy intake per unit of food spending
Spending structure	$SS_j = \frac{spending_j}{spending}$	✓	✓	Share of total food spending allocated to food item j
Total spending	$SP = spending$	✓	✓	Total monetary food spending

$$\Delta E = E^{higher} - E^{lower}$$
$$= \Delta E_{impact.factor} + \Delta E_{nutrition.density} + \Delta E_{energy.density} + \Delta E_{spending.structure} + \Delta E_{spending} \tag{8}$$

where ΔE represents the GWP change along the income gradient. $\Delta E_{impact.factor}$, $\Delta E_{nutrition.density}$, $\Delta E_{energy.density}$, $\Delta E_{spending.structure}$, and $\Delta E_{spending}$ indicate the contribution of the impact per unit of nutrient, nutrition density, energy density, spending structure and total spending on food to such change, respectively. The detailed LMDI expressions for each factor are provided in **Appendix S2**, Eqs. A4–A8.

2.3.2. Dietary GWP intensity decomposition

Furthermore, this study also explored the drivers of differences in dietary GWP intensity. We quantified the contributions of 6 factors: (1) Total spending ($SP = spending$), (2) Spending structure ($SS_j = \frac{spending_j}{spending}$), (3) Energy density of the food ($ED_j = \frac{calories_j}{spending_j}$), (4) Inversed energy level of food, which converts the current energy intake level to a multiple of the "2000 kcal standard" ($NL_j = \frac{2000}{calories_j}$), (5) Nutrition level of food $EL_i = \frac{nutrient_i}{2000}$), and (6) environmental impact per weight equivalent of components ($IF_{ij} = \frac{impact_j}{nutrient_i}$).

$$E = \sum_j impact_j$$
$$= \frac{1}{I}\sum_j\sum_i spending \times \frac{spending_j}{spending} \times \frac{calories_j}{spending_j} \times \frac{2000}{calories_j} \times \frac{nutrient_i}{2000} \times \frac{impact_j}{nutrient_i}$$
$$= \frac{1}{I}\sum_j\sum_i SP \times SS_j \times ED_j \times NL_j \times EL_i \times IF_{ij} \tag{9}$$

where j denotes the food group, and i denotes the nutrient component with the number of 12 in total.

Next, the difference of E along the income gradient is decomposed as:

$$\Delta E = E^{higher} - E^{lower} = \Delta E_{impact\_factor} + \Delta E_{nutrition\_level} + \Delta E_{energy\_level} + \Delta E_{energy\_density} + \Delta E_{spending\_structure} + \Delta E_{spending} \tag{10}$$

where ΔE represents the GWP per 2000 kcal energy change along the income gradient. ΔE_{impact_factor}, $\Delta E_{nutrition\_level}$, ΔE_{energy_level}, $\Delta E_{energy\_density}$, $\Delta E_{spending\_structure}$, and $\Delta E_{spending}$ indicate the contribution of the impact per unit of nutrient, nutrition level, inversed energy level, energy density, spending structure, and total spending on food to such change, respectively. The detailed LMDI expressions for each factor are provided in **Appendix S2**, Eqs. A9–A14.

2.4. Data sources

To calculate $NRF_{9.3}$ index, nutrient composition data are primarily obtained from the FAO nutrient database, which reports values per 100 g of edible portion (EP), along with the edible portion coefficients used to convert raw food weights into edible amounts (Grande et al., 2024). For data limitation, this study uses Total sugar instead of Added sugar. Since the FAO dataset does not provide values for Total sugar, Vitamin E, and Sodium, these nutrients and their edible portion factors are taken from the UK nutrient database (PHE, 2021). The UK database reports nutrient values and edible portion coefficients per 100 g of food (PHE, 2021). The full mapping table for the FABIO–nutrient mapping for each of the 123 FABIO food categories is provided in **Appendix S3**.

To enable the $NRF_{9.3}$ calculation, all nutrient values from the FAO and UK databases need to be standardized against their respective NRVs. These NRVs, which are provided on a per person per day basis, are summarized along with their sources in Table 1. Since the original nutrient data are expressed per 100 g of edible food, population data and food purchase quantities are used to convert the values to daily intake levels, ensuring consistency in units for $NRF_{9.3}$ scoring. Per capita values are calculated by dividing total consumption by population size, without applying adult-equivalent adjustments.

The population of the United Kingdom in 2013 was 64,138,721 (ONS, 2024b). Household food purchase data are obtained from the 2013 FABIO database, specifically from the “food” category under final demand. The choice of 2013 ensures data consistency, as it is the latest year available in the fully documented and publicly released FABIO database (Bruckner et al., 2019). It is important to note that the purchase values used in this study represent the combined total of both domestically produced and imported food, without distinction between the two sources. Therefore, the food purchase analyzed here reflects the total quantity of food required to meet the dietary needs of UK residents, regardless of whether it was supplied through domestic production or imports.

By splitting the total food purchase data according to ten income groups, based on household purchases categorized by equivalized income deciles from the Family Food Survey 2021/22 (UKGov, 2024b), it is possible to calculate the $NRF_{9.3}$ index for each of the ten income groups in the UK. This approach allows analysis of nutritional quality differences across income levels. Income heterogeneity is represented using these deciles (D1–D10). The terms “low-”, “middle-”, and “high-income” are used to describe relative positions along the income distribution.

The greenhouse gas emission indicator used in this study is the Global Warming Potential (GWP) provided by Pinero et al. (2022), which is aligned with the FABIO model data. However, the country listings differ slightly between the two datasets. While the country order is consistent, the GWP data include five additional countries: Belgium-Luxembourg, Czechoslovakia, Serbia and Montenegro, USSR, and Yugoslav SFR. These five countries were excluded from our analysis to maintain consistency. Using the previously divided food purchase data by ten income groups, this study combines the total greenhouse gas emission coefficients to calculate the GWP for each income group in the UK.

For the decomposition analysis, additional data were required to complement the food purchase dataset. Specifically, we employed expenditure data by income decile (equivalized income) in 2013 from Family Food Survey (UKGov, 2024a). Unlike the physical food purchase data described earlier, this dataset reflects monetary expenditure rather than physical quantities.

3. Results

3.1. Nutritional quality of UK diet

Fig. 1 presents $NRF_{9.3}$ scores and per capita daily energy purchase across income levels. The $NRF_{9.3}$ index shows a gradual improvement along the income distribution (**Fig. 1**a), indicating higher nutrient density among wealthier households. It reaches its lowest point at Decile 4 (1.03), indicating the poorest dietary quality, while the highest value appears in Decile 10 (1.26). In contrast, energy purchase peaks among the middle-income groups (Deciles 4–6). It reaches maximum at 3944 kcal in Deciles 6, while the $NRF_{9.3}$ index in Decile 6 remains moderate (1.17). Then energy purchase declines to 3599 kcal in Decile 9. This indicates that while middle-income groups consume the largest amount of dietary energy, their overall nutrient richness does not rise proportionately, whereas higher-income households achieve better nutritional quality with relatively lower energy levels.

Breakdown of nutrient contributions shows that vitamin C exhibits the largest increase (0.50 to 0.65), serving as the main driver of the substantial $NRF_{9.3}$ improvement among high-income groups (**Fig. 1**b). Magnesium (0.25 to 0.30) and protein (0.22 to 0.26) also display steady gains, while fibre remains relatively stable (0.21 to 0.25). Vitamin A records a modest absolute contribution (0.11 to 0.15) but the largest relative percentage increase (+36%). By contrast, vitamin E exhibits an inconsistent trend, declining in some higher deciles (e.g. 0.53 in Decile 9) despite improvements in others, suggesting income-related dietary shifts do not uniformly enhance all micronutrients. Meanwhile, nutrients to limit peak among middle-income groups, particularly total sugar and saturated fat, which are significantly higher in Deciles 6–8 (**Fig. 1**c).

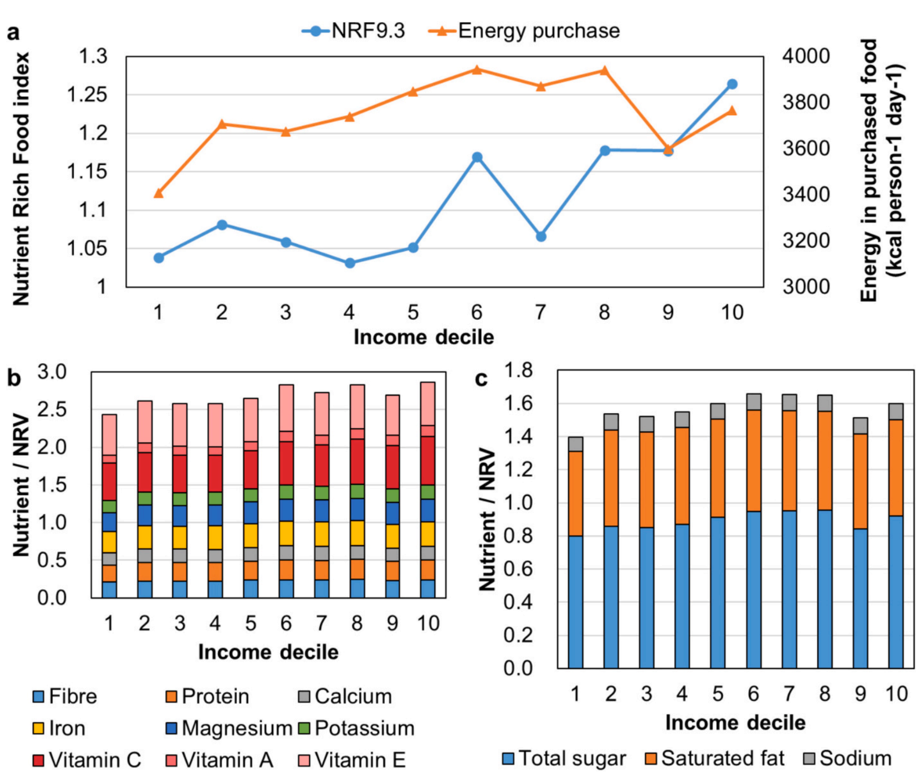

Fig. 1. Nutrient Rich Food ($NRF_{9.3}$) index and energy contained in total food purchased per person per day across income deciles. **a,** Overall $NRF_{9.3}$ score and energy purchase. **b,** Contributions from nutrients to encourage (NR_n). **c,** Contributions from nutrients to limit (LIM).

The increased values of total sugar and saturated fat among Deciles 6–8 explain the relatively lower $NRF_{9.3}$ scores observed in these groups, despite improvements in several beneficial nutrients. Overall, dietary improvements at higher incomes are driven by micronutrients, while middle-income diets remain constrained by high sugar and saturated fat intake.

Fig. 2 shows $NRF_{9.3}$ scores by food item across income deciles. A higher $NRF_{9.3}$ score indicates better nutritional quality, which can be achieved by either a higher intake level of encouraged nutrients and a lower intake level of limited nutrients. 41 food items of 123 food items in FABIO are used due to complete nutrient data and non-zero consumption across all groups. Items with negligible purchases were excluded to ensure comparability (see **Appendix S4** for the full list).

Wheat and products remains the largest positive $NRF_{9.3}$ contributor across all deciles (0.51–0.57), driven by fibre, magnesium, and iron (**Fig. A2**a). Potatoes and products also maintains stable positive values (Fig. 2a), largely attributable to vitamin C (**Fig. A2**a). Micronutrient-rich plant foods underpin the observed improvement in $NRF_{9.3}$ among higher-income households. Vegetables, Other increases from 0.19 in Decile 1 to 0.29 in Decile 10 (Fig. 2a), reflecting strong contributions from vitamin C (0.13) (**Fig. A2**a). Tomatoes and products rises from 0.10 to 0.15 (Fig. 2a), supported by vitamin C (0.07) (**Fig. A2**a). Oranges and mandarins exhibits a U-shaped profile, declining to 0.07–0.08 in Deciles 4–5 before reaching 0.12 in Deciles 10 (Fig. 2a), almost entirely explained by vitamin C (**Fig. A2**a). Nuts and products becomes increasingly important at higher incomes (0.08 in Decile 3 to 0.18 in Decile 10) (Fig. 2b), reflecting their high content of vitamin E (**Fig. A2**a). Fish, Seafood contributes more modestly (0.05–0.08) but diversify the nutrient profile through vitamin E, calcium, and protein (Fig. 2b and **Fig. A2**a).

Edible oils provide heterogeneous contributions. Rape and Mustard Oil contributes positively at lower incomes (0.13 in Decile 2) but declines to 0.09 in Decile 9 (**Fig. A2**a), consistent with its nutrient profile, which combines a high vitamin E contribution with a saturated fat penalty (**Fig. A2**a). Sunflowerseed Oil shows a similar pattern (Fig. 2b), while Soyabean Oil exerts a weaker net effect (Fig. 2c).

Negative contributions are concentrated among sugars, sweeteners, and high-fat animal products, particularly in the middle-income deciles. Sugar (Raw Equivalent) represents the most adverse item, with values consistently below −0.34 and reaching their nadir in Deciles 5–7 (about −0.43) (Fig. 2h), almost entirely attributable to total sugar (**Fig. A2**d). Sweeteners, Other shows a U-shaped profile, declining to −0.18 in Deciles 7 (Fig. 2h), almost entirely explained by total sugar (**Fig. A2**d). Cocoa Beans and products and Butter, Ghee are penalized primarily for saturated fat (**Fig. A2**d). Milk - Excluding Butter, despite providing substantial calcium and potassium, records a negative $NRF_{9.3}$ index due to high saturated fat and total sugar (**Fig. A2**d).

Overall, higher-income households improve dietary quality through increased purchase of micronutrient-dense plant foods. By contrast, middle-income groups face the strongest penalties from sugar, sweeteners, and saturated-fat-rich foods, offsetting the modest benefits derived from cereals and vegetables. This pattern reinforces the earlier finding of an energy-nutrient mismatch, whereby energy purchases peak in the middle of the distribution, but nutrient-rich scores fail to rise proportionately.

3.2. Global warming potential of UK diet

Fig. 3 shows the breakdown of GWP and dietary GWP intensity by income decile and by food item. The top ten food categories (primarily meat, dairy, beer, and cereals) account for 87–89% of total dietary GWP, indicating that the dietary GWP is highly concentrated in a limited number of high-emission foods.

The middle-to-high income groups (Deciles 6–8) generated the highest GWP, mainly due to the purchase of Bovine Meat, Milk (excluding butter), Mutton & Goat Meat, and Pigmeat, with Bovine Meat alone accounting for over 3400 $kgCO_2e$ in Decile 8 (33.6% of Decile 8's total GWP) (Fig. 3a). Interestingly, high-income groups (Deciles 9–10) exhibited slightly lower total GWP compared to these middle groups, despite similar or even greater food purchase volumes (**Fig. A4**a). This decline is likely attributable to a spending shift away from the highest-GWP food items and toward nutrient-dense, lower-carbon choices, such as Vegetables, fruit, nuts, pulses, spices (**Fig. A4**b), which is reflected in their improving $NRF_{9.3}$ scores. Among the 13 common groups, Vegetables, fruit, nuts, pulses, spices was the most purchased category across all income groups (rising from 23.9% in Decile 4 to 30.9% in Decile 10). Also, low-income groups (Deciles 1–3) had huge dietary GWP, driven by Bovine Meat (2700–2900 $kgCO_2e$), Milk (excluding butter) (1400–1600 $kgCO_2e$), and Mutton & Goat Meat (1000–1200 $kgCO_2e$). The contribution of the top ten food categories reaches nearly 89% in these groups, the highest across the income distribution, indicating a strong concentration of GWP in a few carbon-intensive items. By contrast, foods such as beer, butter, pigmeat, and poultry, which expand significantly in middle- and higher-income diets, play a much smaller role among low-income households. This pattern suggests that while overall dietary diversity is limited, the reliance on high-emission staples such as beef and milk means that the total GWP of low-income groups is not markedly lower than that of middle-income groups.

Notably, Bovine Meat consistently remained the top contributor, responsible for around 32% of total GWP, indicating widespread reliance on carbon-intensive meat, regardless of income (Fig. 3a). This pattern is further confirmed by the ranking analysis (**Fig. A3**). The relative ranking of major high-emission foods remains highly stable across income deciles, suggesting strong structural persistence in dietary emission patterns. Even low-income groups (e.g., Deciles 1–3) were responsible for 2720.6 $kgCO_2e$ due to purchase of Bovine Meat (32.4%, 30.9%, and 31.2% of total GWP for Deciles 1–3), underscoring that high-emission food choices are not limited to affluent groups. It indicates that high-carbon food purchase, especially beef, was widespread across all income levels, regardless of economic status.

3.3. Environmental impact drivers of food choices

Fig. 4 shows two decomposition analyses for GWP and dietary GWP intensity. Although both analyses identified total food spending as a key driver.

In the full decomposition of GWP (Fig. 4), total spending is consistently the dominant positive driver across all income groups. Rising incomes increase food expenditure, which directly drives emissions. Some of the largest increases due to changes in spending were observed in Decile 2 (+794.2 $ktCO_2e$), Decile 6 (+905.0 $ktCO_2e$) and Decile 10 (+1723.6 $ktCO_2e$). This indicates that although higher-income groups showed some dietary improvements, the expansion of overall spending remained the primary driver of emission growth.

At the same time, energy density contributed negatively across all income groups, indicating a systematic decline in dietary energy purchased per unit of food expenditure as incomes rise. Although total energy purchases increase from low- to middle-income groups (Fig. 1), energy rise more slowly than food spending, leading to lower energy purchased per unit of expenditure. This mitigating effect becomes strongest at the top of the income distribution, with the largest contribution observed in Decile 10 (−1058.7 $ktCO_2e$), reflecting a shift among wealthier households toward higher-value, lower-carbon foods per unit of energy (such as seafood and certain vegetables), partially offsetting the impact of expenditure growth. This carbon efficiency gain is mirrored by a positive contribution from the nutrition level effect, signaling a simultaneous rise in overall nutritional quality (higher $NRF_{9.3}$). This concurrent reduction in caloric carbon intensity and improvement in nutritional quality validates the high-income groups' transition and demonstrates how they effectively escape the middle-income dietary trap.

For middle-income groups (Deciles 4–8), the decomposition reveals a

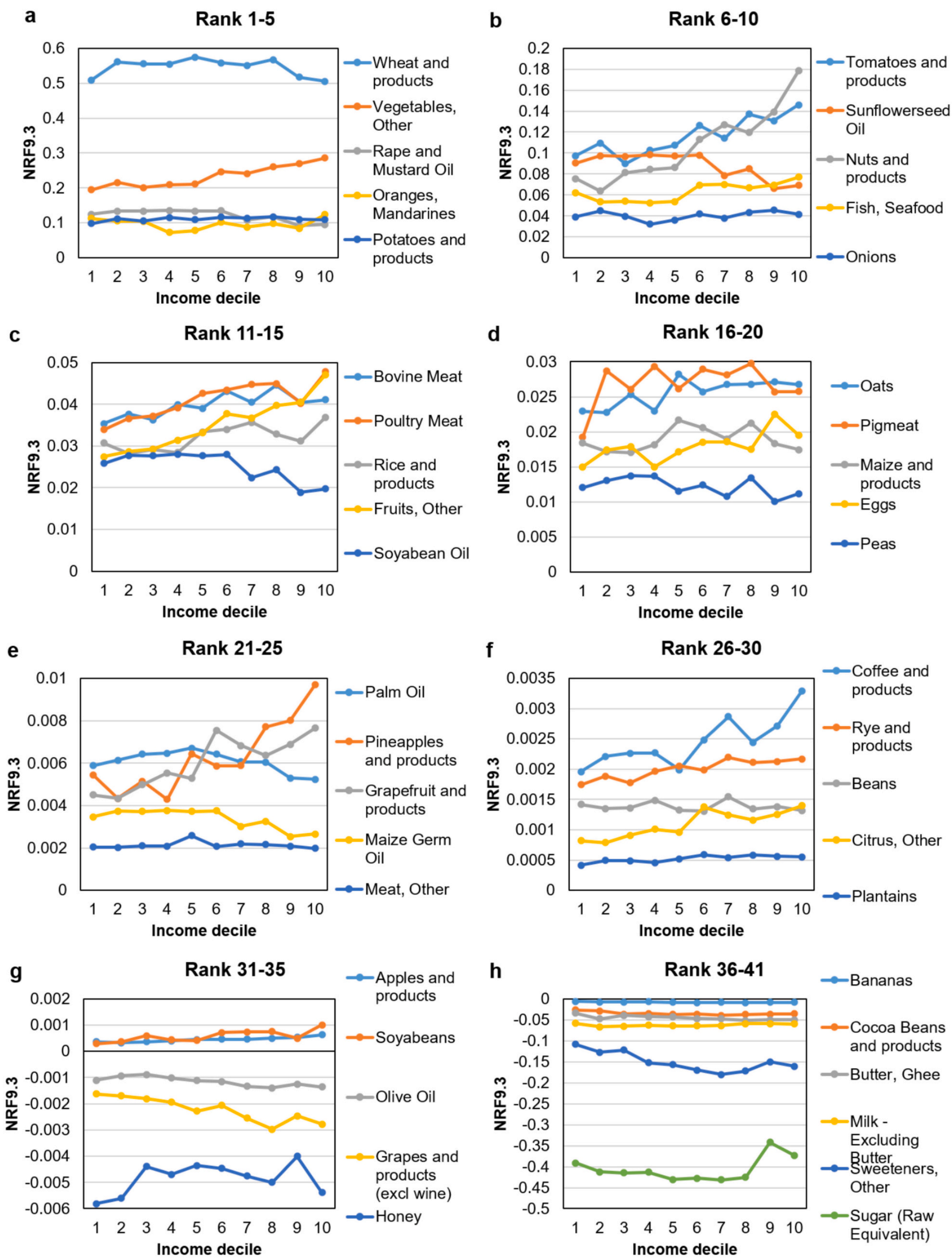

Fig. 2. Nutrient Rich Food ($NRF_{9.3}$) index of each food item by deciles of income. **a,** $NRF_{9.3}$ ranked 1–5. **b,** $NRF_{9.3}$ ranked 6–10. **c,** $NRF_{9.3}$ ranked 11–15. **d,** $NRF_{9.3}$ ranked 16–20. **e,** $NRF_{9.3}$ ranked 21–25. **f,** $NRF_{9.3}$ ranked 26–30. **g,** $NRF_{9.3}$ ranked 31–35. **h,** $NRF_{9.3}$ ranked 36–41.

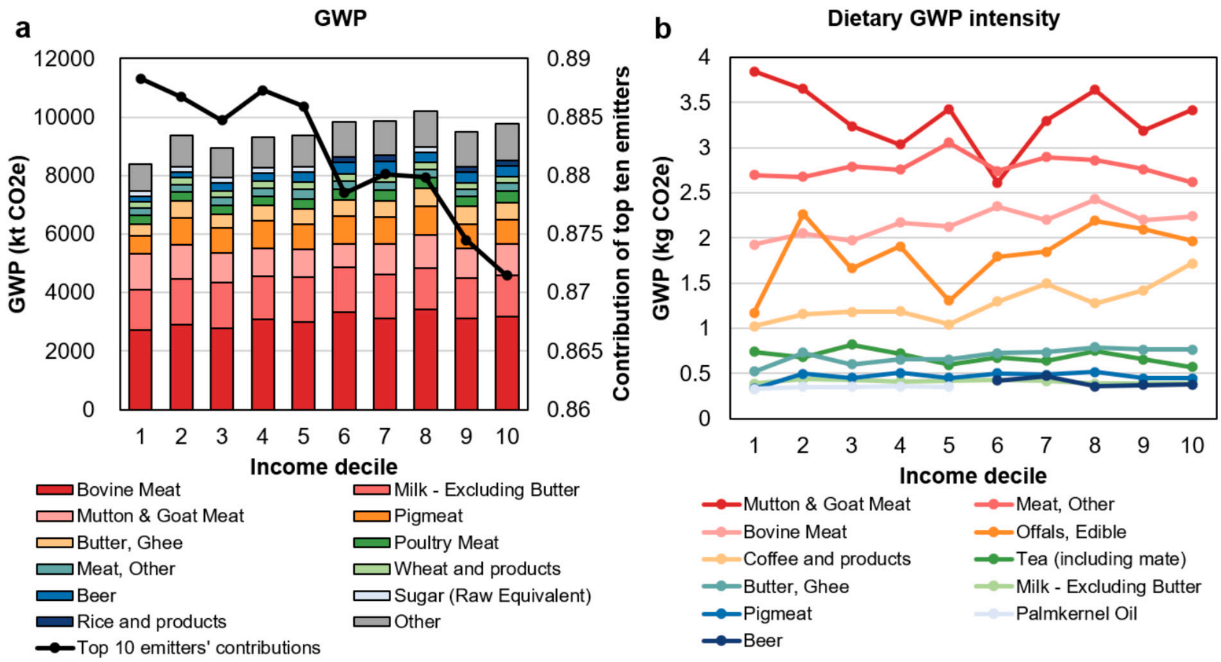

Fig. 3. Global warming potential (GWP) and their composition by food group for deciles of income in 2013. **a,** GWP. The bars show the GWP (left axis) of the top 10 emitting foods for each income decile, combining the rest of food items as "Other". The line represents the relative contribution (right axis) of the combined GWP of the top 10 food items with the largest GWP contributions. **b,** Dietary GWP intensity.

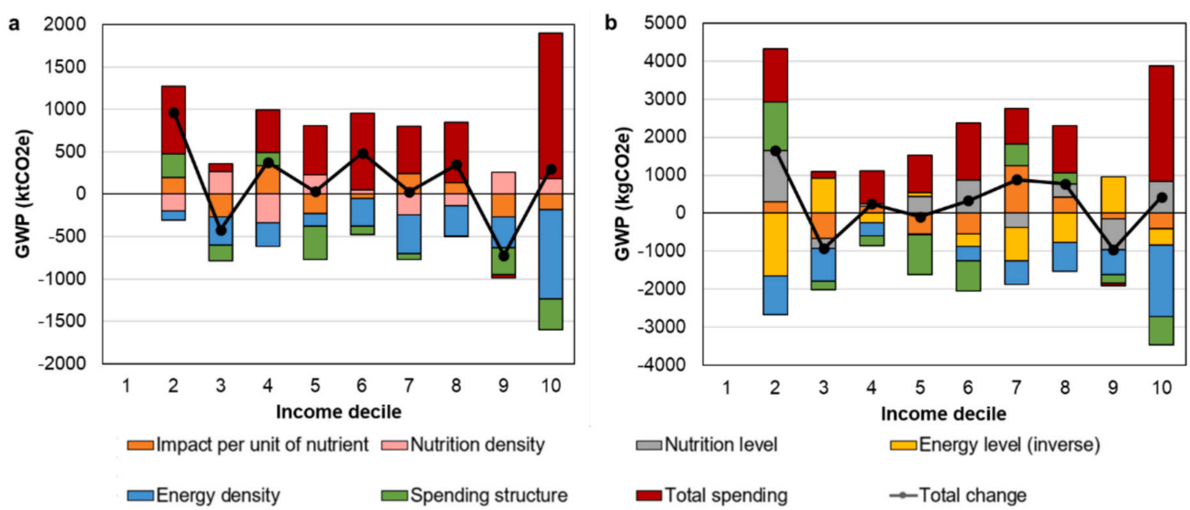

Fig. 4. Decomposition results of differences between income groups in 2013. **a,** GWP. **b,** Dietary GWP intensity. Notes: In panel (a), total GWP is decomposed into five factors: impact per unit of nutrient, nutrition density, energy density, spending structure, and total spending. In panel (b), dietary GWP intensity is decomposed into six factors: impact per unit of nutrient, nutrition level, inversed energy level, energy density, spending structure, and total spending.

more complex pattern of expansion and mitigation. In Deciles 4, 6, and 8, total spending contributed strongly to higher emissions (+499.1, +905.0, and + 713.8 ktCO_2e, respectively). Although declines in energy density produced negative contributions (−281.4, −324.3, and − 358.0 ktCO_2e, respectively), these improvements were insufficient to offset the expansion in spending, leading to net increases (+377.4, +484.8, and + 348.1 ktCO_2e). By contrast, Deciles 5 and 7 showed relative stabilization. Despite continued growth in total spending (+578.4 and + 555.7 ktCO_2e), negative contributions from energy density (−142.6 and − 455.2 ktCO_2e) and spending structure (−400.2 and − 74.7 ktCO_2e) nearly balanced the changes, resulting in minimal net effects (+34.2 and + 27.5 ktCO_2e). Overall, energy intensity declined across middle-income groups, but the improvements were limited and volatile, insufficient to counteract rising expenditure pressures.

In this study, nutrition density is defined as the ratio of total nutrient content to caloric intake (nutrients per kilocalorie), while GWP per nutrient represents greenhouse gas emissions per unit of nutritional intake. The decomposition highlights a striking see-saw pattern between these two indicators: when nutrition density contributed positively, GWP per nutrient was often negative, and vice versa. For instance, in Decile 2, nutrition density contributed −199.9 ktCO_2e, while GWP per nutrient was +198.4 ktCO_2e; in Decile 3, the signs reversed (+270.4 and − 270.0 ktCO_2e, respectively). This divergence was evident across almost all income levels, underscoring a structural misalignment between nutritional improvements and environmental costs: the foods that enhance nutritional quality do not necessarily lower carbon intensity and may instead carry additional emission burdens.

In the dietary GWP intensity analysis (Fig. 4b), total spending again remained the dominant positive driver, with sharp increases in Deciles 2 (+1404.0 $kgCO_2e$), 6 (+1502.6 $kgCO_2e$), and 10 (+3047.3 $kgCO_2e$). This suggests that higher expenditure did not automatically translate into improved carbon efficiency; if dietary structures remained unchanged, additional spending could actually worsen emissions per unit of energy consumed. By contrast, inverse energy levels and energy density effects were largely negative (e.g., −1884.5 $kgCO_2e$ between Deciles 9 and 10), reflecting that higher-income groups tended to maintain caloric sufficiency while shifting toward lower-calorie, lower-emission foods such as fruits, vegetables, and seafood, thereby reducing GWP per unit of energy.

Notably, nutrition level contributed positively to dietary GWP intensity in most income groups. For example, between Deciles 1 and 2 the effect was +1354.4 $kgCO_2e$, suggesting that nutritional improvements often relied on foods with higher carbon intensity per unit of energy. This finding highlights a fundamental tension: improvements in dietary quality do not necessarily yield environmental benefits and may instead increase climate pressures, complicating the design of dietary transitions that are simultaneously health-promoting and climate-friendly.

4. Discussion

4.1. Middle-income dietary trap and high-income escape

Results indicate a gradual improvement in dietary quality along the income distribution, but nutritional gains lag behind increases in energy purchase. High-GWP foods such as bovine meat, butter, and sugar, have negative $NRF_{9.3}$ scores, while nutrient-dense foods such as vegetables, fruits, and seafood, show positive $NRF_{9.3}$ scores but low GWP contributions. This reveals a structural pattern consistent with previous studies (Clark et al., 2019; Scarborough et al., 2014): carbon-intensive foods provide limited nutritional value, whereas nutrient-rich foods are generally low in emissions.

This dual burden of high carbon and low nutrient is most pronounced among middle-income groups (especially Deciles 5–6), where food purchases reach their highest energy levels while $NRF_{9.3}$ remain moderate. Micronutrient gains (including vitamin C, protein, and magnesium) coincided with higher sugar and saturated fat intake, reinforcing a carbon-intensive and nutritionally imbalanced diet. We characterize this pattern as a "middle-income dietary trap": a transitional stage where rising food expenditure and calorie purchase precede nutritional improvements. During this stage, dietary expansion is largely driven by foods such as pigmeat, bovine meat, sugars, and vegetable oils.

High-income groups (Deciles 9–10) exhibit a different trajectory: $NRF_{9.3}$ continues to rise, while GWP slightly declines despite higher expenditure, reflecting a shift from caloric sufficiency toward a nutrient-dense and lower-carbon food basket. Beyond a certain income threshold, households shift from caloric sufficiency toward diet quality and diversity, consistent with evidence on income-related dietary diversification (Springmann et al., 2016; Drewnowski, 2010).

Among low-income groups, $NRF_{9.3}$ remains modest while GWP is relatively high, mainly due to limited dietary diversity and reliance on a narrow set of carbon-intensive foods. This pattern reflects affordability and access constraints that limit shifts toward healthier, lower-carbon diets (Berkman et al., 2011; Larson et al., 2009; Adam and Epel, 2007; Drewnowski and Specter, 2004).

These findings are consistent with evidence on socio-economic gradients in UK dietary pattern: high-income groups consume more fruits, vegetables and fish, while low-income groups rely more on energy-dense, nutrient-poor foods (Maguire and Monsivais, 2015). Healthier diets are often more costly, creating barriers for lower socio-economic groups (Tong et al., 2018). Existing research largely focuses on low-income disadvantages, including food affordability, limited access to healthy foods, and nutritional inequalities (Penne and Goedemé, 2021; Darmon and Drewnowski, 2015; Evans et al., 2015), with less attention to how dietary patterns evolve beyond the low–high income dichotomy. Recent evidence further shows that nutritious, low-emission, and affordable diets remain unevenly distributed across socio-economic groups (Aceves-Martins et al., 2023; Reynolds et al., 2019b), and that mitigation pathways can diverge (Carr et al., 2025). At a broader level, this is consistent with evidence that rising incomes can initially increase consumption of fats, sugars, and animal-based foods, while improvements in diet quality tend to lag behind (Deng et al., 2025; Herrero et al., 2023; Ambikapathi et al., 2022; Clark et al., 2019; Willett et al., 2019; Popkin, 2001). Together, these findings suggest that dietary improvement does not progress linearly with income.

Despite growing recognition of non-linear dietary transitions, the middle-income stage remains underexplored. Our results show that dietary emissions peak among middle-income groups, consistent with evidence from China that animal-based food consumption rises rapidly at this stage and increases carbon emissions (Pang et al., 2024). This suggests that rising income first expands demand for carbon-intensive foods, while diet-quality improvements lag behind, making the middle-income stage a critical policy window.

Overall, dietary transitions reflect interactions between nutrition, environmental impact, and expenditure, echoing the FAO and WHO framework for sustainable healthy diets, which emphasizes adequate nutrition, environmental sustainability, and affordability (WHO, 2019). However, these dimensions do not improve simultaneously across income groups, with middle-income groups facing the most pronounced dual burden.

Beyond these income-specific dynamics, two consistent food-level patterns stand out. First, bovine meat remains the largest GWP contributor, indicating that reducing beef consumption is a broadly relevant mitigation strategy. The higher GWP multiplier of imported beef compared with domestic beef (35.7 vs. 21.2 $ktCO_2e/kt$; based on Eq. 6) further highlights the importance of supply-chain origins. Second, foods such as vegetables, fruits, and seafood, simultaneously combine higher $NRF_{9.3}$ with lower GWP, suggesting a pathway for achieving nutritional and climate co-benefits through shifts toward nutrient-dense, lower-carbon foods (Springmann et al., 2018; Tilman and Clark, 2014).

4.2. Mechanisms of nutrition-carbon double burden

Middle-income groups represent a critical stage of dietary transition, where rising food expenditure dominates emission changes, whereas dietary structural improvements remain insufficient to offset the associated emission increase. Decomposition results reveal the essence of "middle-income dietary trap" as an imbalance between consumption expansion and dietary upgrading: although energy density declines slightly, indicating early signs of improvement, rising food consumption still drives higher emissions. Near-zero net emission changes in Deciles 5 and 7 suggest an approaching turning point, where structural changes begin to counterbalance expenditure-driven emission growth. Thus, the middle-income stage is not only where dietary emissions are highest, but also a sensitive transition window for steering diets toward healthier and lower-carbon patterns.

By contrast, high-income groups provide a reference for this turning point. In Deciles 9–10, GWP stabilizes or declines despite higher expenditure, mainly due to lower energy density and greater consumption of nutrient-dense foods. This suggests that, once budget constraints are relaxed, dietary patterns can shift toward low-carbon and nutrient-rich foods that offset expenditure-driven emission growth. Therefore, the issue at the middle-income stage is not the absence of structural change, but that its effect has not yet become dominant.

This mechanism can be further understood as structural adjustment under constraints. Dietary choices are not fully optimized, but shaped by budget constraints and existing consumption patterns. For low-income groups, achieving nutrition and emission targets within current budgets is technically feasible but requires drastic deviations from existing diets, creating a high adjustment burden rather than simply a direct cost barrier (Reynolds et al., 2019b). At the middle-income stage, budget constraints are less binding, but dietary patterns are still influenced by habit and preference (Webb and Byrd-Bredbenner, 2015). As a result, additional spending tends to shift toward carbon-intensive foods such as meat and fats, leading to a pathway in which consumption expands while structural upgrading lags behind.

Therefore, the key issue at the middle-income stage lies in how they shape heterogeneous transition pathways within existing consumption structures. Béné (2022) suggests that profit-driven marginal substitutions within the existing food system may crowd out more meaningful systemic transformation. Carr et al. (2025) further show that meat-reduction pathways can diverge, with plant-based shifts generating stronger co-benefits than meat-to-dairy substitutions. This suggests that dietary transitions do not inherently converge toward optimal outcomes. Under existing constraints, substitution pathways can diverge, leading to systematically different nutritional and environmental consequences.

A further synthesis of the decomposition results identifies two key mechanisms that persist across income groups (**Appendix S9**). First, food expenditure and energy density exert opposite effects: higher spending generally increases dietary emissions, whereas lower energy density reduces them. Second, there is a dynamic tension between nutrient density and the carbon intensity of nutrients. When additional nutrients come mainly from carbon-intensive foods, improvements in diet quality do not lead to lower emissions and may even increase them. Thus, health and environmental goals are not inherently aligned.

Overall, the shift from expenditure-driven to structure-driven effects reflects a non-linear income–emissions relationship, consistent with the EKC hypothesis (Dinda, 2004). At the middle-income stage, rising expenditure drives emission growth. At higher income levels, stronger dietary structural change begins to offset this effect, leading emissions to stabilize or decline.

Within this framework, current interventions that focus on population averages or low-income groups may overlook the middle-income stage, where emissions are highest and delayed dietary upgrading is most pronounced. This indicates a misalignment between policy design and the drivers of dietary emissions, particularly the gap between rising expenditure and delayed dietary upgrading that existing approaches often fail to address. Middle-income households face less binding budget constraints than low-income groups, but are more likely to follow inefficient substitution pathways. The policy goal should therefore not be limited to reducing high-carbon foods, but should guide substitution toward structural upgrading so that dietary change can offset emission growth earlier in the transition.

Policy design should therefore move from an average-optimal approach to a stage-specific approach. Interventions need to reflect the dominant constraints at each income level, with middle-income groups treated as a key policy window. A detailed discussion of policy pathways and their potential impacts is provided in **Appendix S10**.

4.3. Limitations and future research

(1) This study uses household food purchase rather than actual dietary intake, which may bias estimates of nutritional quality. Unmeasured food waste may overestimate nutrients-to-encourage and underestimate nutrients-to-limit. Cross-income differences in waste may also affect GWP comparisons, particularly because higher waste among high-income groups could narrow their observed GWP gap with middle-income groups.

(2) Out-of-home foods are excluded because their composition and portion sizes cannot be reliably standardized to FABIO categories. Although FABIO reflects total domestic supply, our analysis relies on household purchases, which may underestimate diet-related emissions and bias income-group comparisons if out-of-home consumption varies systematically across income groups.

(3) Although widely validated, the $NRF_{9.3}$ index captures a limited set of nutrients and does not account for nutrient interactions, bioavailability, or many other micronutrients. Uniform NRVs may also obscure differences by age, gender, and health status. In addition, total sugar is used as a proxy for added sugar, and such substitution modestly reduced the explanatory power of $NRF_{9.3}$ (Fulgoni et al., 2009). Finally, sodium intake may be underestimated, as nutrient values are derived at the commodity level rather than from typically salt-rich composite foods.

(4) FABIO provides national-average CO_2e intensities, which do not capture sub-national variation in production practices, technologies, or supply chain characteristics. EEIO framework assumes fixed production structures and average input shares, potentially overlooking recent changes or non-linear responses to policy and market shifts. Emissions are also measured on a farm-to-gate basis and exclude downstream processes such as transportation.

(5) LMDI approach assumes additive and independent effects, potentially oversimplifying interactions between expenditure, dietary structure, and nutrition. Although normalization to a 2000 kcal baseline improves comparability, it does not reflect differences in actual energy needs or consumption.

(6) Per-capita dietary consumption is calculated without adult-equivalent scaling. Although income groups are defined using equivalised income, age- and sex-specific dietary requirements are not explicitly captured, which may bias comparisons across income groups, especially those with different household compositions.

(7) This study focuses solely on carbon emissions, without incorporating other environmental indicators. A broader multi-impact assessment would offer a more holistic understanding of the environmental trade-offs of dietary transitions.

Future research should address these limitations by incorporating out-of-home consumption and food waste, expanding the analysis to multiple environmental indicators, and further integrating supply-chain perspectives to trace how dietary demand translates into emissions across production systems and regions. Longitudinal analysis is also needed to examine the dynamic evolution of dietary patterns over time. In addition, future studies should give greater attention to heterogeneous substitution pathways and broader socio-economic differences beyond income, including age, gender, education, and urban–rural characteristics.

5. Conclusions

This study investigates the intricate relationships between income gradient, dietary quality, and greenhouse gas emissions in UK, using micro-level data from the 2013 LCFS. By combining $NRF_{9.3}$ and GWP from the FABIO database, and applying the LMDI decomposition method, we provide a detailed assessment of nutrition-carbon trade-offs across income deciles.

Our findings reveal marked heterogeneity across income groups in both nutritional quality and dietary carbon emissions, establishing a non-linear income-emission relationship consistent with the EKC hypothesis. Middle-income households appear locked in a “middle-income dietary trap”, where rising food purchases are dominated by carbon-intensive and nutrient-poor items, leading to peak calorie intake, high GWP, and lagging nutritional improvements. This phase is driven by an imbalance between consumption expansion and delayed structural upgrading. In contrast, higher-income households demonstrate a more favorable trajectory, with improvements in diet quality accompanied by stable or slightly lower emissions, reflecting a co-beneficial shift toward nutrient-dense, low-carbon foods. This LMDI dynamic trade-off enables the escape from the dual burden. These findings highlight the critical need to concurrently address dietary quantity and composition to achieve a sustainable food system.

Policy frameworks should move beyond population-average approaches and adopt a stage-specific perspective. Current interventions overlook the middle-income stage, where dietary emissions are highest due to the imbalance between expenditure expansion and delayed structural upgrading. At this stage, the priority is not reducing consumption per se, but steering substitution away from carbon-intensive, low-nutrient foods toward nutrient-dense, lower-carbon alternatives. Accelerating this structural transition earlier, rather than relying on income growth alone, is key to aligning nutrition and climate objectives. The policy implications and potential applications of these findings are provided in **Appendix S10**.

Declaration of generative AI use

During the preparation of this work the authors used ChatGPT5 in order to improving language and readability. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Yunhuan Gao: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Pablo Piñero:** Writing – review & editing, Resources, Formal analysis, Data curation. **Eduardo Aguilera:** Writing – review & editing, Resources, Formal analysis, Data curation. **Martin Bruckner:** Writing – review & editing, Resources, Formal analysis, Data curation. **Alberto Sanz Cobeña:** Writing – review & editing, Resources, Formal analysis, Data curation. **He He:** Conceptualization. **Christian Reynolds:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Conceptualization.

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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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2026.109143.

Data availability

Data will be made available on request.

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