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Pathways for the US food processing sector under economy-wide net zero in a multisector dynamic framework

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ABSTRACT

The food processing sector is a large, energy-consuming and CO_2-emitting industrial sector. The sector was estimated to account for 6 % of US industrial CO_2 emissions in 2020. The sector uses significant amounts of fossil fuels, biomass, and electricity to perform a range of operations such as baking, drying, and refrigeration. Additionally, the sector is tightly linked to the agriculture and land use sectors. In this analysis, we use the Global Change Analysis Model (GCAM), a coupled, energy-economy-agriculture-land-use-water-climate systems model, to examine the role of the food processing sector in the EMF37 2050 US net-zero CO_2 scenario. We explore the implications for technology and fuel choice and go beyond to examine US food consumption, food prices, and land-use change. To better understand the sensitivity of our results to alternative developments, we assess multiple sensitivity scenarios for the US and other world regions, with a focus on varied food processing energy intensity pathways.

We find that along the EMF37 US net-zero path, the food processing sector electrifies the majority of its process heat. We also find that the industry phases-down natural gas use and completely phases-out coal. Additionally, we observe a marginal decrease in US food consumption per capita relative to our reference scenario. This primarily occurs due to the increase in consumer food prices resulting from increased demand for purpose-grown biomass crops, which compete with food crops for land resources. Finally, cumulative energy savings of 4.2 EJ are achieved from 2020 to 2050 in a scenario in which the US reduces its food processing intensity to EU-15 levels.

1. Introduction

The food processing sector plays a unique role in bridging the energy and agri-food sectors. It transforms raw or primary agricultural materials into processed consumer-ready products, augmenting the value of the agri-food supply chain and constituting a significant proportion of the total food cost [1,2]. The value of shipments from the food processing sector was about $983 billion in the United States (US) in 2020, highest among the US manufacturing industries [3]. Although the energy consumption per dollar value of food products tends to be low when compared to other manufacturing sectors, food processing is a large source of manufacturing energy demand in several regions in absolute terms, with considerable growth potential.

In the US, the food processing sector has consistently been the fourth largest energy-consuming industry since the early 2000s, demanding close to 1.25 EJ of final energy annually [4,5]. The sector was directly responsible for 6 % of the total US industrial CO_2 emissions in 2020 and accounted for 1 % of the total global greenhouse gas emissions (GHG) in 2010 [6-8]. The sector employed a total of 1.7 million workers in 2021, across 41,080 food processing plants scattered across the country, with most plants located in California (6301), Texas (2782), and New York (2662) [9]. Understanding the energy consumption in the food processing sector and its associated costs is crucial for establishing a comprehensive assessment of emissions linked to the food system and for evaluating the price transmission from energy to food systems. In this study, we aim to explore the role of the food processing sector and its energy-economy-agriculture-land-use-water-climate linkage in deep decarbonization pathways. Our study contributes to the Energy Modeling Forum (EMF) 37 [10], initiated to enhance the understanding of the role of electrification in key economic sectors, e.g., transportation, buildings, and industry, in achieving net zero US CO_2 emissions by the year 2050.

The food processing sector is heterogeneous in its processes and outputs, producing products ranging from dairy products and canned

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fruits to baked goods and prepared meals [11,12]. Energy use in food processing is predominantly driven by process heating, primarily low temperature heat, e.g., for boilers, direct heating, and drying, often sourced from coal, natural gas, or biomass [13]. Most electricity use is for cooling and refrigeration as well as machine driven processes and mechanical equipment [14]. Processes within the sector vary widely depending on the food and desired final product, but can include drying, pasteurization, baking, melting, cooling or chilling, freezing, extraction, filtration, fermentation, size reduction processes, mixing, peeling, washing, and packaging [11,12].

A range of historical studies have reviewed the mitigation strategies and technologies to decarbonize the food processing sector [15–17], identifying primary emissions reduction strategies of energy efficiency improvements, heat recovery [18–20], use of combined heat and power systems [21], electrification of heat [15,22,23], and fuel switching to renewables (particularly solar thermal heating systems) [24]. However, limited studies have assessed and quantified the deep decarbonization pathways for this sector globally or in the US [25–29]. Zuberi et al. conducted a bottom-up analysis to estimate the energy savings from electrifying the US food industry [28]; Worrell et al. aggregately assessed the US industrial sector decarbonization pathways, briefly addressing the role of food processing [25]; and Gowreesunkar et al. (2018) examined decarbonization pathways for the food industry in the UK [27]. No study to date has comprehensively assessed the food processing sector's deep decarbonization pathways for the US or at a global level using a comprehensive multi-sector dynamics (MSD) framework. Notably, as highlighted by the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) [30], the food processing sector is among the least represented sectors in global and national MSD models.

In this study, we fill this gap by enhancing the Global Change Analysis Model (GCAM) [31], a widely used and open-source research tool that couples energy-economy-agriculture-land-use-water-climate systems, to explicitly represent the food processing sector and refine its connection to the agri-food sector. Our primary objective is to examine the role of the food processing sector in achieving net zero CO_2 emissions in the US by 2050. We also briefly assess the global food processing sector pathways to provide comparison across regions, construct sensitivity scenarios, and evaluate the scale of decarbonization transitions globally for this sector. The key research questions of this study are as follows: (1) what scale of technological transitions may be required to decarbonize the US food processing industry to be consistent with a net zero future, (2) what would be the impact of these transitions on the sector's fuel usage patterns and total emissions, (3) will the net zero transitions impact the total US food demand, land allocation trends, and/or consumer food prices, and (4) how could increases in food processing energy intensity levels across the globe affect energy demands and net zero transitions.

Our research indicates that the US food processing sector will need to electrify the majority of its process heat to be consistent with the EMF37 US net-zero future, which would entail the installation of at least 16 GW of new industrial heat pump capacity by 2050. In a parallel manner, the industry would be required to substantially phase down the usage of fossil-based heating by mid-century. Furthermore, we find that the industry may face a significant increase in agriculture crop costs (+30 %) in the EMF37 US net-zero scenario, largely due to the increased land competition with bioenergy crops required for a net-zero 2050 transition. However, the increased agriculture crop costs may have a relatively less pronounced impact (+10 %) on the processed food prices, as other components of the costs for processed foods also play an important role. Finally, we find that implementing measures to gradually reduce the US food processing levels to match with that of EU-15 could reduce the sector's energy requirements by a quarter by 2050. Meanwhile, the potential increase in food processing levels across regions might raise the prominence of the food processing sector as an important mitigation sector globally.

2. Methodology

GCAM has been widely used in recent studies for exploring the implications of deep mitigation policies, in which agri-food sectors could be critical [32,33]. In this study, we improve the representation of the food processing sector in GCAM v7.0 to explore the key role of the sector in decarbonization pathways. GCAM v7.0, calibrated to a base year of 2015, is open-source, and the full documentation is available on the GCAM documentation page (http://jgcri.github.io/gcam-doc/) [34]. In this section, we document the new developments for representing the food processing sector.

2.1. GCAM food processing sector structure

Due to the diversity and complexity of the processes involved in the food processing sector, we structure GCAM's food processing sector around fuel usage (Fig. 1). However, to reflect the important division between process heating and other solely electricity-based processes and to prevent unrealistic fuel switching between them, we incorporate an intermediate subsector of "process heat food processing" (blue box in Fig. 1). This subsector includes all of the technology and fuel options for process heat production (green and yellow boxes). The overall food processing sector then takes in both process heat food processing and a direct input of electricity, with the latter representing all non-heating uses of electricity (red box).

For process heat generation, we include both conventional options–including biomass, coal, gas, district heat, and refined liquids-based technologies–as well as electricity-based technologies (including both a standard electricity technology, representing direct electrification of process heat, and an electric heat pump technology). As the food processing sector is one of the industrial sectors thought to have a relatively high potential for employing solar thermal energy, we also model two solar-equipped technologies: gas with solar and electricity with solar [36–39]. These are represented as technologies that combine a solar thermal system with another source of process heat, as solar thermal units are unlikely to supply all the necessary process heat demand (even when paired with storage) due to the diurnal and weather-dependent variation in solar radiation intensity [36,37].

We do not model any CCS-equipped or hydrogen-based technologies for food processing process heat generation in this study. The literature indicates that these technologies do not currently appear to be cost-competitive along decarbonization pathways in the food processing sector. They do, however, play a prominent role in other industrial sectors in GCAM and the economy in general along net-zero pathways. In the food processing sector the relatively lower energy demands (and resulting CO_2 emissions) on a per-facility or per-output basis make CCS investments costly, and the dominant low temperature heat demands are better satisfied by electrification or renewables rather than continued usage of fossil fuels with CCS or hydrogen [25,26].

The competition between process heat technologies for the future market share is determined by GCAM's modified logit discrete choice model (Eq. (1)) [31,40]. GCAM's modified logit model estimates the future market share (S_i) of food processing technologies based on several monetary and non-monetary inputs. Technology cost (c) is a key monetary input, which is determined by summing the exogenously specified non-energy costs ($/EJ), endogenously estimated fuel costs ($/EJ), and carbon prices endogenously determined as needed to satisfy the emissions constraint ($/t$CO_2$). The key non-monetary inputs include share weights (α, which parameterize the historical preferences and future growth potential for technologies in a region) and logit exponent (γ, which determines the extent to which relative technology cost changes may impact process switching).

$$S_i = \frac{\alpha_i c_i^{\gamma}}{\sum_{j=1}^{N} \alpha_j c_j^{\gamma}} \tag{1}$$

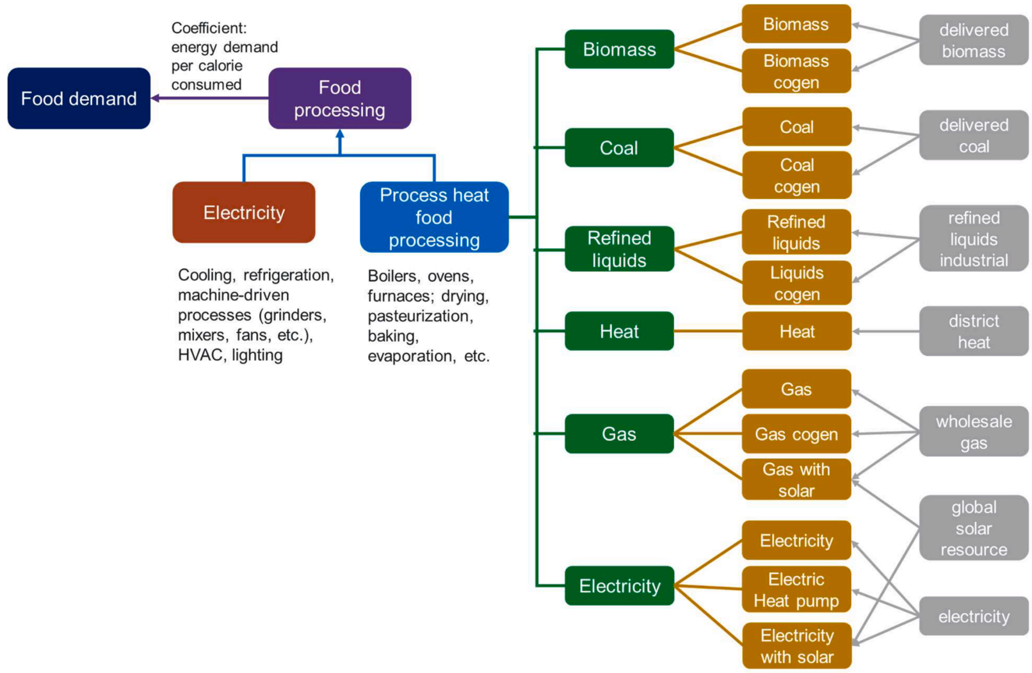

Fig. 1. The structure of the food processing sector in GCAM. The left side of the diagram indicates the division of energy demands into process heating and electricity; the right side shows the sources of process heat represented in the model. Combined heat and power technologies, also known as cogeneration technologies, are abbreviated as "cogen" in this figure. The food processing sector in GCAM represents all the activities listed under Divisions 10 to 12 of the International Standard Industrial Classification of All Economic Activities, which include the manufacture of food, beverage, and tobacco products [35].

Furthermore, the food processing sector is directly coupled to GCAM's food demand module and agriculture-land-use sector. The future food processing energy-service requirement for each region in each period is determined by multiplying the region's endogenously calculated food demand (Pcal) with its food processing energy intensity. Here, the food processing energy intensity (PJ/Pcal) is defined as a ratio between the total food processing energy-service demand (PJ) and the total food calories consumption in a region. These intensities are derived based on historical data (see Section 2.2) and depict the food processing energy-service requirement per calorie supplied. The future food demand (which, along with the energy intensity, drives the food processing energy-service demand) is determined using the Edmonds et al. (2017) modeling framework [41]. This framework estimates the demand for various GCAM crop commodities (staple and non-staples) at different levels of income (GDP per capita) and prices. The parameterization of this food demand framework along with the key input data is documented in the literature [42]. The detailed description of GCAM's food demand module and its linkages with GCAM's primary agriculture supply is available in the Supplementary Information (SI-1).

2.2. Input data, sources, and assumptions

The population and GDP pathways used in the model follow the updated SSP2 shared socioeconomic pathway projections (Fig. 2A) [43]. The technological assumptions, including energy efficiencies [36,37], technology lifetimes [44–47], and water withdrawal intensities [48,49], are obtained from a range of literature sources. The technology non-energy costs are obtained from Rismann (2022) [13] and Schoeneberger et al. (2020) [39]. The remaining food processing service costs are incorporated using the GTAP (Global Trade Analysis Project) database [50], so that the total food prices in GCAM represent the full cost along the supply chain.

The share weights for the conventional process heating technologies are endogenously calibrated at the 2015 levels within GCAM and are kept fixed at those values for future years. For emerging low-carbon options with minimal market presence in 2015, we linearly increase their share weights to 1 by 2050. This represents the gradual reduction of deployment barriers and increased cost-based competition with conventional technologies for future market share. All of these assumptions are tabulated and further elaborated in SI-2.

Furthermore, we calibrate the model in the base year using the food processing energy use data (Fig. 2C) from the International Energy Agency's (IEA) World Energy Balances (flow code: FOODPRO) [51]. This data is paired with calorie consumption by region, calculated within GCAM from the Food and Agriculture Organization (FAO) data (Fig. 2D) [52,53], and technological efficiencies, to estimate the historical coefficients of food processing energy-service demand per calorie consumed by region. The model uses these coefficients to set the scale of food processing energy-service requirements in the future.

For some regions, IEA data on food processing energy use is incomplete, leading to unrealistically low energy use coefficients. Thus, imputation of energy data is warranted for such regions to accurately calibrate the base-year coefficients. To perform this imputation, we fit a linear model between food processing energy use, calorie consumption of non-staples, and GDP for regions with sufficient IEA food processing energy use data. Our model fitted the data well (with an R^2 of 0.95) and generated reasonable predictions of imputed energy values for regions with limited data (Fig. 2E and S4). Further details on the linear model fitting are discussed in SI-3.

3. Experimental design

In this study, we explore four US-centric and two global scenarios which examine the food processing sector's technological transitions as well as changes in food demand, food prices, and land-use allocation across a set of reference and net zero (NZ) by 2050 pathways (Table 1). The reference scenarios are GCAM's SSP2 scenarios, which model a "Middle of the Road" future for the food processing sector and the broader economy. Meanwhile, the NZ by 2050 scenarios enforce a linear decrease in EIP (energy and industrial processes) CO_2 emissions to zero from 2020 to 2050 both in the US and globally (Fig. 2B and S5). GCAM includes an approach to value terrestrial carbon storage at a carbon price

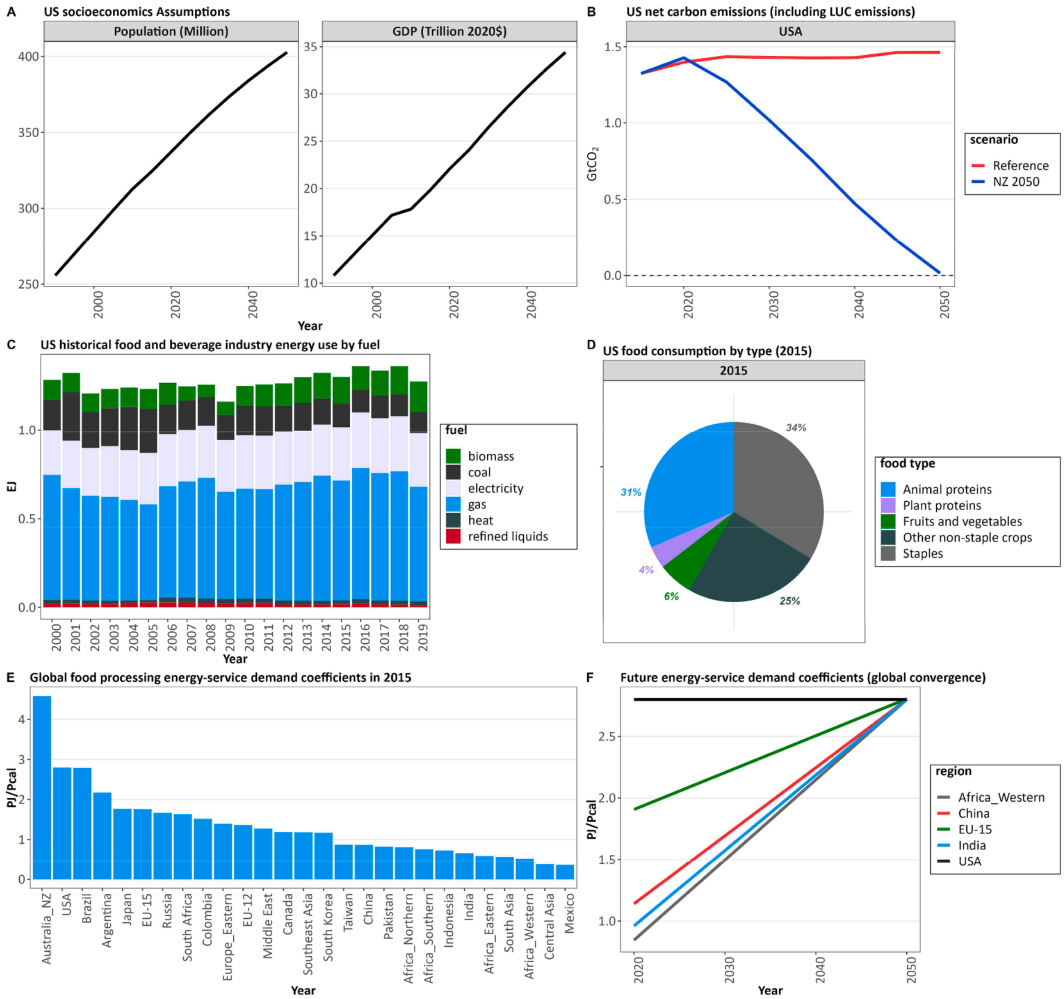

Fig. 2. GCAM modeling input assumptions: (A) US population and GDP assumptions for all scenarios, (B) US net CO_2 emissions (including land use change emissions) across scenarios, (C) US historical food industry energy use by fuel, (D) shares of US 2015 food calorie consumption by type, (E) 2015 food processing energy-service demand coefficients for all GCAM regions after imputation, and (F) future food processing energy-service demand coefficients for selected regions in the global convergence scenarios. Except for Australia and New Zealand, all GCAM region's energy-service demand coefficients are linearly increased to match with the 2015 US levels in the global convergence scenarios.

Table 1
Scenario design around US and non-US food processing sector energy intensity assumptions. The EU-15 region in GCAM includes the following countries: Andorra, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Greenland, Ireland, Italy, Luxembourg, Monaco, Netherlands, Portugal, Sweden, Spain, and the United Kingdom.

Scenario	Policy	US food processing energy intensity	All other countries' food processing energy intensities
Reference	–	Fixed at 2015 level across all future years	Fixed at 2015 levels
Reference (Food Processing Low)		Linear decrease to EU-15's 2015 level by 2050	Fixed at 2015 levels
Reference (Global Convergence)		Fixed at 2015 level	Converge to US 2015 level by 2050
NZ (net zero) 2050	U.S + global net zero CO_2 by 2050	Fixed at 2015 level	Fixed at 2015 levels
NZ 2050 (Food Processing Low)		Linear decrease to EU-15's 2015 level by 2050	Fixed at 2015 levels
NZ 2050 (Global Convergence)		Fixed at 2015 level	Converge to US 2015 level by 2050

that is linked to energy system carbon market [54]. Given food security and institutional concerns, mitigation efforts in the Agriculture, Forestry and Other Land Use (AFOLU) sectors are sluggish and uncertain. In this study, we assume that land carbon is priced at 20 % of energy system carbon prices, which are endogenously calculated to meet the emission constraints. In keeping with the EMF37 protocol, other GHG emissions (CH_4, N_2O, and F-gases etc.) are not directly taxed in these scenarios, but are modeled by GCAM and considered when evaluating climate outcomes such as temperature change.

The key distinguishing factor among the different reference and NZ by 2050 scenarios are their food processing energy intensity pathways. In the base "reference" and "NZ by 2050" scenario, the energy intensities are kept fixed at their 2015 levels across all future years (Fig. 2E). This assumes that the energy intensity in food processing will remain the same in the US and across other regions through 2050. These two scenarios are the primary scenarios in our analysis; the remaining scenarios serve as sensitivities and help evaluate the impact of varying future energy intensities on technological transitions, fuel usage, and emissions. In the "reference (food processing low)" and "NZ by 2050 (food processing low)" scenarios, we examine a future where the US food processing energy intensity linearly decreases to the EU-15 2015 levels by 2050. This implies a significantly more efficient future where the average food processing levels decrease in the US, resulting in a 38 %

reduction in the food processing energy-service requirement per unit calorie supplied by 2050. Lastly, in the "reference (global convergence)" and "NZ by 2050 (global convergence)" scenarios, we explore the impact of increased food processing levels globally. In these scenarios we linearly increase the energy intensities of all GCAM regions to match with the US 2015 levels by 2050 (Fig. 2F). As the energy intensity of food processing is tied to the degree to which foods are being consumed in highly processed versus minimally processed forms, this assumption reflects a case in which most regions elevate their level of processing of food products. The sensitivity scenarios described here are exploratory in nature, aiming to offer plausible alternative scenarios based on available information. Future work is needed to further investigate regional heterogeneity and test regional pathways.

4. Results

In the reference scenario, the US food demand increases from about 372 Pcal in 2015 to 480 Pcal in 2050 (Fig. 3A). Meanwhile, in the NZ 2050 scenario, the US food demand grows at a marginally slower rate and reaches 465 Pcal by 2050. This divergence in demand becomes more apparent when examined at a per capita basis. While the food consumption per capita per day increases from 3140 kcal/person in 2015 to 3265 kcal/person in 2050 in the reference scenario, it increases to a lower value of 3210 kcal/person in the NZ 2050 scenario (Fig. 3B). These lower food demand levels in the NZ 2050 scenario lead to 5 % less useful energy demanded by the US food processing sector in 2050 (Fig. 4A).

The lower food demand in the NZ 2050 scenario primarily occurs due to the rise in consumer food prices (Fig. 3D). While the consumer food price index grows by just 1 % by 2050 relative to 2015 in the reference scenario, it increases by 10 % in the NZ 2050 scenario. This increase in the consumer food prices is mainly driven by the rising costs of primary agricultural products, i.e., +5 % in reference compared to +40 % in NZ by 2050. In a rapidly decarbonizing future, the competition for land intensifies with the rise in bioenergy feedstock production and the higher demand for land carbon storage through afforestation. This competition for land drives up the prices of primary agricultural products. The cost of food processing energy also escalates due to higher carbon prices. However, the transmission of these price increases from primary agricultural products and food processing energy to food is mediated, as they constitute only a partial share of the overall cost along the supply chain (e.g., <10 % in the US).

In the NZ 2050 scenario, an additional 7.94 EJ of biomass is demanded by the US in 2050 to decarbonize the power sector through the use of bioenergy with carbon capture and storage (BECCS) and for producing biofuels in the refining sector. This increase in bioenergy use as a key decarbonization option leads to an increase in the demand for purpose-grown biomass, which directly competes with food crops for land allocation and increases the primary food prices. In our NZ 2050 scenario, we find that an additional 8 Mha of land is allocated to purpose-grown biomass by 2050 when compared to the reference. This largely comes at the expense of food crops and pasture, which lose 7.7 and 2.3 Mha of land in 2050, respectively (Fig. 3C).

In 2015, the US food industry's process heat requirements were largely met by natural gas (74 %), biomass (14 %), and coal (12 %) (Fig. 4A). This breakdown broadly remains unchanged in our reference scenario's future market share projections. Natural gas continues to remain the largest source of process heat by 2050, providing 0.61 EJ of useful heat. However, the use of conventional gas-based technologies slightly decreases to 0.46 EJ in 2050 due to the moderate increase in the uptake of gas cogeneration and hybrid solar thermal systems. Furthermore, coal-based technologies provide 0.145 EJ of process heat by 2050, which is 46 % higher than their 2015 levels. Similarly, the use of biomass-based technologies in the US food industry also increases, with these technologies providing 0.15 EJ of process heat by 2050 (compared to 0.1 EJ in 2015). There are minimal levels of electrification for process heating applications in the reference scenario.

In our NZ 2050 scenario, we observe a dramatic shift in the technology use and fuel consumption patterns by mid-century when compared to the reference scenario. In response to the increasing carbon price used to implement stringent emissions constraints of the NZ 2050 scenario, fossil-based process heat production declines notably. By 2050, we find that coal completely phases out as a fuel source for process heat production, while natural gas consumption decreases from 0.54 EJ in 2015 to 0.2 EJ in 2050 (Fig. 4B). Biomass-based technologies play an important role from 2025 to 2040, providing a source of low carbon fuel

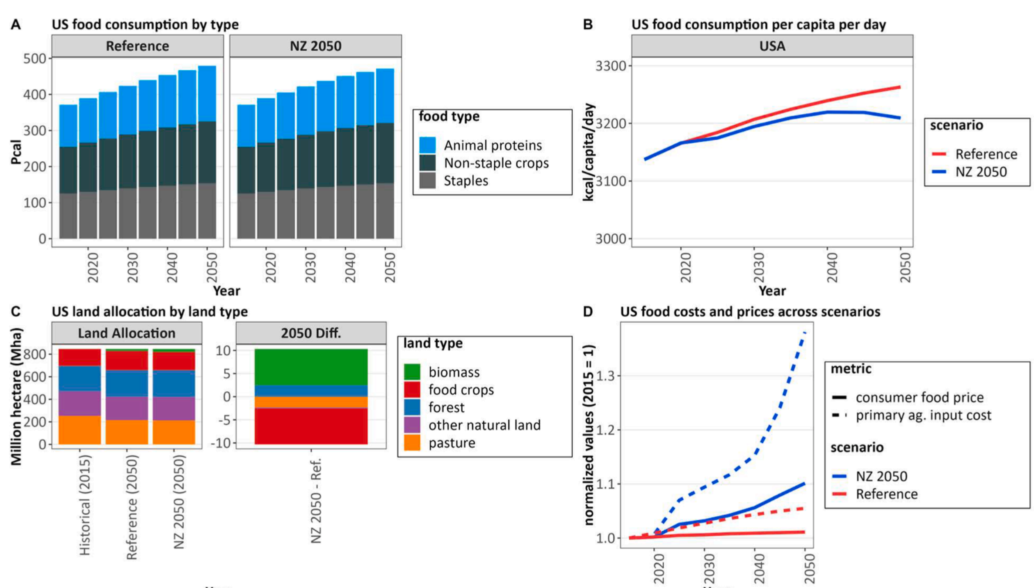

Fig. 3. Food consumption and land allocation in the US by 2050. (A) US food demand by type, (B) US food consumption per capita per day, (C) US land allocation by land type, and (D) US primary agricultural crop costs and consumer food prices across reference and NZ 2050 scenarios. The US consumer food prices illustrated in Fig. 3D (as solid lines) are a sum of total primary agricultural costs (shown as dashed lines) and food processing costs. Based on our calculations, the food processing costs accounted for 84 % of the total US consumer food price in 2015 (figure S6). The remaining costs were attributed to the primary agricultural products.

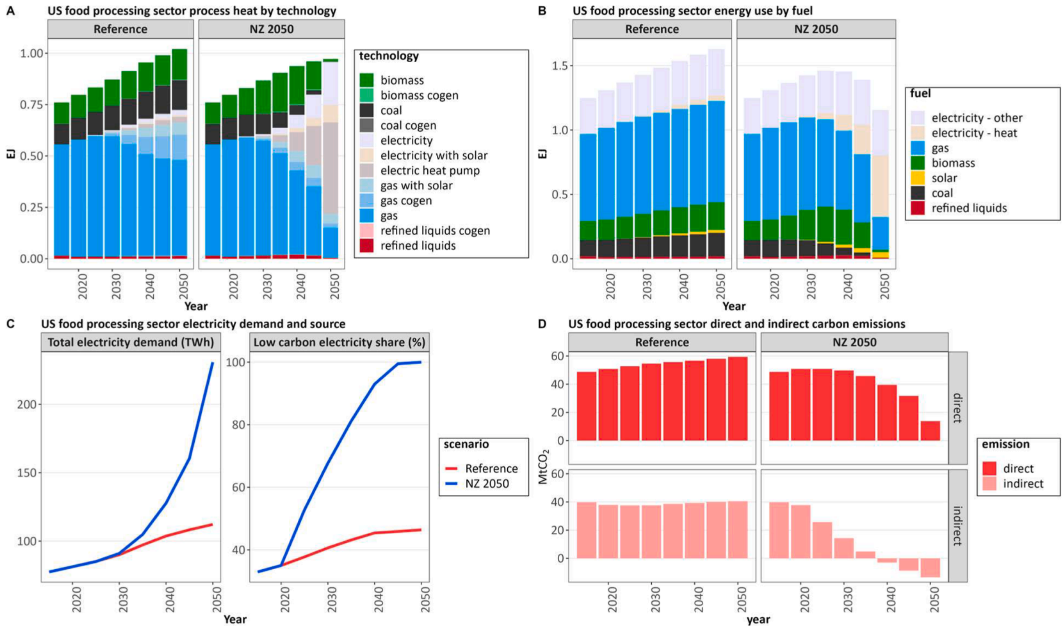

Fig. 4. Energy consumption and carbon emissions in the US food processing sector by 2050. Food processing sector (A) process heat production by technology, (B) energy use by fuel, (C) electricity demand and low carbon electricity share, and (D) direct and indirect carbon emissions across scenarios. In Fig. 4B the total electricity use in the sector is the sum of "electricity – heat" and "electricity – other". The former corresponds to the electricity consumed to provide process heat, whereas the latter corresponds to the electricity consumed for all other food industry applications. In Fig. 4D direct emissions correspond to scope 1 emissions from onsite fuel combustion in the food processing sector and indirect emissions correspond to scope 2 emissions associated with purchased electricity from the power sector. The indirect emissions consist of both combustion-based emissions and carbon sequestration associated with electricity generation. The information on electricity generation by technology and the breakdown of indirect emissions by source are illustrated in Figure S12 and Figure S14 respectively.

in the short- and medium- term and replacing the conventional fossil-based technologies as they gradually phase down. However, post-2040 biomass use for process heat in this sector drastically decreases, due to the increasingly favorable economics of electrification and the growing demand for biomass in the power sector and other industrial sectors where it is paired with CCS to provide carbon sequestration services.

By 2050 we find that electrification will be a key emissions reduction strategy for the US food processing sector, particularly through the increased usage of industrial heat pumps and direct electrification. In our NZ 2050 scenario, we observe high levels of process heat electrification by 2050. Seventy-six percent of process heat (or 0.74 EJ) is provided by electricity-based technologies in 2050, of which 60 % is provided by industrial heat pumps (16 GW) and 30 % by direct electrification processes. Hybrid solar thermal systems (i.e., direct electrification and/or gas-based technologies paired with solar thermal) play a smaller but crucial role, providing 15 % of total usable heat by 2050. While the electrification of process heat is gradual from 2020 to 2035, it ramps up from 2040 onwards as the rising carbon prices increase the cost competitiveness of electrification relative to conventional, fossil-based technologies (Figure S-13).

High levels of electrification in the US food processing sector allow for significant emissions reductions, especially when paired with upstream power system transitions. Overall, the total electricity demand for both process heat electrification and other applications reaches 230 TWh in 2050 (up from 77 TWh in 2015) in the NZ 2050 scenario, which is two times more than the corresponding projections in the reference scenario (Fig. 4C). By 2040, 100 % of the electricity used by the sector is sourced from low-carbon technologies. This leads to the drop in indirect CO_2 emissions (associated with the sector's offsite electricity consumption) from 40 $MtCO_2$ in 2015 to −13.4 $MtCO_2$ by mid-century (Fig. 4D). The negative indirect emissions resulting from the upstream power sector decarbonization allow the food processing sector to continue using some unabated natural gas through 2050. This results in some residual direct emissions (13.8 $MtCO_2$) from onsite fuel combustion, making the sector approach-though not quite achieve-net zero CO_2 by 2050.

Substantial energy savings can be achieved if the US were to reduce its average food processing levels to that of EU-15 in 2015 by 2050. Our primary reference and net zero scenarios assume a fixed food sector energy demand coefficient of 2.79 PJ/Pcal in the US from 2015 to 2050. To understand the impact of a reduced energy demand coefficient, we examine two sensitivity scenarios (reference low and NZ 2050 low). In these scenarios, the US food processing levels linearly decrease to 1.75 PJ/Pcal (EU-15′s 2015 food processing energy intensity) by 2050. We find that decreasing the energy intensity of the US food processing sector to these levels reduces its total energy needs by 28 % and 25 % in the reference and net zero case respectively by 2050 (Fig. 5). In the net zero case, this translates to reduced investments in the need for industrial heat pumps in the food processing sector (by 40 % in 2050), as well as substantial natural gas savings (0.08 EJ per year). In addition, cumulative energy savings of 4.2 EJ are attained from 2020 to 2050 in the NZ 2050 scenario, which is equal to 3.2 times the energy consumed by this sector in 2015.

While the US is one of the largest food industry energy consumers, particularly on a per capita basis, considering the role of other countries is crucial for understanding how the US fits into the broader global picture for emissions mitigation from this sector. Current food processing energy intensities vary widely across the globe. On a per capita basis, food industry energy use is highest in countries such as the US (3892 MJ/capita) and Brazil (4376 MJ/capita). Meanwhile, the energy use per capita is markedly low in China (1215 MJ/capita), India (711 MJ/capita), and the continent of Africa (789 MJ/capita), suggesting that, on average, food is currently consumed in less processed forms in these regions. These regions, however, have significant growth potential for food processing services, due to their large populations and economic growth potential, which may lead to a shift towards more highly processed food consumption. Thus, to explore the impact of increased food processing levels in these regions and globally, we investigate two global convergence scenarios ("reference global convergence" and "NZ 2050 global convergence") in which the food processing sector energy

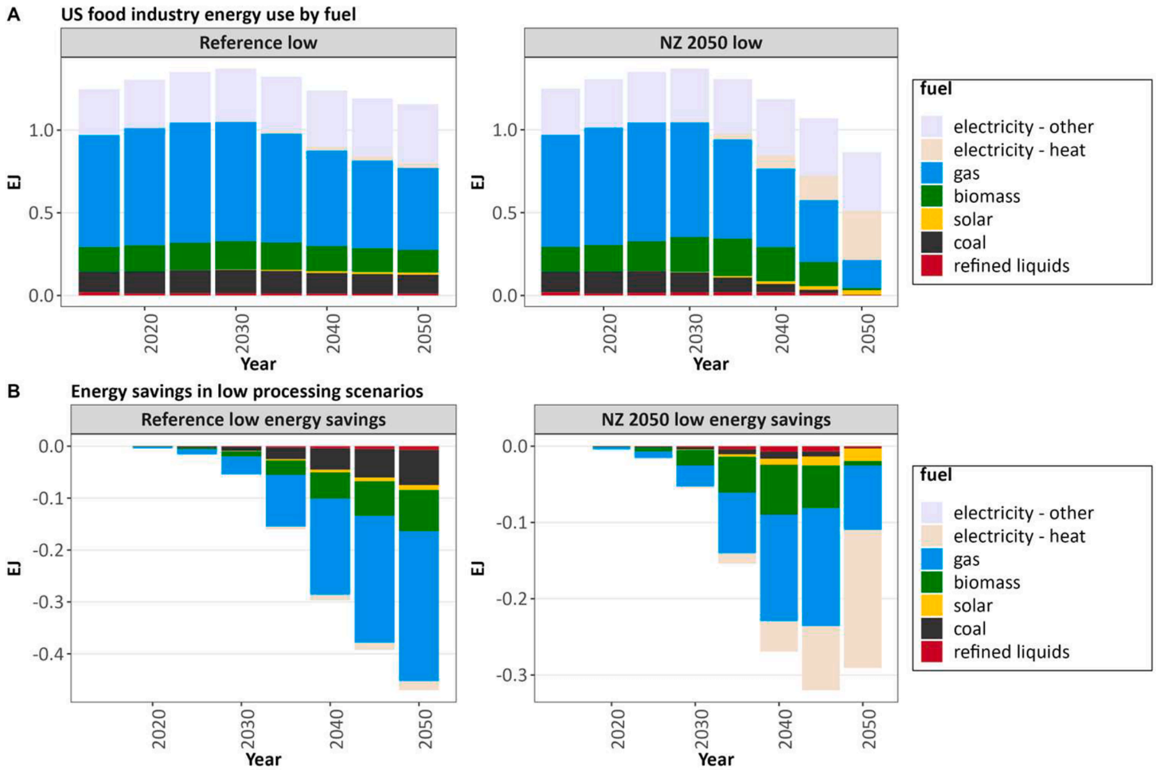

Fig. 5. US food processing energy use in lower energy intensity scenarios. (A) US food processing sector energy use by fuel in the "reference low" and "NZ 2050 low" scenarios, and (B) energy savings by fuel in the "reference low" and "NZ 2050 low" scenarios when compared to the "reference" and "NZ 2050″ scenarios. In these scenarios the decrease in US food processing energy intensity can be interpreted as an aggregate effect of reduced processed food consumption and/or shifts towards less energy intensive forms of processed food.

intensity across all GCAM regions converges to the US 2015 levels by 2050 (Fig. 2F).

If China approaches US food processing intensity by 2050 in a scenario with no net-zero climate policies, the country's food processing industry could require 2.6 times more energy by mid-century compared to the base reference scenario (Fig. 6 and S10). We find that this growth in energy demand could be substantially satisfied by coal, whose consumption triples from 0.99 EJ in 2015 to 2.7 EJ in 2050, resulting in an increase in the sector's absolute emissions from 200 $MtCO_2$ in 2015 to 456 $MtCO_2$ in 2050. Similar high growth levels also occur in India and Africa, with their total food sector energy demand increasing nearly by a factor of three when compared to the base reference scenario's 2050 projections.

With the growth in food processing levels in these regions, their national food processing industries would account for increasing shares of their industrial energy demands and CO_2 emissions. For example, in China, the food processing industry currently accounts for 2.7 % of industrial energy use but could account for over 5.5 % by mid-century if the processing demands increase (Figure S11). This would necessitate an even larger scale-up of technological transitions to electrify the sector, requiring about 3 times more installed capacity of heat pumps by 2050 when compared to the base net zero scenario. Additionally, it would also increase the sector's reliance on electricity as a fuel source making upstream power sector transitions even more critical.

5. Discussion

In this analysis, we used GCAM to explore the role of the US food processing sector in achieving the US EMF37 NZ 2050 outcome. We also explored how the US agriculture and food processing sectors interact. The data and analysis presented in this study improve understanding of the current state of the food processing industry globally and its role in achieving net-zero emissions in 2050. We also quantify the extent and the rate at which technological transitions occur in this sector along 2050 net zero pathways. In addition to providing a macro-level road map for decarbonizing this industry, our analysis also explores linkages between the food processing industry and the agricultural sector and their evolution over time.

Explicitly representing the food processing industry in GCAM effectively completes the representation of the entire agri-food supply chain and consumer demand system. The coupled system better represents supply chains and associated prices and quantities in each component, from primary agricultural resources to final food products and consumption. Furthermore, explicitly modeling the food processing industry and its linkage to primary food production (and food demand) substantially improves the future projections of food processing energy requirements. This integration also provides the flexibility to construct future scenarios with varied levels of food processing, technology choices, and mitigation pathways. Our results demonstrate significant technological and energy transitions in the food processing sectors under net-zero pathways, with implications for both energy and food systems.

Although we provide detailed insights on the food processing sector transitions and its connection to the agricultural sector, there are some limitations to our study. First, we did not model detailed technology- or process-level energy efficiency improvements, waste heat utilization measures, nor material efficiency measures. This was mainly due to the heterogeneity of processes in the food industry and the resulting difficulty in representing these measures in our aggregated, systems-wide analysis and the lack of detailed information in the literature. Incorporating these efficiency measures, however, could allow for realization of lower food industry energy demands than those reported in this study.

Second, we assume the same food processing energy use coefficients for all food types. While it is possible that the intensity of food

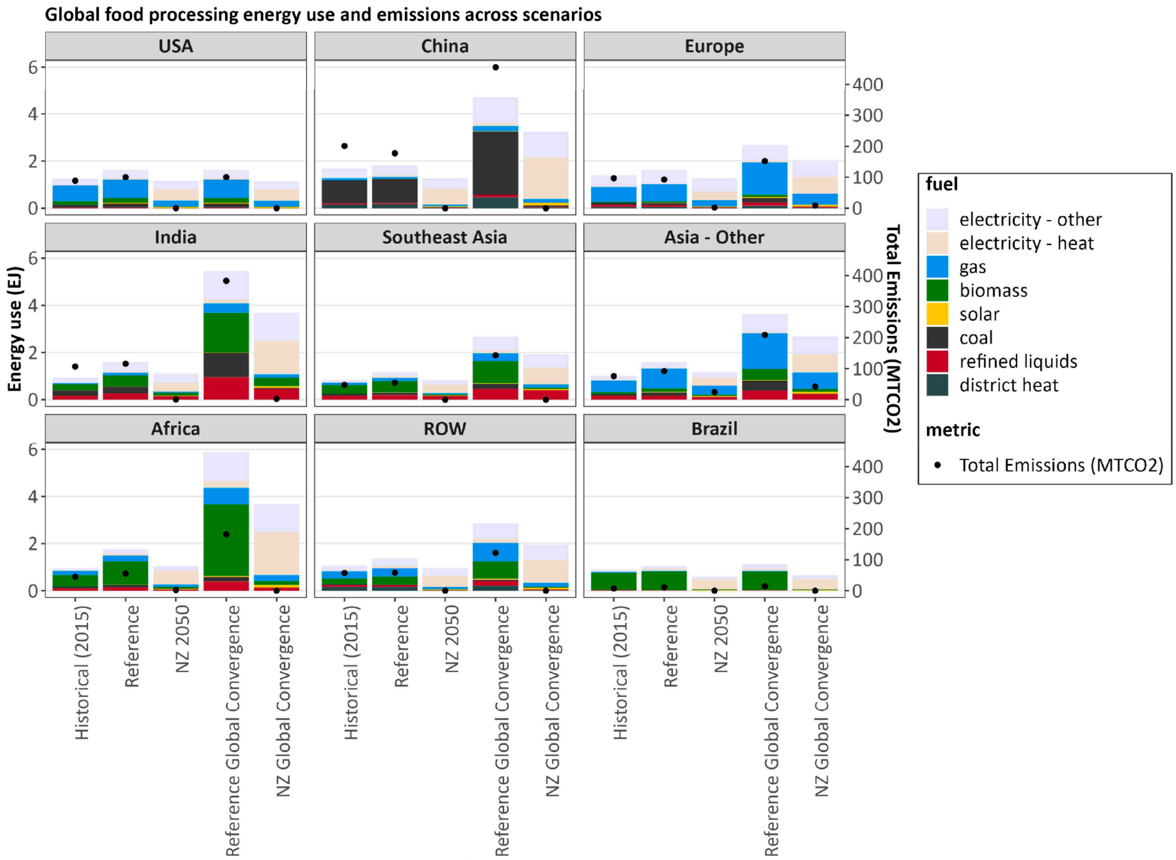

Fig. 6. Global food processing sector emissions and energy use by fuel in 2050 across scenarios (reference, NZ 2050, reference global convergence, and NZ 2050 global convergence).

processing energy demand varies across agriculture, dairy, poultry, and meat sectors, we do not have sufficient information to distinguish them since food processing energy demand is mainly available at the regional level and our food demand data is highly aggregated (and includes both primary and processed foods). However, the current representation could be refined in the future by having varied coefficients of food processing energy intensity between food types to reflect differences in their average levels of processing, should adequate data on this become available.

Third, our analysis constrained CO_2 emissions, implying an economy-wide mitigation policy, while other policies or preference change scenarios were not explored. A particularly relevant and important area for future research is dietary change [55] and the reduction of food waste and loss [56]. Our study assumed no explicit changes in dietary preferences or food waste, while drastic changes in future dietary preferences and food waste may occur due to mitigation policies or health concerns [57,58]. For example, a more sustainable diet often involves increased demand for plant protein and decreased demand for animal protein and dairy products. Such shifts would necessitate major technological advancements in the food processing sector, consequently impacting food processing energy demand both in the US and globally [59]. Similarly, reducing food waste, a key Sustainable Development Goal set by the United Nations, particularly along the food processing chain, will also affect the sector and related value chains [60]. Conversely, a more detailed and integrated representation of the food processing sector enhances the evaluation of dietary change and food waste reduction scenarios.

Finally, it is important to acknowledge the uncertainties associated with our historical data and future modeling results. We used aggregate food processing sector energy use by fuel data from the IEA to calibrate our model at the regional level. This data was not broken out by industrial process nor by food industry subsectors. This data was also missing or under-reported for some important regions such as India and countries in Africa. To mitigate this issue, we built a linear model that relates food industry energy use with food consumption and GDP and estimated the missing data. Nevertheless, we did not find any data sources in the literature to validate the estimated data for these regions, and thus the uncertainty in our results for those regions should be appropriately acknowledged.

It is important to note that missing data was not an issue for the US, and we used the IEA data as reported for the region. Other data sources such as the Manufacturing Energy Consumption Survey (MECS) [61] and Bureau of Economic Analysis (BEA) input-output tables [62] can also be used to calibrate the US food processing sector model. Future studies should compare these data options and quantify the associated uncertainty.

In terms of the future modeling results, there are several drivers of uncertainties which could impact the magnitude of the energy and emission projections. We use SSP2 population and GDP assumptions across all of our scenarios; other choices of SSP pathways and associated socioeconomic assumptions could yield varied food demand pathways and energy use outcomes. Furthermore, regional food processing energy intensities are likely to vary in the future as a result of socioeconomic development, consumer preferences, and technological development and efficiency improvements. While we consider some possible shifts in energy intensities in our sensitivity scenarios, future work could more broadly explore the parameter space and evaluate the resulting implications for food processing energy demand and decarbonization ambitions.

6. Conclusions

In this analysis, we improve the representation of the food processing sector in GCAM v7.0 to generate food processing sector deep decarbonization pathways. We evaluate food processing mitigation potential and the corresponding implications for energy and food systems for the US in a global context. We enhance the representation of the food processing sector in this model by linking it with GCAM's food demand module, which sets the level of future food processing sector energy demand. Using this version of the model, we then explore the updated reference scenarios and the corresponding net zero by 2050 scenarios, with a primary focus on the US and a secondary emphasis on other regions. The key findings of this study are as follows:

- Electrification of process heat paired with complete power sector decarbonization will be key to decarbonizing the US and global food processing sectors. In the US, we estimate that 76 % of process heat (0.74 EJ) will be sourced from electricity-based technologies by 2050 to be consistent with a net zero CO_2 by 2050 target. In our technological parameterization, a majority of this electrified process heat is provided by 16 GW of industrial heat pumps by 2050.
- In the net zero scenarios, electrification of process heat occurs concurrently with the phase down of fossil fuels and biomass. In the US, the consumption of natural gas drops by 63 % by mid-century relative to 2015, whereas coal and biomass are nearly phased out. Hybrid solar thermal technologies make up a notable market share (15 %) of process heat by 2050.
- While direct emissions of CO_2 remain positive in 2050 even as the aggregate US economy achieves net zero emissions in 2050, the food processing sector's direct plus indirect CO_2 emissions are negative due to electrification. Net power sector emissions are negative in 2050 due to the use of BECCS technology.
- Per capita food calorie consumption drops by 2 % in the net zero case when compared to the reference case, as consumer food prices increase by 10 % in 2050 when compared to their 2015 levels. This occurs primarily due to the increased demand for purpose-grown biomass, which competes with food crops and pasture for land resources. The direct price transmission from carbon prices to food prices through energy consumption in food processing is relatively weak due to the sector's rapid decarbonization and the relatively small contribution of energy costs to total consumer food prices.
- The US could save a cumulative 4.2 EJ of energy between 2020 and 2050 if the country lowers its food processing levels to match that of EU-15′s 2015 energy intensity by 2050. Meanwhile, if regions such as India and China increase their food processing intensities from their currently low values to match that of the US by mid-century, their food industry's energy and emissions footprints would increase substantially. Such a shift would also make the net zero transition more challenging, as the scale of electrification needed would increase by several times when compared to the net zero case with 2015 food processing levels continued into the future.

CRediT authorship contribution statement

Siddarth Durga: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simone Speizer:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xin Zhao:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stephanie Waldoff:** Writing – review & editing, Conceptualization. **Jae Edmonds:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, 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.

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Supplementary materials

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