Core Model Proposal #377: Breaking out food processing sector in GCAM

Product: Global Change Analysis Model (GCAM)

Institution: Joint Global Change Research Institute (JGCRI)

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Purpose: This Core Model Proposal (CMP) expands the representation of detailed industry (CMP-326) in GCAM by separating the food processing sector from the aggregate "other industry sector". Historical energy use is calibrated to IEA data for food processing, with some infilling for regions with limited IEA data. Food processing is linked to the GCAM food demand module, setting the energy demand for food processing in future periods based on food demand. While the direct price feedback is currently muted and the linkage is represented at the aggregated regional level, this CMP establishes the groundwork for a more detailed connection between the agrifood sectors and energy sectors in future work.

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1. Introduction

The food processing sector is highly heterogeneous, generating outputs ranging from dairy products and canned fruits to baked goods and prepared meals using a wide range of processes. Though energy consumption per dollar value of product tends to be low, food processing is a large source of manufacturing energy demand in some regions (**Figs. 1 & 2**). Most energy use in the sector is for low temperature heat, primarily process heating and drying. The main emissions reduction strategies for the sector include energy efficiency improvements, heat recovery, combined heat and power systems, electrification of heat, and fuel switching to renewables (particularly solar thermal heating systems). Understanding food processing energy use and its associated costs is important for accurately evaluating food prices, as well as for developing a complete accounting of the emissions associated with the food system and assessing how these emissions evolve under carbon management pathways.

Specifically, 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, thus augmenting the value of the agri-food supply chain and constituting a significant proportion of the total food cost. Therefore, the inclusion of the food processing sector in global multi-sectoral dynamic modeling, effectively completing the agri-food supply chain, enhances the portrayal of food prices. This adjustment enables the model to more accurately capture the transmission of price changes from primary agricultural resources to final food products. Furthermore, by explicitly incorporating the energy consumption of food processing and its interconnectedness with food production, the projection of food processing energy demand is improved. This integration also provides the flexibility to construct future scenarios pertaining to the energy efficiency of food processing. Simultaneously, it enables the tracing of energy price fluctuations to resultant changes in food prices arising from food processing. Enhancing the depiction of the food processing sector also lays the foundation for subsequent investigations, such as: (1) delving deeper into the segmentation of the food processing sector to encompass sector-specific intricacies and accounting for the international trade of food processing services, and (2) exploring macroeconomic implications by establishing links between factor inputs (e.g., labor and capital) within the food processing sector and the broader economy (Patel et al., 2023).

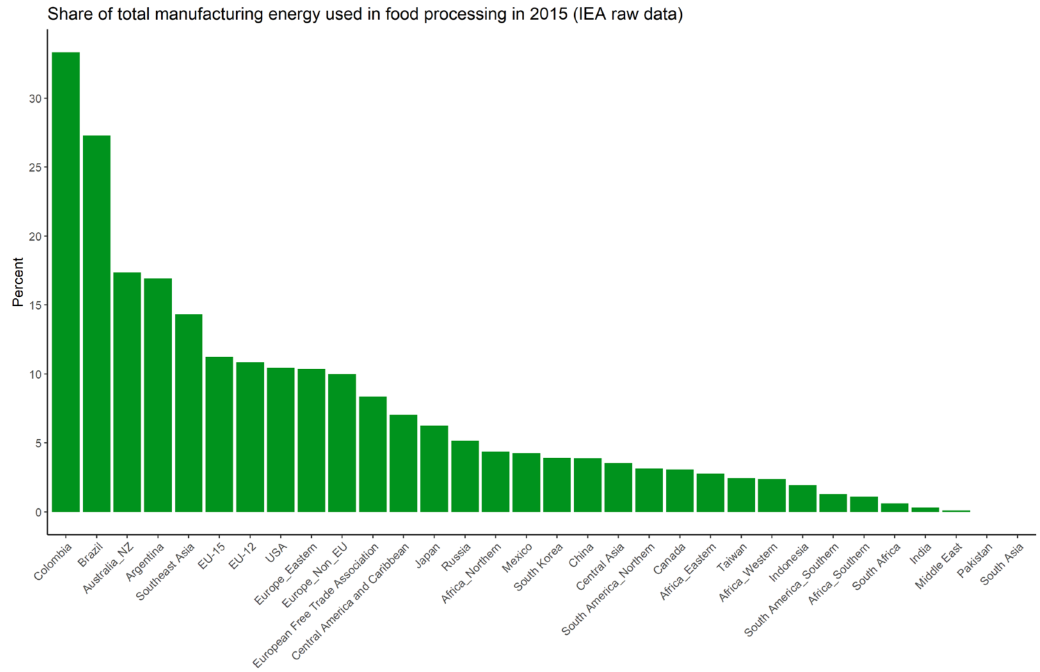


Fig. 1 Share of energy use in total industry sectors that is allocated to food processing in the raw IEA Energy Balances data, at a GCAM region level. The IEA sectors included here as industry sectors are mining and quarrying; construction; iron and steel; chemical and petrochemical; non-ferrous metals; non-metallic minerals; transport equipment; machinery; food and tobacco; paper, pulp, and print; wood and wood products; textiles and leather; and industry not elsewhere specified.

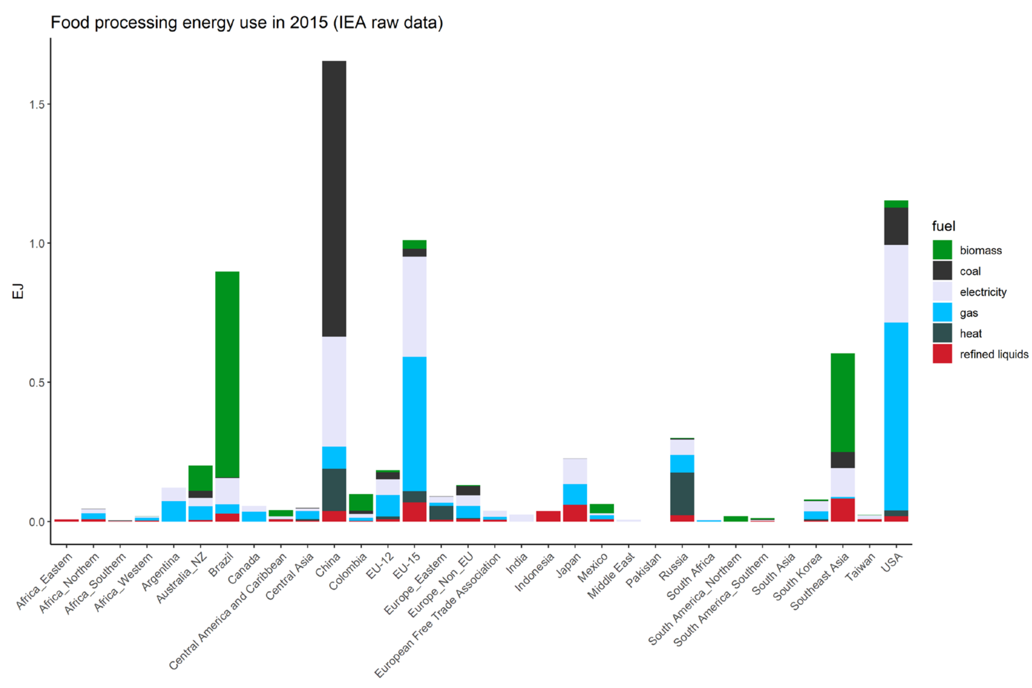


Fig. 2 Energy used in the food processing sector (food and tobacco) by fuel in the IEA Energy Balances raw data in 2015 at a GCAM region level.

2. Description of changes (Methods)

2.1. Sector structure

Energy use in food processing is dominated by process heating, including boilers and direct heating, most often obtained from coal, natural gas, or biomass sources. Most electricity use is for cooling and refrigeration as well as machine driven processes and mechanical equipment. Processes used in the sector vary widely depending on the food and desired output product, but can include drying, pasteurization, baking, melting, cooling or chilling, freezing, extraction, filtration, fermentation, size reduction processes, mixing, peeling, washing, and packaging. Due to the diversity and complexity of the processes involved, we structure the sector based on fuel use; however, to reflect the division between process heating and other solely electricity-based processes and prevent unrealistic fuel switching between them, we incorporate an intermediate supplysector of process heat. This sector includes all of the technology and fuel options for heat production. Thus, 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 (**Fig. 3**). The sector is linked to the food demand module, such that calorie consumption sets the demand for food processing energy use, with regionally varying coefficients of energy demand per calorie consumed.

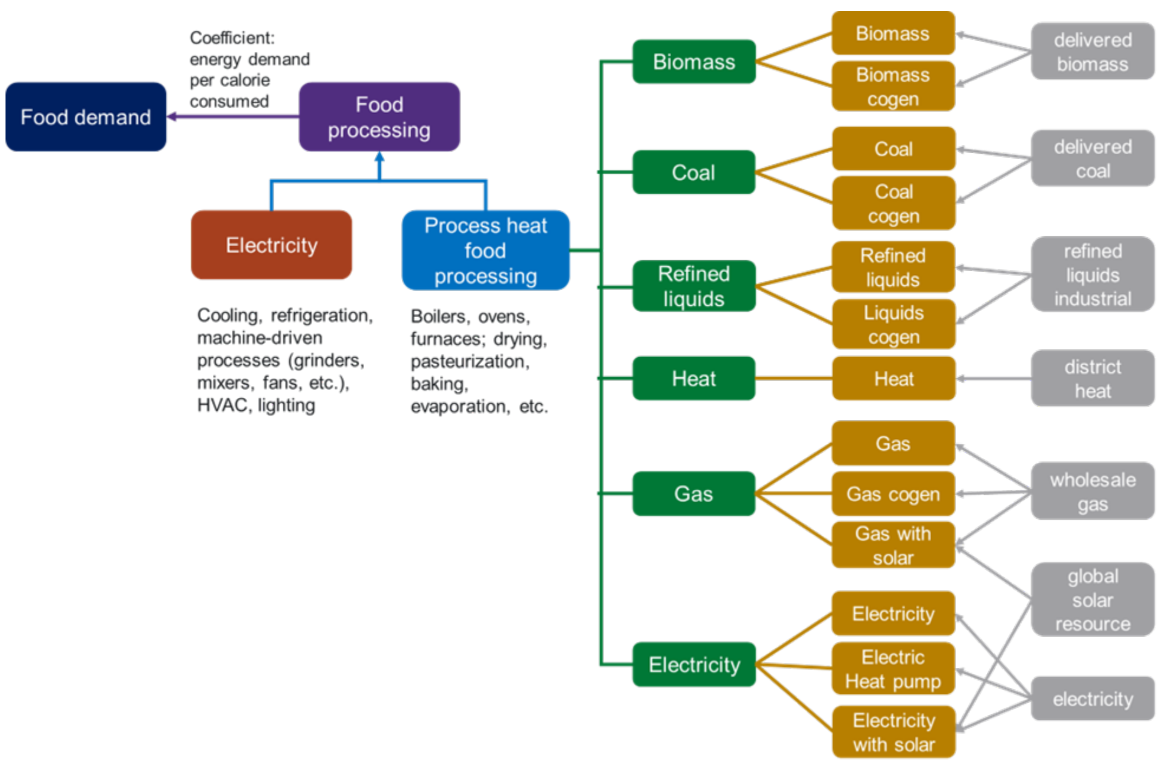


Fig. 3 Structure of the food processing sector, including technologies and fuels used for process heat generation, inputs to the overall food processing sector, and the link to food demand. The left side of the diagram indicates the division of energy demands into process heating and electricity; the 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.

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 the use of solar thermal energy, we also model two solar-equipped technologies, gas with solar and electricity with solar (IEA-ETSAP & IRENA, 2015; Schoeneberger et al., 2020; Sharma et al., 2017; Taibi et al., 2012). These are represented as technologies that combine a solar thermal system with another source of process heat, as solar thermal units are unlikely to be able to supply all the necessary process heat demand (even when paired with storage) due to variations in solar radiation intensity (IEA-ETSAP & IRENA, 2015; McMillan et al. 2021). Note that we do not model any CCS-equipped or hydrogen-based technologies for food processing process heat generation, as neither of these types of technologies is expected to play a substantial role in decarbonization pathways for the food processing sector because of the relatively lower energy demands (and resulting CO_2 emissions) on a per-facility or per-output basis that make costly CCS investments illogical and the dominance of low temperature heat demands that are better satisfied by electrification or renewables rather than hydrogen (Cresko et al., 2022; Worrell & Boyd, 2022).

The linkage to food demand is accomplished by including an input of food processing to each of the food crop technologies, as shown in **Fig. 4**. In the current implementation, all crops take in one "food processing calorie" per crop calorie (efficiency = 1). This representation is analogous to a food processing sector that manufactures food products (measured in calorie units) through a combination of an aggregated food calorie input and food processing services. The indexing of the food processing service to calorie units simplifies the linkage within the Leontief production framework. While it is possible that the intensity of the food processing service usage varies across GCAM sectors (e.g., staples vs. non-staples or crops vs. meats), we do not have quality information to distinguish it by sector since (1) the food processing energy demand is only available at the regional level and (2) our food data is highly aggregated, e.g., including both primary and processed. However, the current representation could be refined in the future by having varied efficiencies between crops to reflect differences in their average levels of processing, should adequate data on this become available. Furthermore, these efficiency factors offer the opportunity to formulate future scenarios that reflect advancements in technology within food processing sectors or composite shifts in aggregation.

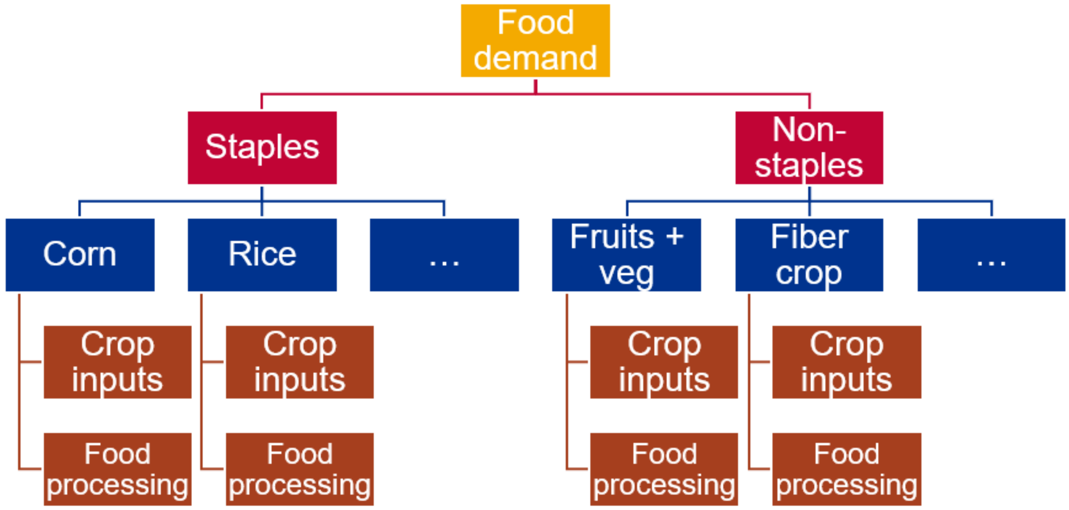


Fig. 4 Linkage between food demand and food processing, indicating how food demand sets the demand for food processing energy use.

2.2. Calibration and energy use data infilling

We use IEA data on energy use in food processing (sector FOODPRO in the IEA energy balances). These data are paired with calorie consumption by region, calculated within gcamdata from FAO data, to obtain historical coefficients of food processing energy use per calorie consumed by region.

For some regions, IEA data on food processing energy use is incomplete, leading to unrealistically low energy use coefficients. This is a result of the IEA's convention for handling cases in which the industrial breakdown of the use of a particular fuel is not available; in this situation, the IEA allocates all of that fuel use to the non-specified industry. This leads to a large portion of the total industry energy use being categorized as non-specified industry for some regions where data are limited, and correspondingly low energy use in other industrial sectors. Unlike some other industrial sectors, such as steel or chemicals production, which may not have a notable share in the economy in all regions, we expect at least some energy to be consumed for food processing in all regions. Thus, infilling energy data for regions with very low food processing energy use coefficients and high fractions of their total industry energy use in non-specified industry is warranted.

To perform this infilling, we first fit a linear model between food processing energy use, calorie consumption, and GDP for regions with sufficient IEA food processing energy use data. Specifically, we use data for regions and years from 1990 onwards in which the fraction of total industry energy in non-specified industry energy use is less than 0.5 and the fraction in food processing is greater than 0.01, or even if the non-specified industry fraction is high, the food processing fraction is greater than 0.1. The IEA food processing energy use data that fit this criteria and thus are used in the model fitting are shown in **Fig. S1**.

We tested a variety of best fit models, including different options for the predictor variables, ultimately determining that a linear model between food processing energy use, calorie consumption of non-staples, and GDP, incorporating regional fixed effects, fit the data well and generated reasonable predictions for infilled energy values for regions with limited data. The final model used is shown below; its R squared value is 0.95.

$$E = a * C + b * GDP + c + d_R$$

where

E	=	energy use in EJ
C	=	calorie consumption of non-staples in Pcal
GDP	=	GDP in million 1990 USD
a	=	0.00152 EJ/Pcal, derived from best fit model
b	=	9.77*10^-8 EJ/(million 1990 USD), derived from best fit model
c	=	0.0467 EJ, derived from best fit model
d_R	=	additional intercept for region R, if that region is present in the data used to calculate the best fit model; derived from best fit model and shown in the table below

The value of c represents the standard intercept derived from the best fit model and is included for all regions. d_R represents the regional fixed effects and thus is only included for regions that were used in the calculation of the linear model. Regions without sufficiently complete IEA data for any years, and thus that were not included in the calculation of the linear model, have no value for d_R. The resulting regionally-varying intercepts are shown in **Table S1**.

When performing the infilling of food processing energy use data, we use the same criteria specified above (but inverted) to determine which regions and years to infill data for (i.e., from 1990 onwards when the fraction of total industry energy in food processing is less than 0.01, or the fraction in non-specified industry is greater than 0.5 and the fraction in food processing is less than 0.1), plus an additional requirement that the coefficient of food processing energy use per calorie consumed must be less than the minimum value from the data deemed "reasonable" and used to calculate the linear model (0.000413 EJ/Pcal). (Note that allowing for the evaluation of the former part of this criteria within gcamdata required generating a new prebuilt data table containing the fraction of total industry energy from the IEA Energy Balances that in the food processing sector and the fraction that is in non-specified industry, at a GCAM region level.) For the regions and years that meet these criteria and require infilling, we calculate the predicted food processing energy use using Equation 1 and determine the difference between the energy use reported by the IEA and this predicted value. We then pull energy from the remaining "other industry" energy use and add it to food processing to counterbalance this difference and bring up the food processing energy use to meet our predicted values. (Note: the quantity of each fuel pulled from "other industry" is calculated as the total amount of energy that needs to be infilled multiplied by each fuel's share of the remaining "other industry" energy use.) The resulting final food processing energy use for regions where infilling is performed is shown in Fig. 5; in that figure, original indicates the food processing energy use from the raw IEA Energy balances data, infill indicates the quantity of energy that is pulled from "other industry", and updated indicates the final food processing energy use (updated = original + infill) which matches the predicted food processing energy use calculated using the Equation above.

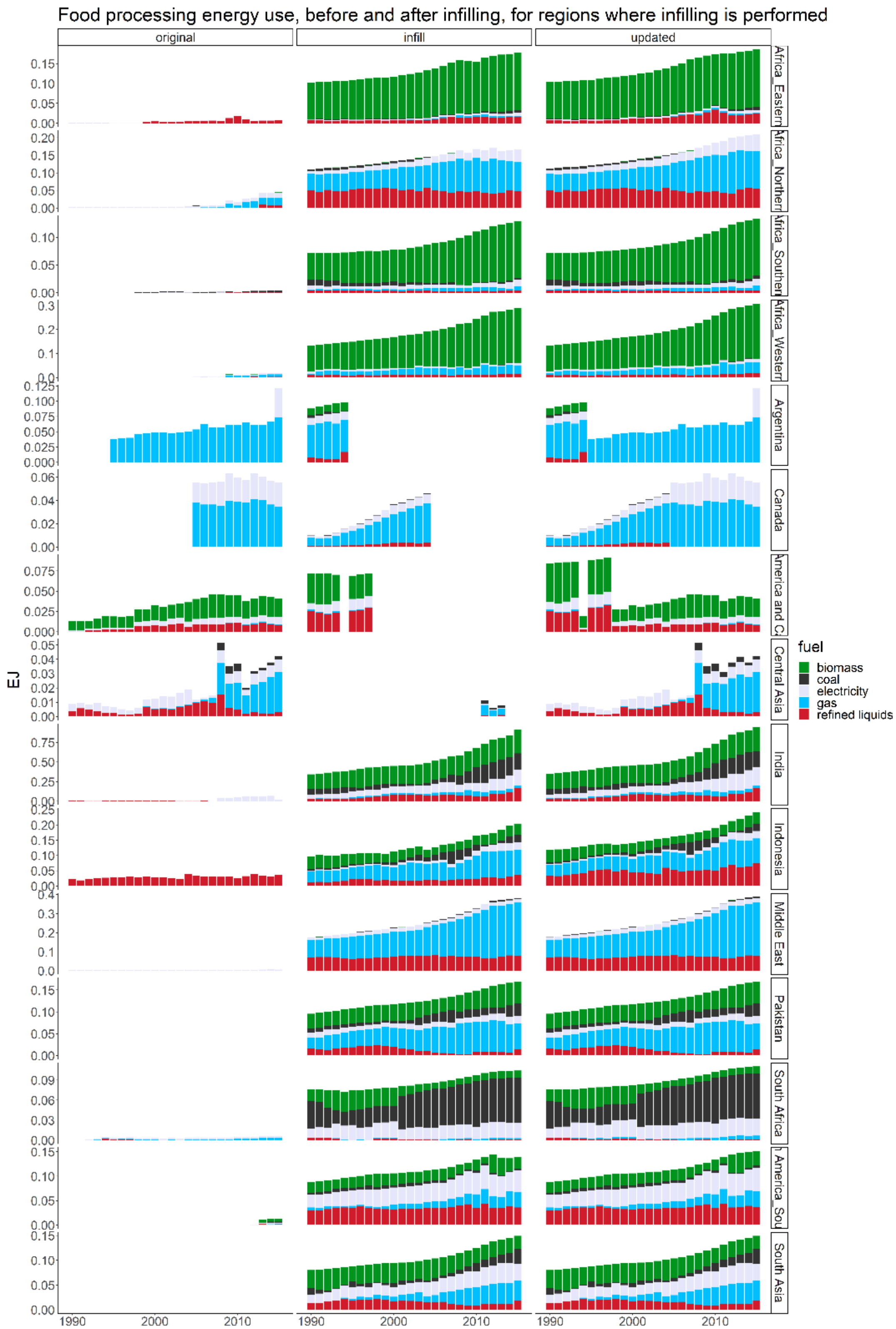


Fig. 5 Food processing energy use, before and after infilling, for regions where infilling is performed. Original indicates the raw data from the IEA Energy Balances for food processing energy use. Infill

indicates the quantity of energy pulled from "other industry" and added to the original raw data to generate the updated values, which represent the final estimates for food processing energy use for these regions (updated = original + infill). The updated values, when summed over all fuels, are the predicted values for food processing energy use generated using Equation 1. Note that, as visible in the figure, some regions only had infilling performed in certain years; years with infill = 0 had no infilling, while years with infill > 0 did have infilling performed.

2.3. Linking primary agricultural supply to food demand

In GCAM v7.0, a new primary commodity equivalent approach has been developed to establish a connection between primary agricultural supply and final calorie consumption (see CMP360; Zhao and Wise, 2023). This approach relies on recently updated FAO Supply-Utilization Account and Food Balance Sheet datasets, enabling the aggregation and tracing of physical flows along the vertical agricultural supply chain. GCAM represents primary agricultural production technologies, encompassing 17 GCAM crop commodities (aggregated from about 180 FAO crop items) and 6 GCAM livestock commodities (aggregated from over 60 FAO livestock items). The food availability by crop, in million tonnes, as reflected in the supply utilization balance, is converted to calorie consumption using the calorie intensity information, compiled based on historical data. These calorie values by crop are then aggregated into 5 staple food commodities and 15 non-staple food commodities (Zhao et al. 2024).

To facilitate the integration of the food processing service into the existing GCAM food system, we index the food processing service output to total food calorie consumption so that they have the same unit, i.e., peta-Calories (Pcal) or peta-kilocalories. In particular, we define the food processing energy intensity (EJ/Pcal) as a ratio between the total food processing energy demand (EJ) and the total food calorie consumption in a region. The food processing energy intensity, derived based on historical data, depicts the food processing energy use per calorie supplied. The resulting coefficients of food processing energy use per calorie consumed in 2015, before and after infilling, are shown in **Fig. 6**. The future food processing energy 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. Currently, these 2015 coefficients are maintained for all regions in all future periods; however, this could be refined with future work to develop varied scenarios for the evolution of these food processing energy use coefficients with time, reflecting different socioeconomic development trajectories.

Notably, the feedback is currently one way. I.e., food demand is driving food processing service, but not the other way around. For food prices, we now need to add the food processing cost to the primary part (what we had before) in an ex-post manner. If we fully integrated the two (allowing price responses; in future work), the food processing cost would be passed to food prices endogenously (and there could be energy price change induced-dietary changes).

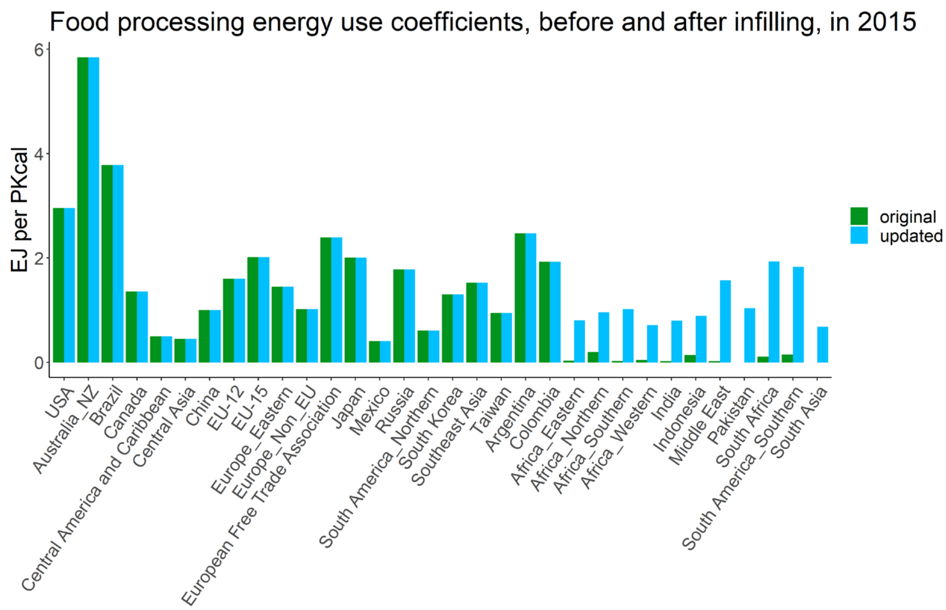


Fig. 6: Food processing total energy use coefficients by region, before and after infilling, in 2015. Regions where *original* = *updated* had no infilling performed in 2015.

2.4. Technology specifications

2.4.1. Technology costs

The technology costs assumed are shown in **Table S2**. For gas, gas cogen, electric, and electric heat pump technologies, costs are calculated from data in Rissman 2022, "Decarbonizing Low-Temperature Industrial Heat in the U.S.", for natural gas boilers (with and without cogen), electric boilers, and electric heat pumps. This thus assumes that boilers are a representative technology for the food processing sector, which is a reasonable assumption to make as data suggests that boilers tend to consume 60% or more of the natural gas used in food processing (see, for example, Compton et al. 2018). We use the higher temperature (100-180 degrees C) heat pump data from Rissman 2022, to cover all potential heating demands in the food processing sector (Arpagaus et al., 2018; Schoeneberger et al., 2020; IEA-ETSAP & IRENA, 2015). To calculate the levelized non-energy costs in \$/GJ, a capacity utilization factor of 31% is assumed (this is the average capacity factor for food processing boilers in the U.S., according to the report "Characterization of the U.S. Industrial/Commercial Boiler Population"), alongside a 25 year lifetime for capital cost amortization (see "How to Extend Boiler Life"; Gowreesunker et al., 2018; IEA-ETSAP, 2010) and a 10% discount rate. Refined liquid technologies are assumed to have the same non-energy costs as gas technologies, while coal and biomass technologies are assumed to have 2.5 higher costs, based on estimates of the relative costs of boilers with these fuels from the Energy Efficiency and Conservation Authority of New Zealand. District heat-based technologies are assumed to have the same non-energy costs as gas technologies.

For the solar-equipped technologies, we calculate the costs associated with both the solar thermal system and the other fuel source. We assume that the installation of a solar thermal unit would not affect the selected installed capacity of the other technology (e.g., the gas boiler) even when paired with storage, as when the solar thermal unit is not able to operate (such as on a rainy or cloudy day) and the stored energy has been exhausted, the same maximum power will be required. The solar thermal unit will displace some of the energy that would have otherwise been produced by the other fuel source, but the total annual output of the combined system will be the same. Thus, we can obtain the costs of gas with solar and electricity with solar as the sum of the levelized costs for the gas/electricity component and the solar component. For the solar thermal portion of the system, we use technology costs associated with parabolic trough collectors (PTCs), which can be designed to produce low to medium-high temperature heat. Though most heat demands in the food processing sector are for relatively low temperature heat (<120 degrees C)–which can also be produced using other, lower cost collector types–we make a conservative estimate in using the higher costs associated with PTCs to ensure that all heat demands for the sector can potentially be covered by this representative technology and because some existing analyses have considered and/or implemented these collectors in solar thermal systems for the food processing sector (Arpagaus et al., 2018; Schoeneberger et al., 2020; IEA-ETSAP & IRENA, 2015; Sharma et al., 2018). We use the median investment cost for PTCs for industrial process heat (for systems > 400m^2 in gross area) from Schoeneberger et al., 2020. We calculate the average installed capacity of current solar process heat installations in the food processing sector also using data from Schoeneberger et al., 2020, and assume this value as a representative installed capacity for our cost calculations. We assume that annual OPEX costs are 1.5% of the total CAPEX costs, as literature values range from 1-5% for solar industrial process heat systems, with most on the lower end of this range (Allouhi et al., 2017; Lemos et al., 2019; Lillo et al., 2017; Meyers et al., 2018; Sharma et al., 2018). Reported lifetimes range from 15-30 years (Kurup and Turchi, 2019; Lemos et al., 2019; Lillo et al., 2017; Meyers et al., 2018; Sharma et al., 2018; Sturm et al., 2015); we use 25 years as it is in the middle of this range and is consistent with the assumptions for the fossil-based technologies. We again use a 10% discount rate for the solar thermal portion of the system.

For generating the CapitalTracking tables needed for integration with GCAM macro, we employ a capital ratio of 0.7 and a lifetime of 25 years, slightly different from the values of 0.9 and 30 years assumed as default for the other industry sectors but more consistent with the values observed in the literature for food processing and used in the calculations of technology costs described here.

We estimate the overall food processing supplysector non-energy costs using Global Trade Analysis Project (GTAP) data (Aguiar et al., 2019). We obtain GTAP data for the food processing sector, utilizing specifically the household and government consumption data for 2014. We calculate the sum of expenditures on FoodProduct and BeverageTobacco, the two categories representing processed foods, to obtain total costs for the food processing sector (or value output of the sector) according to GTAP data. From these values, we then exclude the primary agricultural input costs and subtract the total energy costs for the food processing sector from GCAM output values for 2015. These total energy costs incorporate both the costs associated with electricity and other fuel inputs into food processing and process heat food processing, as well as the non-energy costs associated with the process heat food processing technologies (which have gotten folded into the "energy costs" of process heat food processing). Thus, the resulting difference between the GTAP total costs and the GCAM "energy" costs represents the portion of the non-energy costs that are currently not being captured in GCAM and that should be included as the non-energy costs for the overall food processing sector. We divide these costs by food demand to obtain the non-energy costs on a per calorie basis. We perform this calculation on a regional level, but also calculate a global weighted average non-energy cost (weighted by calorie consumption) which is used as the global value in the global technology database. The global technology database value will be employed for any new regions added if they are not explicitly specified in A328.regionaltech_cost.csv (**Table S3**); we include a warning in gcamdata that indicates if there are new regions added that are not specified in this file and that highlights that the global default value will be used for those regions. Also note that we use GTAP costs for 2014 and GCAM costs for 2015, as these are the closest years present in the two datasets; this may introduce some variations, but for the purposes of estimation should be reasonable.

2.4.2. Technology coefficients

For most technologies for process heat generation, coefficients are taken from GCAM-USA assumptions for industrial boilers with each of these fuels (**Table S4**). The coefficient for electric heat pumps is from Rissman, 2022. The coefficient for district heat is assumed to be 1. For solar-equipped technologies, the solar fraction (fraction of energy supplied by the solar thermal system; i.e., the share of the desired total energy load that can be met by solar energy) is assumed to be 0.2, as literature values range from 0.14-0.6 depending on the type of solar collector and location/climate characteristics (solar irradiance, temperature, etc.), but with most values in the 0.15-0.3 range (Allouhi et al., 2017; IEA-ETSAP & IRENA, 2015; Kurup & Turchi, 2019; McMillan et al., 2021; Meyers et al., 2018; Sharma et al., 2018). This leads to a 20% reduction in the coefficient of the fuel that the solar thermal system is paired with. The efficiency of conversion of solar energy into heat is assumed to be 60% based on data for PTCs in the appendices of the report "Renewable Energy Options for Industrial Process Heat" (Lovegrove et al., 2019).

2.4.3. Technology vintage and retirement

We use the same capital stock retirement assumptions employed in other detailed industry sectors for all technologies except electric heat pumps and technologies paired with solar thermal systems (**Table S5**). Electric heat pumps are often assumed to have lifespans in the 15-25 year range (Jibran S. Zuberi et al., 2022; Obrist et al., 2022); here, we use a 25 year lifetime for consistency with the heat pump assumptions in the paper sector breakout. Solar thermal collector system lifetimes tend to range from 15-30 years (Kurup and Turchi, 2019; Lemos et al., 2019; Lillo et al., 2017; Meyers et al., 2018; Sharma et al., 2018; Sturm et al., 2015); we use 25 years as a mid-range value for electricity with solar and gas with solar systems.

2.4.4. Share weights and logit

As with the other detailed industry sectors, we employ the modified logit discrete choice model. Logit exponents for the process heat food processing subsectors are set to -6, with the overall food processing sector logit exponent set to zero to represent a fixed relationship between electricity and heat. This parameter should be examined and tested in future work. For all regions, electricity subsector share weights for process heat food processing are zero in the base year, as all historical electricity consumption in the food processing sector is assumed to be for non-heating uses since current levels of electrification of process heat in the sector are low (Atuonwu & Tassou, 2021). We set these share weights to increase linearly to 0.5 by 2050, and remain constant thereafter, to allow for the introduction of electric process heating with time but at a moderate level. For all other subsectors, we maintain fixed share weights through 2100. At the technology level, we set all technology share weights to 1 excepting the cogen technologies, electric heat pumps, and technologies paired with solar; for these technologies, share weights increase linearly from 0 in 2020 to 0.5 in 2100, reflecting a measured phase-in.

2.4.5. Water use

Food processing sector water withdrawal intensities are calculated for Canada and the United States using food processing industry water withdrawal data from Cameron et al. (2014) for Canada and from Rehkamp & Canning (2018) and Rehkamp et al. (2021) for the US, paired with calorie consumption data from gcamdata's food demand module. For all other regions, water withdrawal intensities are obtained by assuming that the level of water use in food processing scales with the level of energy use in food processing. For each region, the water withdrawal intensity in food processing is thus calculated as the US's food processing water intensity scaled by the ratio of that region's food processing energy use coefficient to the US's food processing energy use coefficient in 2015. These withdrawal intensities are then used to compute total withdrawals, as well as total consumption using the consumption to withdrawal ratio in Vassolo & Döll (2005). Water withdrawals and consumption for the food processing sector are subtracted from the total industry water use data.

2.4.6. Emissions

Consistent with the methodology for most other detailed industry sectors, CEDS combustion-related emissions from food processing (1A2e_Ind-Comb-Food-tobacco) are mapped to the food processing sector by fuel type.

For consistency with the energy data infilling, in which some of the other industrial energy use data is reallocated to the food processing sector, we also re-map some of the other industrial energy use non-CO2 emissions to the food processing sector. To do this, we calculate the fraction of the remaining other industry energy use data that is reallocated to food processing in the infilling process for each region, year, and fuel. We then apply this fraction to the non-CO2 emissions from the other industry sector to obtain the quantity of non-CO2 emissions to remove from other industry and reallocate to food processing (again for each region, year, and fuel).

Note that while some process emissions from the CEDS sector "2H_Pulp-and-paper-food-beverage-wood" are also from food processing, these are currently included as undifferentiated industrial process emissions elsewhere in GCAM. Similarly, non-trivial CH4 emissions are from industrial wastewater treatment associated with food processing (in the US, particularly from meat and poultry processing), but industrial wastewater CH4 emissions are not broken out separately in current global inventories, so they are not included in the food processing sector.

2.5. Overview of key changes in GCAM, gcamdata, and Model Interface queries

Table 1 key data and code changes made in gcamdata and queries

Data file/R chunk/CPP	Input/changes
zenergy_L1328.food_processing.R (added)	energy/A328.globaltech_coef.csv (added) energy/A328.energy_infill_model_coefs.csv (added) energy/A328.energy_infill_model_intercepts_R.csv (added)
zenergy_L2328.food_processing.R (added)	energy/calibrated_techs.csv (modified) energy/A328.sector.csv (added) energy/A328.subsector_interp.csv (added) energy/A328.subsector_logit.csv (added) energy/A328.subsector_shrwt.csv (added) energy/A328.globaltech_coef.csv (added) energy/A328.globaltech_cost.csv (added) energy/A328.regionaltech_cost.csv (added) energy/A328.globaltech_shrwt.csv (added) energy/A328.globaltech_retirement.csv (added) energy/A328.demand.csv (added)
zenergy_xml_food_processing.R (added)	Generate xml
zenergy_L232.other_industry.R (modified)	Modified input of remaining "other industry" energy to come from food processing chunk output
zemissions_L112.ceds_ghg_en_R_S_T_Y.R (modified)	emissions/CEDS/ceds_sector_map.csv (modified) emissions/CEDS/CEDS_sector_tech_combustion.csv (modified) emissions/CEDS/CEDS_sector_tech_combustion_revised.csv (modified) emissions/A51.max_reduction.csv (modified) emissions/A51.min_coeff.csv (modified) emissions/A51.steepness.csv (modified) Modified input files to include food processing process heat technologies; modified R chunk to take an input of food processing energy use and to reallocate some "other industry" CEDS non-CO2 emissions to food processing for consistency with the energy data infilling and reallocation.
zwater_L232.water_demand_manufacturing.R (modified)	water/food_mfg_intensity.csv (added) Modified to calculate food processing sector water use as the product of regionally-varying estimated water intensities and food production, and subtract the resulting values from aggregate industry water use
zwater_xml_water_demand_industry.R (modified)	Modified to include food processing sector water withdrawal and consumption coefficients

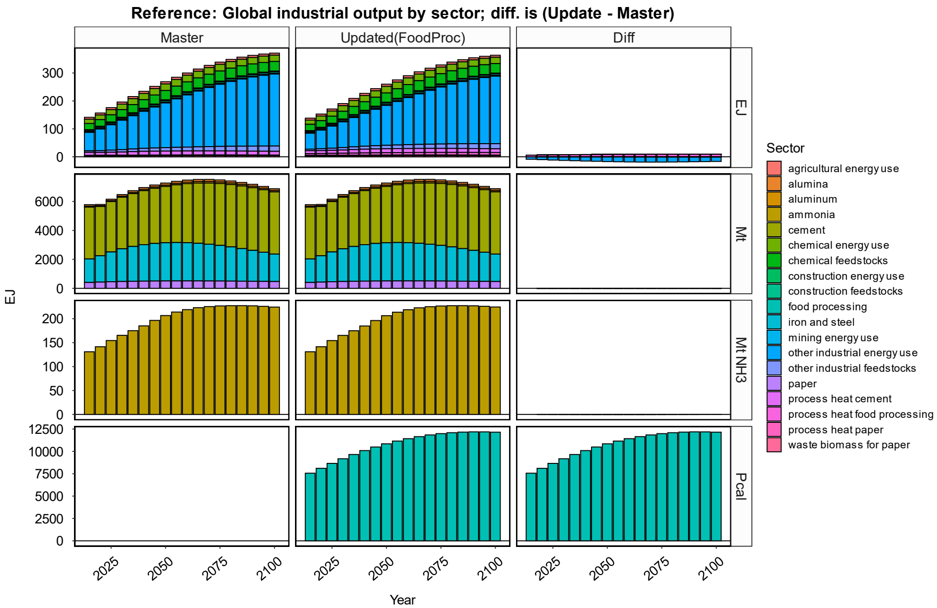
zsocio_L281.macro_account_tracking.R (modified)	Modified to include food processing sector in final energy service tracking
generate_package_data.R (modified)	Modified to include additional level 2 data names as well as to indicate a new prebuilt data output, which contains the fraction of total industry energy from the IEA Energy Balances that is in the food processing sector and the fraction that is in non-specified industry, as these data are needed to determine which regions and years will have infilling performed on food processing energy use data.
constants.R (modified)	Modified to include new constants needed for the food processing sector breakout, in both the energy and water chunks, specifically for performing the infilling of energy use data and for estimating regional variation in water use intensities. Also modified constants for GCAM macro to make sure food processing is properly incorporated.
zgcamusa_L232.industry.R and zgcamusa_xml_industry.R (modified)	Modified to ensure the food processing sector information is deleted appropriately for GCAM USA
energy/mappings/IEA_flow_sector.csv (modified)	Modified to include mapping for IEA food processing energy use to GCAM food processing sector
ModelInterface_headers.txt	Modified to include an additional header
output/queries/Main_queries.xml (modified)	Added queries for the food processing sector. Modified some of the total final energy and industry total final energy queries as needed to exclude the intermediate supplysector of process heat food processing and to ensure that solar energy inputs to food processing are captured.

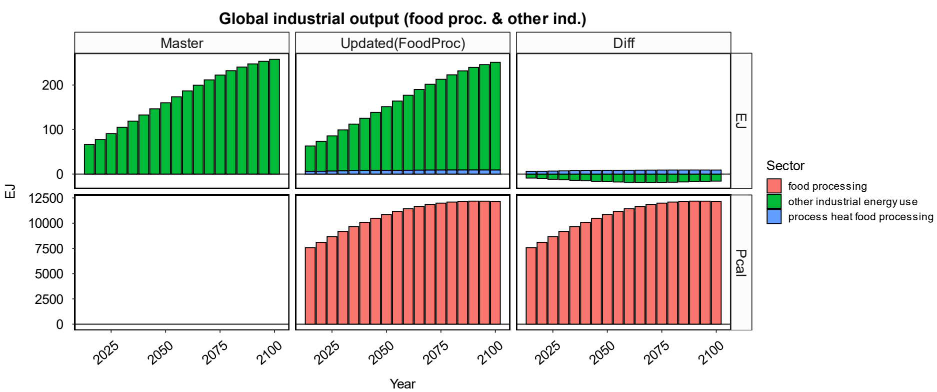
3. Shared policy assumption (SPA) GCAM validation runs

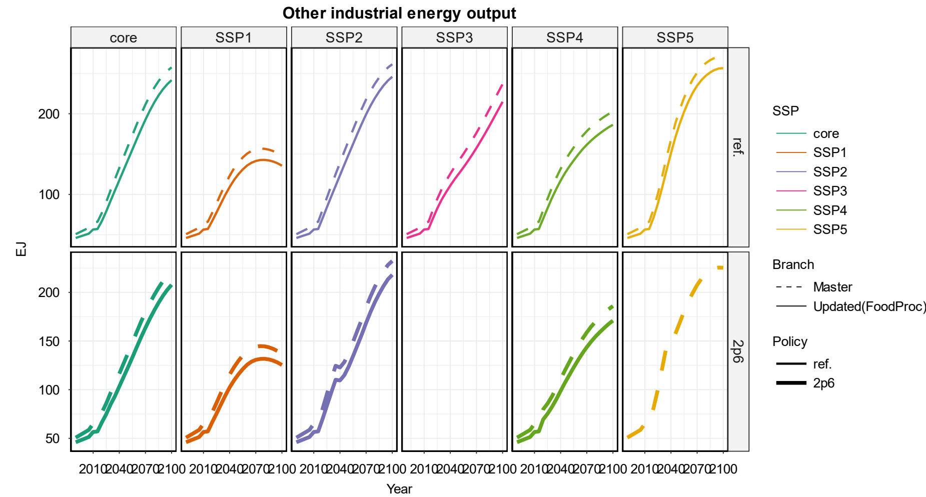
In accordance with the GCAM CMP convention, we present GCAM projection results, comparing the Updated (FoodProc) branch with the Master branch (CMP-370; Breaking out pulp and paper industry) for reference and RCP 2.6 scenarios across shared socioeconomic pathways (GCAM core & SSP1-5 assumptions; excluding SSP3-RCP2p6 and SSP5-RCP2p6). Note that SSP5-2p6 wasn't solved in the food processing branch, so ignore the comparison of this scenario.

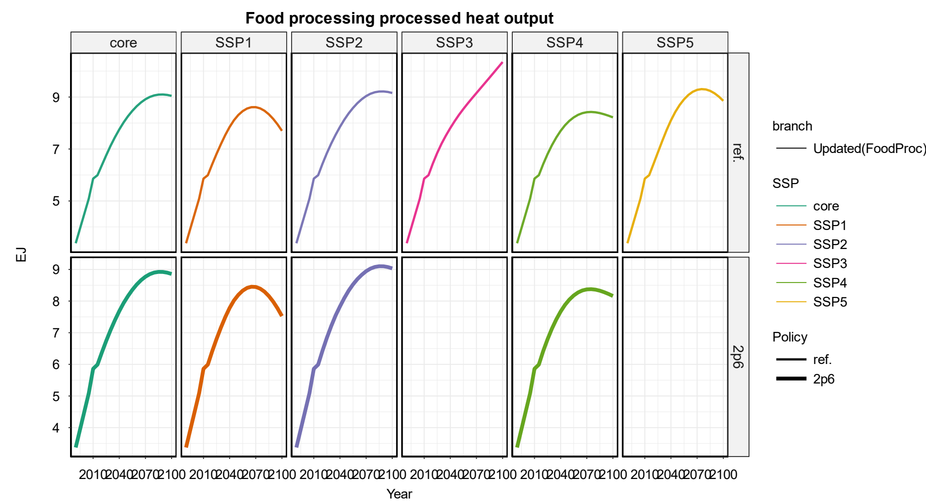
We provide key global results in the figures below, with more detailed results available in supplementary information.

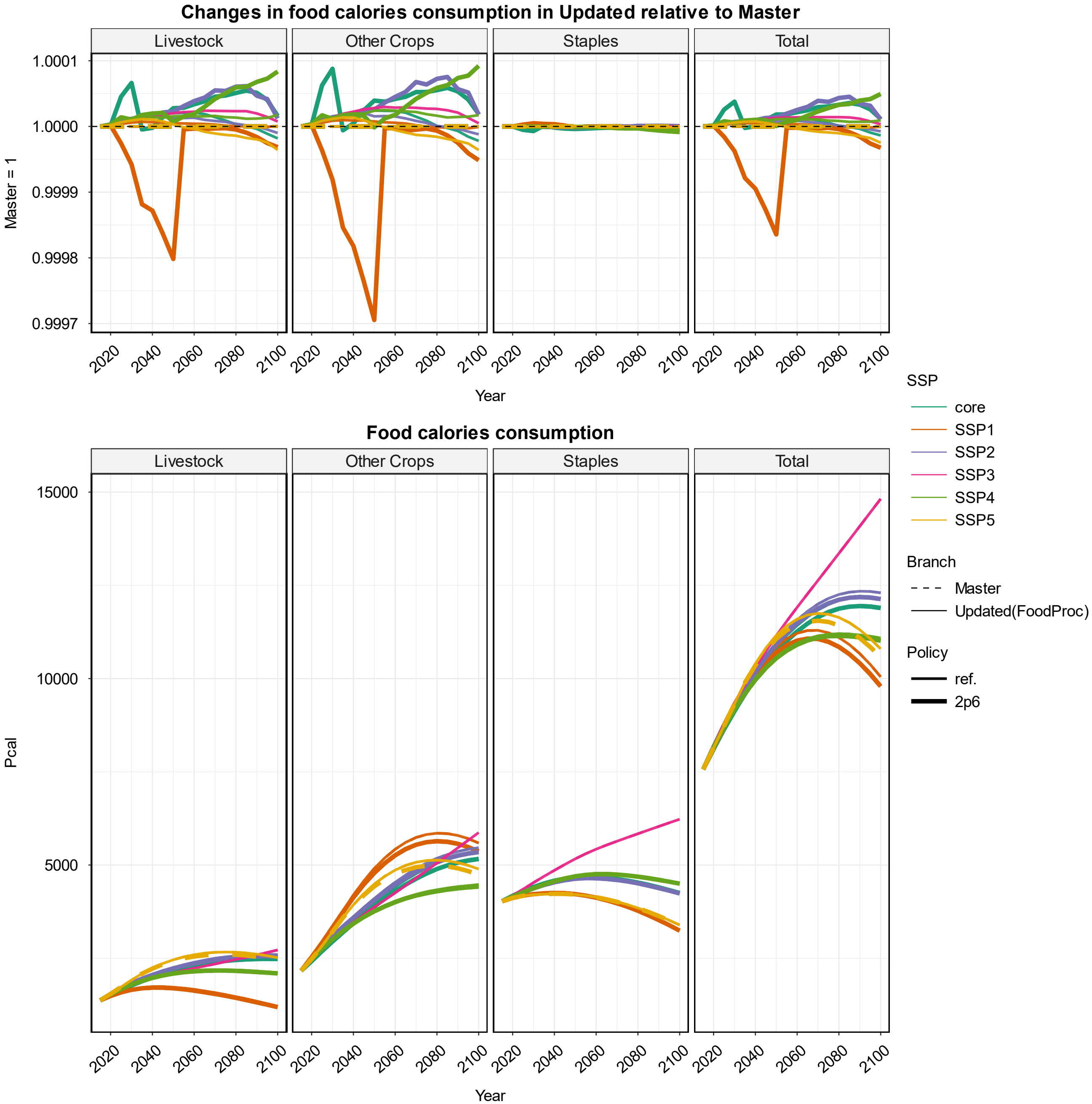
Global industrial output, with a focus on food processing and other industrial sectors. The food processing output (food calories) is indexed to food demand. Since the feedback is only one way, the impact of the update on the food calorie consumption is minimal.





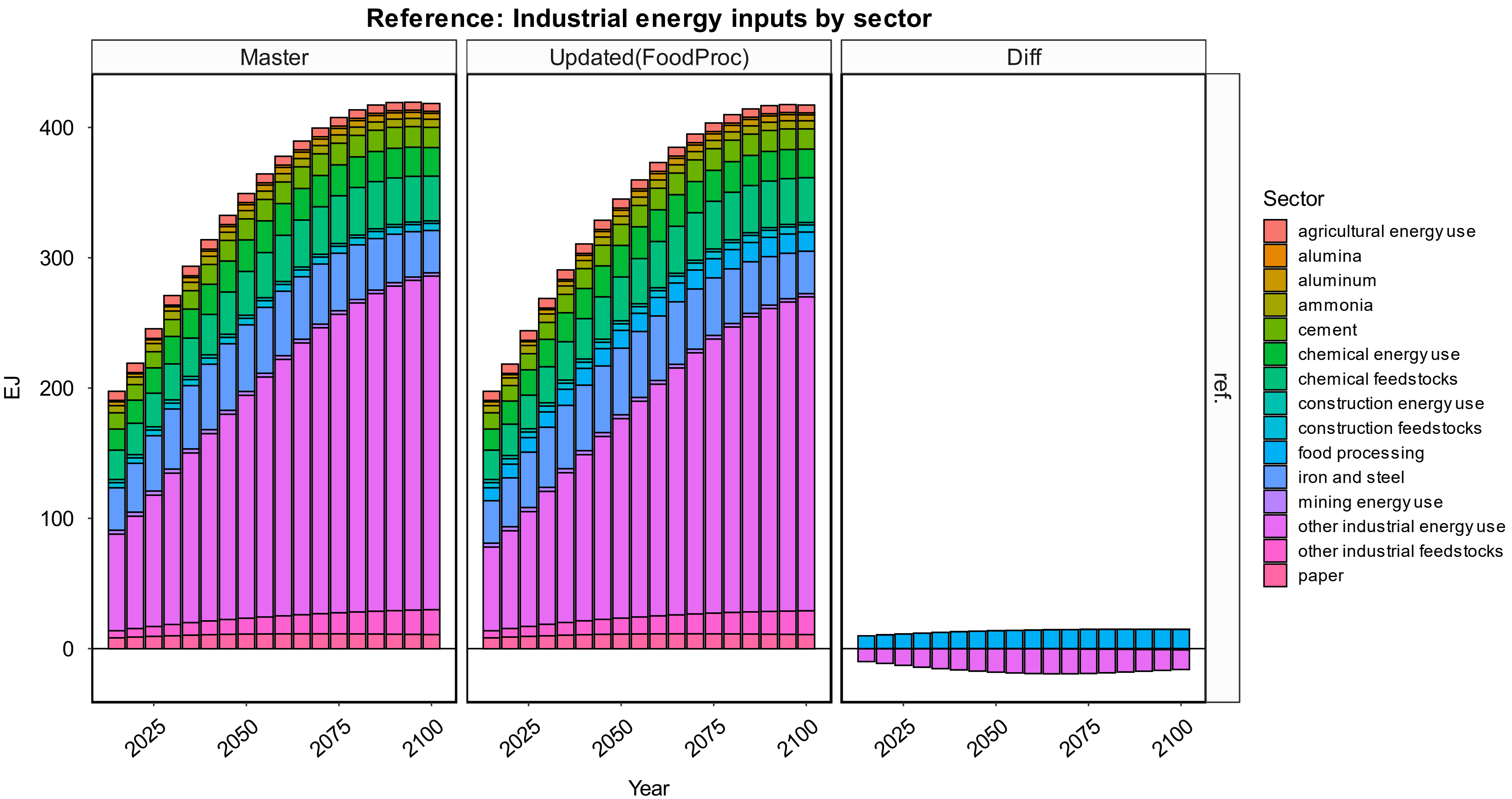




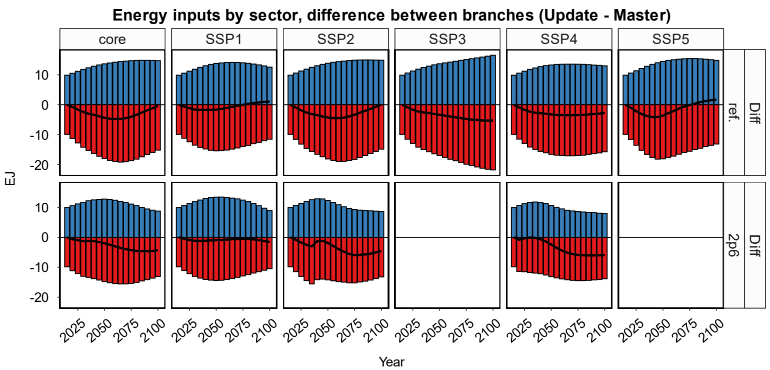


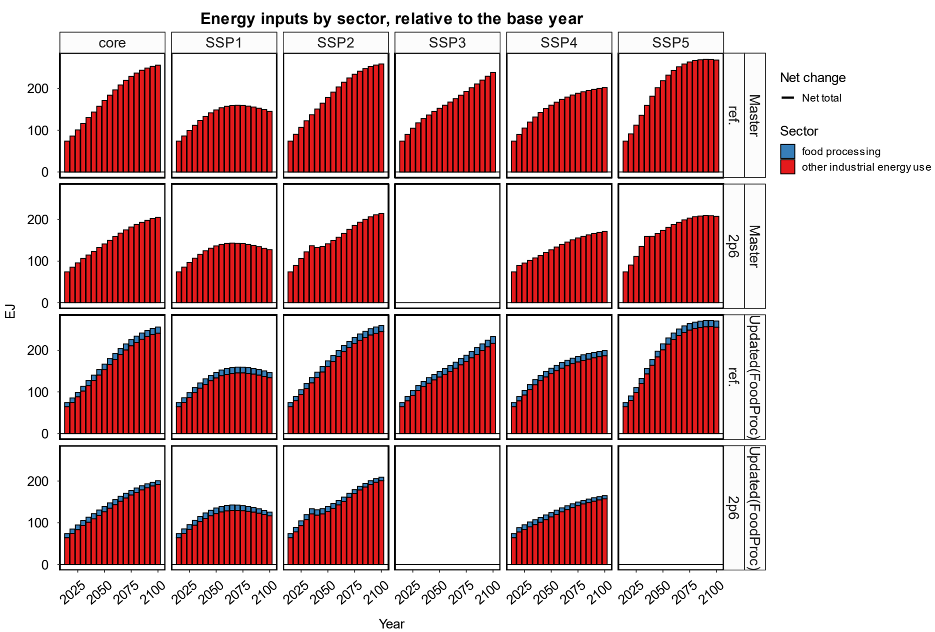
Changes in food calories consumption in Updated relative to Master
Livestock
Other Crops
Staples
Total
Master = 1
1.0001
1.0000
0.9999
0.9998
0.9997
2020
2040
2060
2080
2100
Year
Food calories consumption
Pcal
15000
10000
5000
SSP
core
SSP1
SSP2
SSP3
SSP4
SSP5
Branch
Master
Updated(FoodProc)
Policy
ref.
2p6

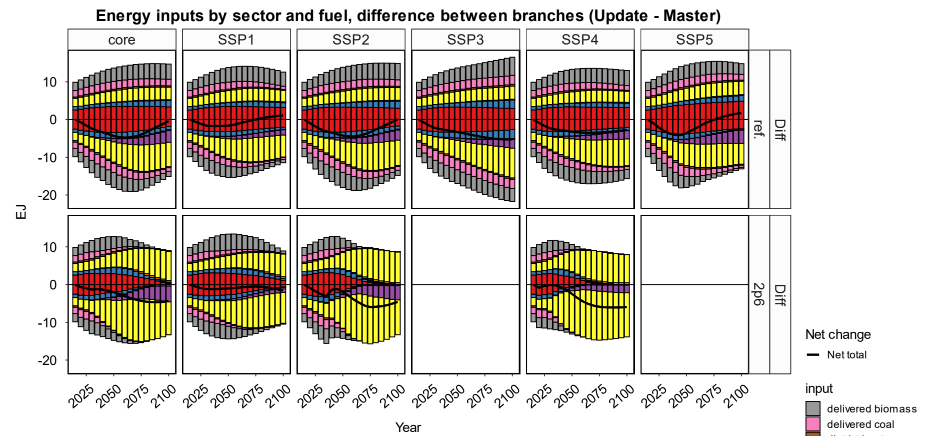
Global industrial energy input, with a focus on food processing and other industrial sectors. Similar to industrial outputs (above), only food processing and other industrial sectors are affected by the updates since food processing is separated from the other industrial sector. In the base year, the net change is indeed zero, confirming the consistency with the data processing.

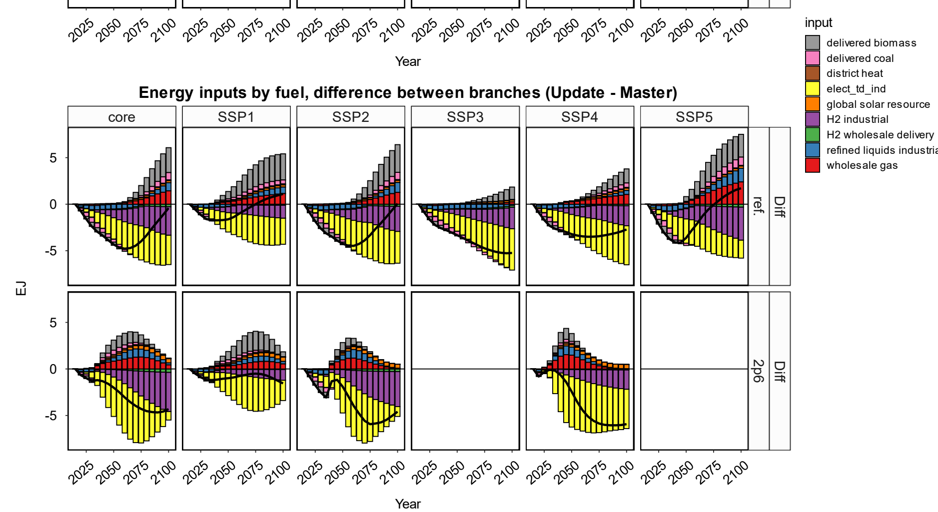


Further comparison and decomposition indicate (1) the energy input increase in food processing (driven by food demand) is lower than the decrease in other industrial sector and (2) there are some changes in energy sources, e.g., on average, less electricity and H2 uses in food processing compared to the other industry sector.

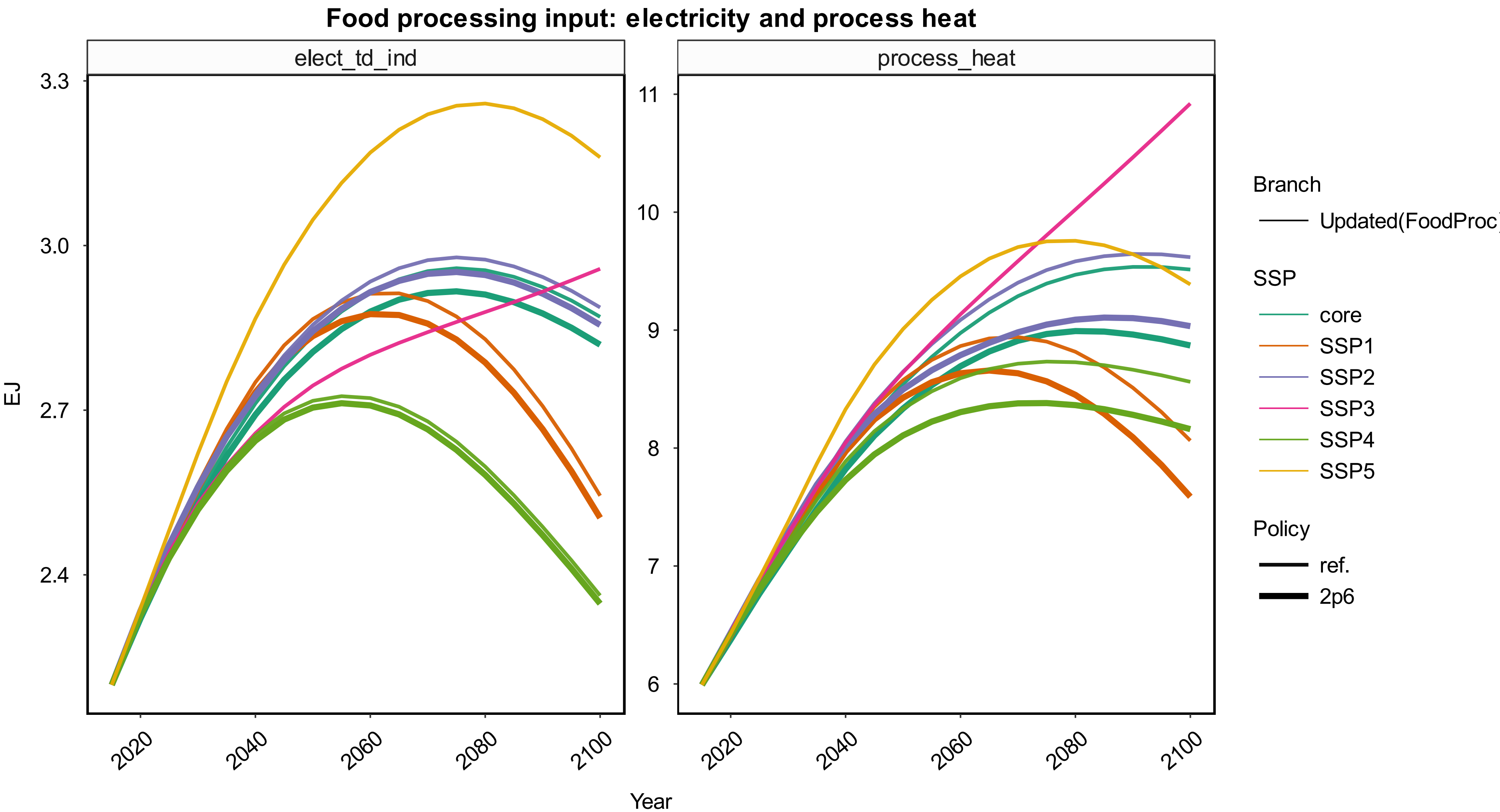




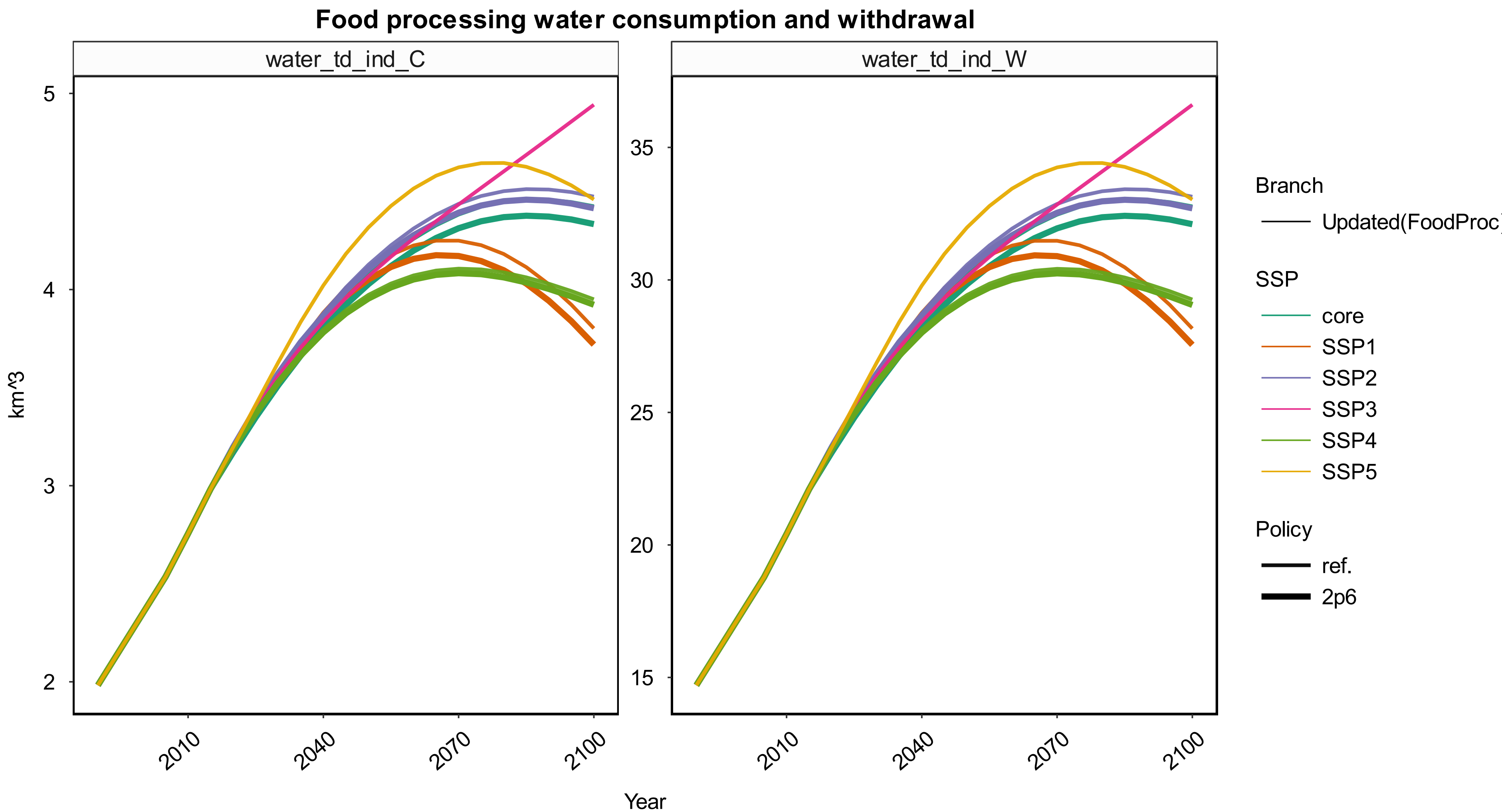




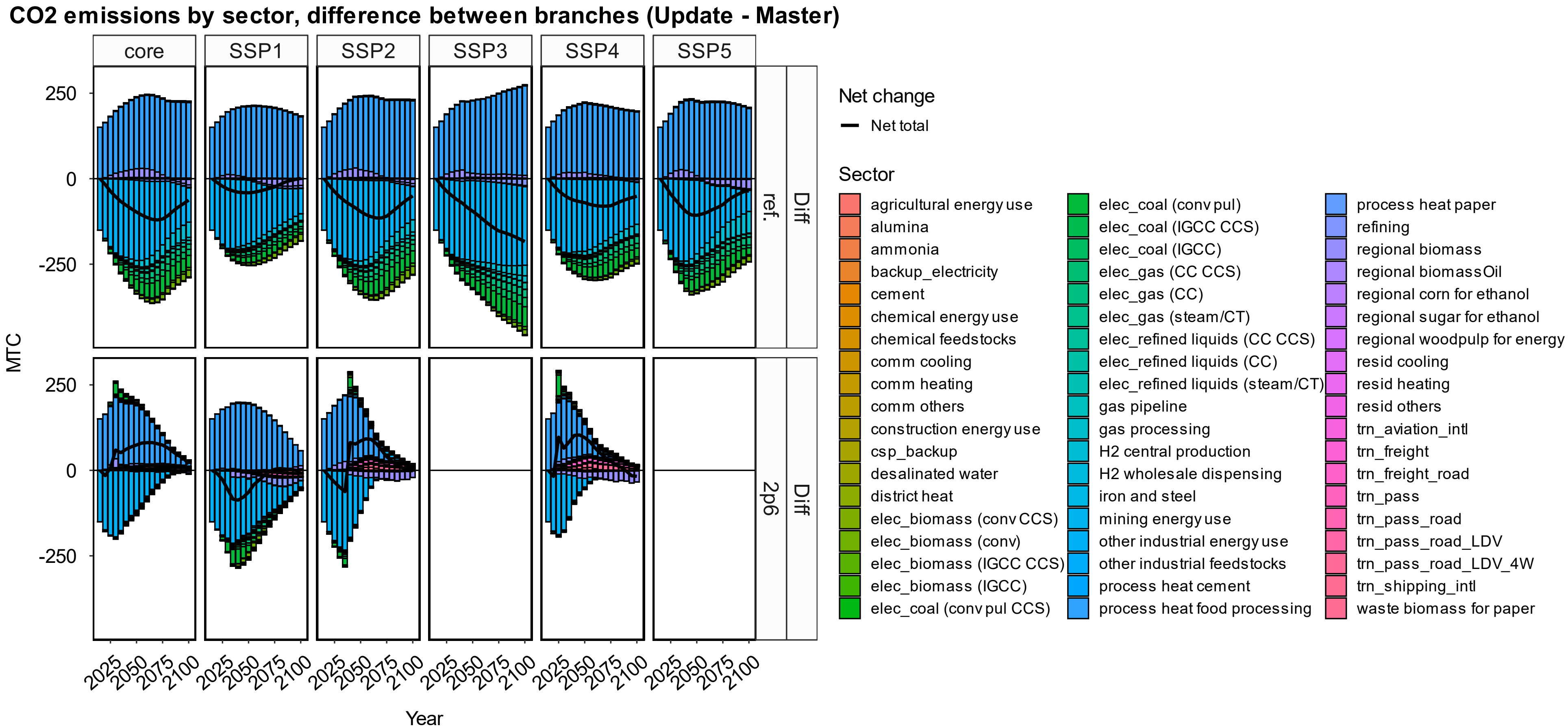
Global food processing electricity and process heat inputs. Note that the relative relationship between electricity input and the aggregated processed heat input is fixed at the regional level, while substitutions among technologies producing process heat are possible.



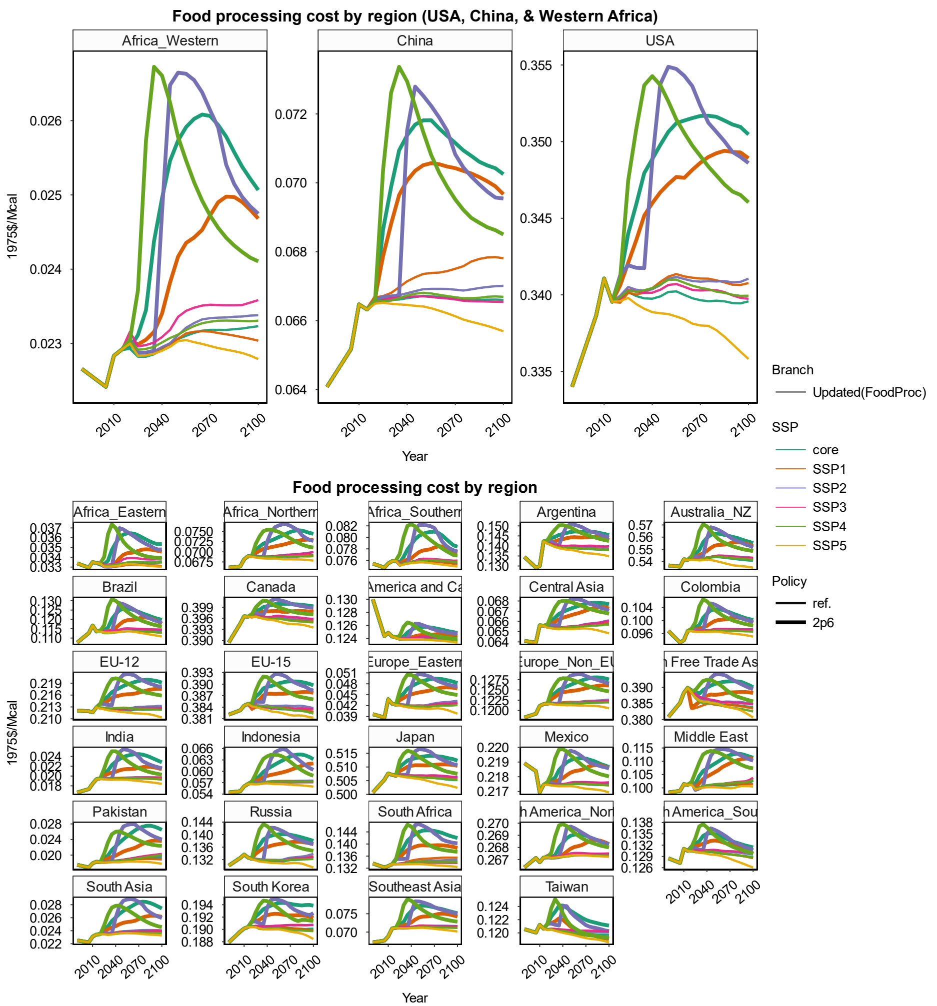
Global food processing water consumption and withdrawal.

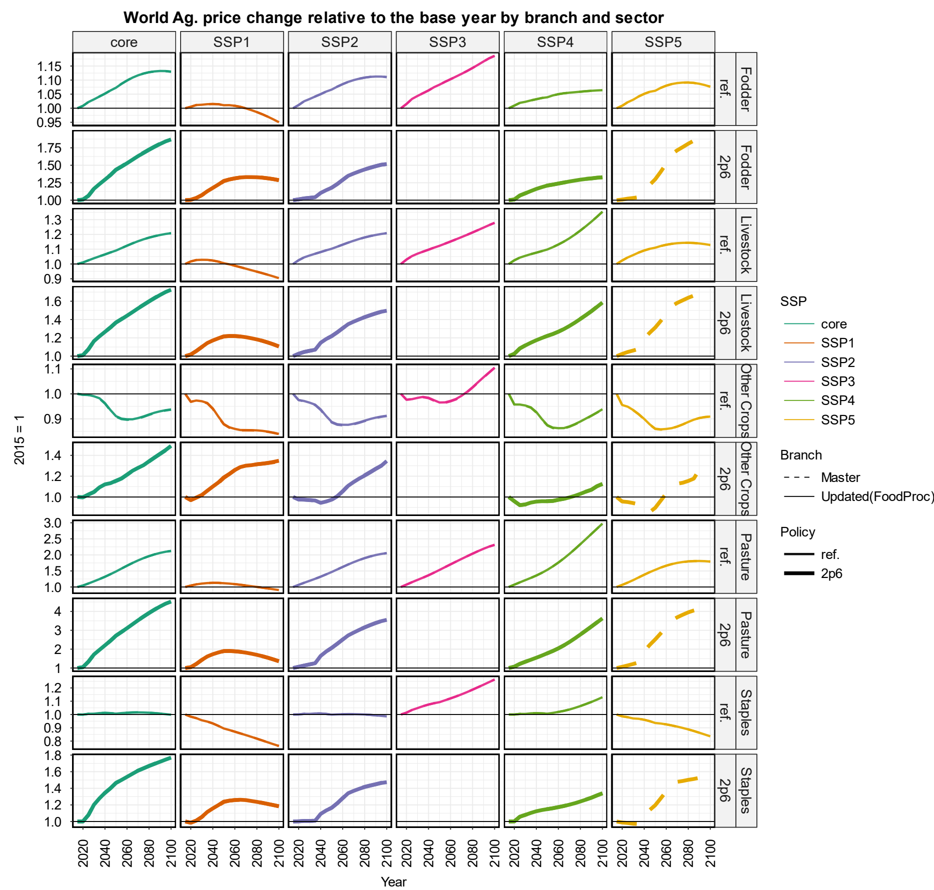


Impact of the updates on CO_2 emissions by sectors. There are relatively higher emissions from food processing but fewer emissions from other industries and electricity. The net total also decreased in reference, consistent with changes in energy inputs.

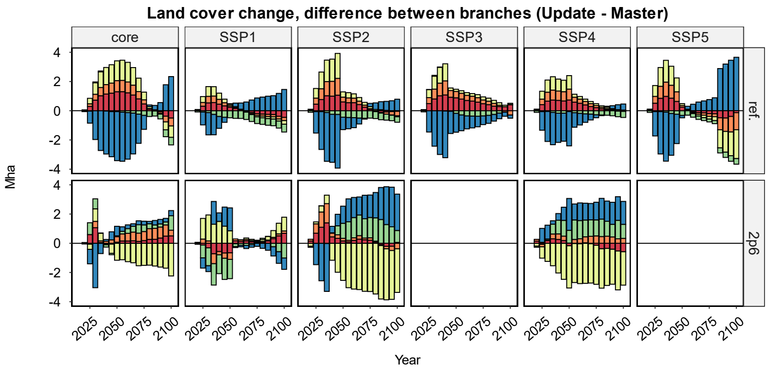


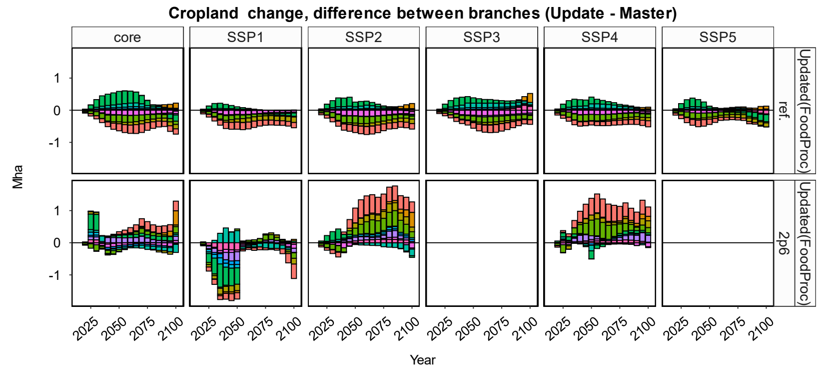
Food processing cost (left) and primary agricultural price changes (right). Developed regions have higher costs of food processing since more food processing services are used. The food processing cost may be affected by the mitigation policies due to changes in energy prices. However, the variation is small since the majority of the cost is non-energy. The model development has a negligible impact on primary agricultural prices (ignore SSP5-RCP2p6). In addition, if deriving an agroeconomic-wide food price index, both primary supply cost and processing cost need to be considered.

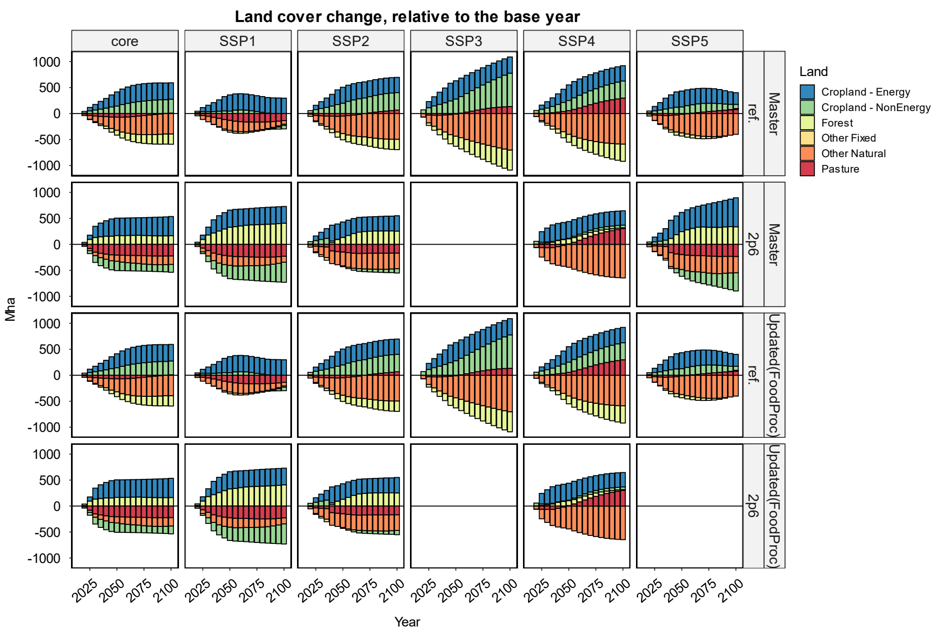


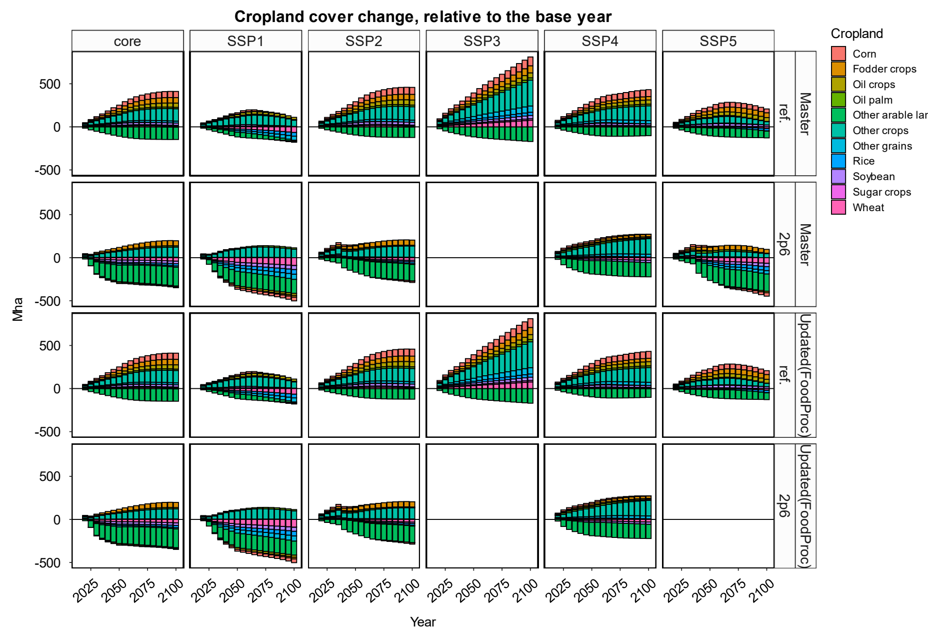


Confirming the impacts of the food processing break out on the overall land results are small.

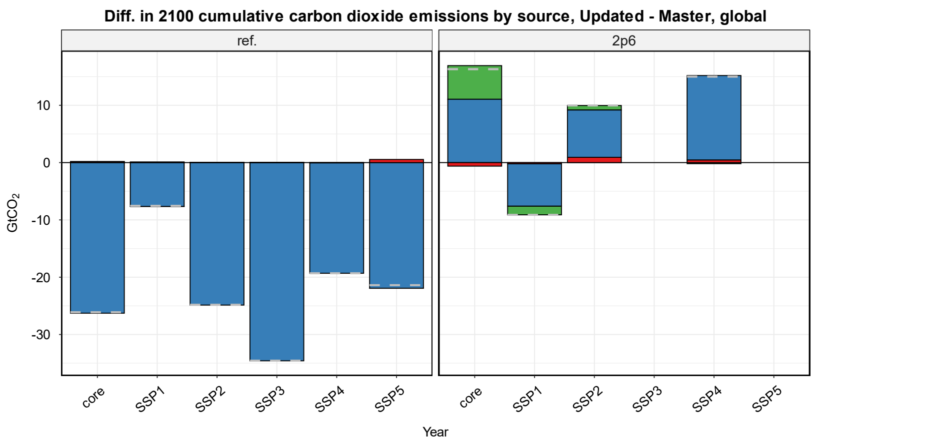


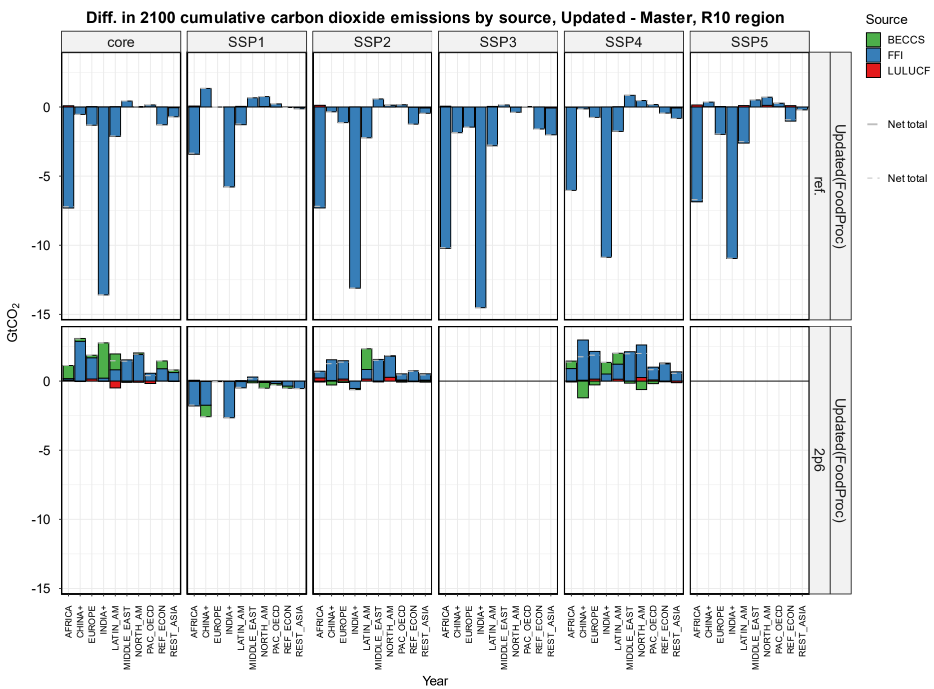


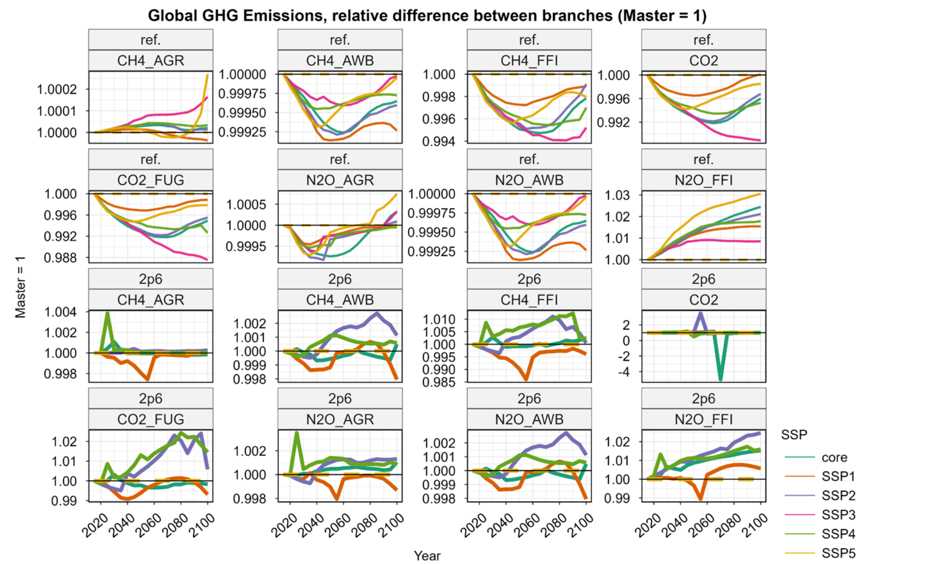


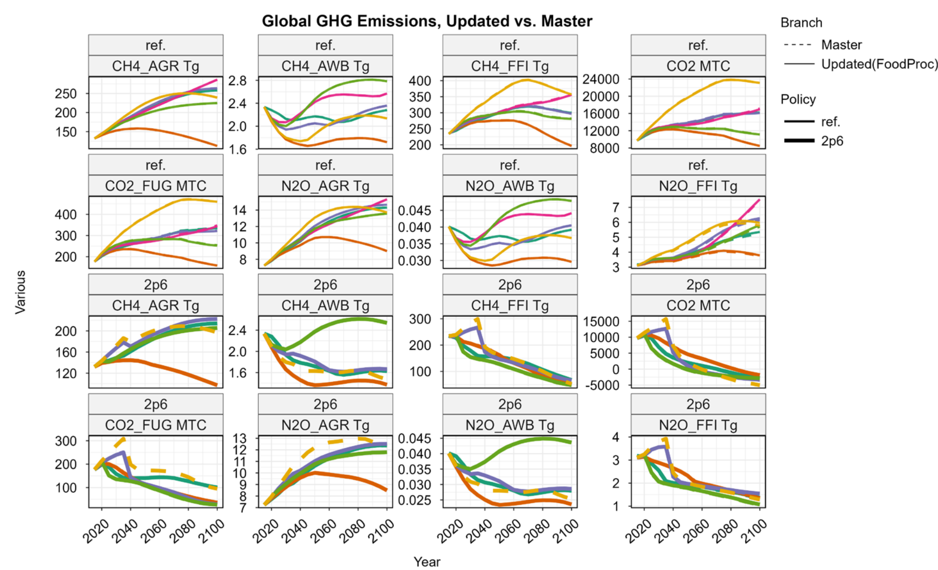


Confirming the impacts of the food processing break out on the overall emissions is small. In reference, the lower total FFI (Fossil Fuel and Industry) emissions were driven by the lower food processing emissions (than the corresponding other industrial emissions before the breakout).

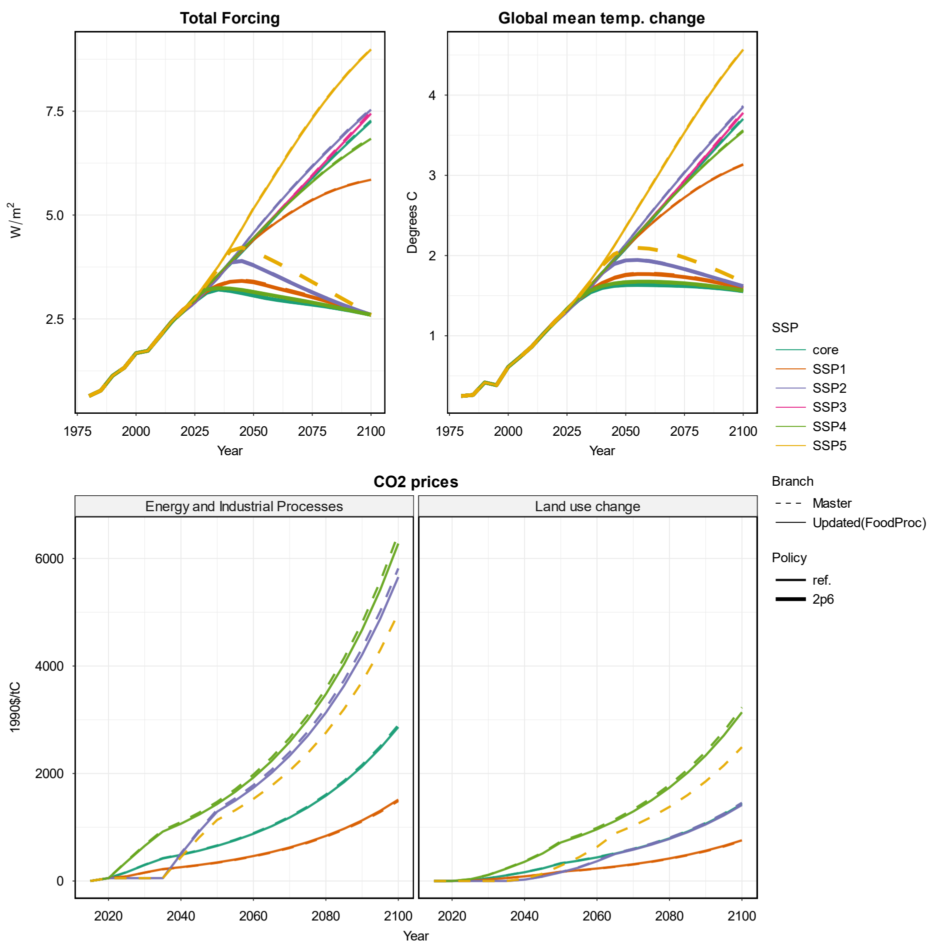


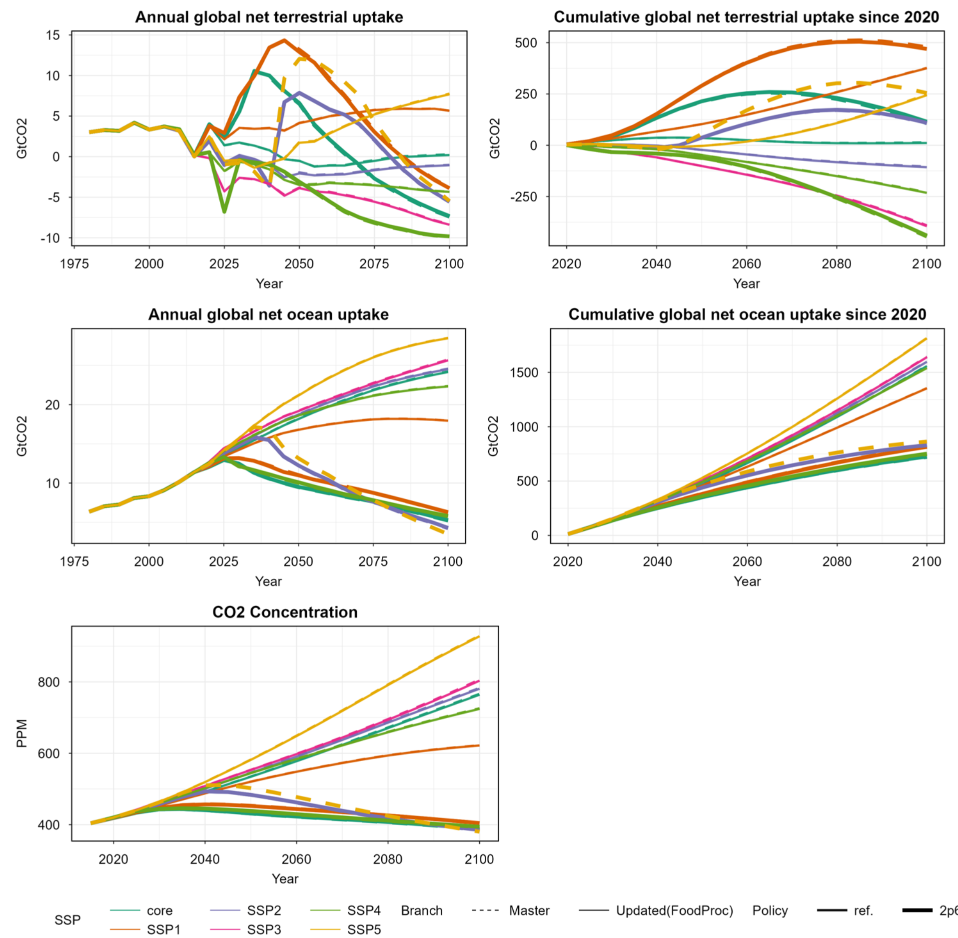






The impact of the updates on climate variables and the carbon cycle is also small. There are relatively higher emissions from food processing but fewer emissions from other industries and electricity. The net total also decreased in reference, consistent with changes in energy inputs.





4. Future work

a) International trade of food processing "service"

Not representing the trade of food processing service is a limitation of this work. The food processing service (with a unit of calories of this service) is linked to food demand with a fixed coefficient. However, all food processing energy is domestically supplied. For example, if a region is a large importer of processed food, we will underestimate the energy intensity of food processing. Thus, instead of assuming the food processing energy intensity is domestic, we should understand it as "trade-adjusted" energy intensity. That is, if a region consumes more food, the import of the service will also be higher so domestic energy consumption won't increase as much. It's not a perfect explanation as the trade partner is not reflected. In addition, a related issue is that we do not have energy intensity by food items. Instead, we only have IEA total food processing energy consumption. That will be another important area to work on further. That is, the trade modeling will need more detailed information on the food processing sector.

b) Food processing technology nonenergy cost (Table 2)

Currently, refined liquid technologies are assumed to have the same non-energy costs as gas technologies, while coal and biomass technologies are assumed to have 2.5 higher costs (based on data in a developed region). These assumptions need to be revisited to recognize the potential regional differences.

c) Regional cost and parameters for solar.

The PTC efficiency should vary by region using the CSP data we use now in GCAM (since it's only direct sunlight that can be used, not diffuse light, as for a PV system). The cost of the solar component can be scaled to DNI used for CSP calculations (there's an update in the BYU branch). What that will do is prevent this option from coming in in regions (or ultimately US states) without good Direct Normal Irradiance (DNI) resources. With the correction in the BYU branch, for example, this will keep solar from entering in regions such as Russia, etc., which have very few sunny days (few clouds) to make any such system workable.

d) Food demand responses to food processing costs

Currently, the food processing linkage to food demand is only "volume-based" with no price transmissions. That is, when food demand increases (due to income or primary crop or livestock input cost changes), the food processing service demand also increases. But when food processing costs increase (e.g., due to higher energy prices), food demand won't be affected. In other words, food demand is not responsive to food processing cost changes.

Technically, the linkage was implemented so that the food processing service is an input (`minicam-energy-input`) to the food demand model. However, `price-unit-conversion = 0` implies no price linkage/feedback (the cost of food processing in food demand is zero). If `price-unit-conversion = 1`, food processing cost changes would affect food demand. This price response has not been turned on mainly because we didn't differentiate the food processing service coefficient by agricultural sectors. This should be tested and examined in future work, e.g., when more detailed sectoral information is available.

5. Supplementary information

Table S1 Regionally-specific intercepts of the linear model used for estimating total food processing energy use based on calorie consumption and GDP data. Value listed for region=default is the default value used for regions that were not employed in model-fitting and that will also be used for any new regions not specified in the GCAM input file (i.e., if any new region is broken out); a warning is included in gcamdata that warns the user of this if they have added a new region. The coefficients and intercepts of this linear model are stored in energy/A328.energy_infill_model_coefs.csv and energy/A328.energy_infill_model_intercepts_R.csv, respectively.

Region	***d_R* value (in EJ)**	***c* + *d_R* (in EJ)**
USA	-0.2449	-0.1982
Australia_NZ	-0.0002	0.0465
Brazil	0.3701	0.4168
Canada	-0.1334	-0.0867
Central Asia	-0.0936	-0.0469
China	0.135	0.1817
EU-12	0.0098	0.0565
EU-15	-0.3552	-0.3085
Europe_Eastern	-0.0055	0.0412
Europe_Non_EU	-0.0889	-0.0422
European Free Trade Association	-0.0866	-0.0399
Japan	-0.2567	-0.21
Mexico	-0.0862	-0.0395
Russia	0.1275	0.1742
South America_Northern	-0.0632	-0.0165
South Korea	-0.0601	-0.0134
Southeast Asia	0.0608	0.1075
Taiwan	-0.063	-0.0163
Argentina	0	0.0467
Colombia	-0.035	0.0117
Africa_Eastern	N/A	0.0467
Africa_Northern	N/A	0.0467
Africa_Southern	N/A	0.0467
Africa_Western	N/A	0.0467

Central America and Caribbean	N/A	0.0467
India	N/A	0.0467
Indonesia	N/A	0.0467
Middle East	N/A	0.0467
Pakistan	N/A	0.0467
South Africa	N/A	0.0467
South America_Southern	N/A	0.0467
South Asia	N/A	0.0467
default	N/A	0.0467

Table S2 Global technology food processing non-energy costs. Units are 1975$/GJ for the process heat food processing supplysector and 1975$/Mcal for the food processing supplysector.

supplysector	**subsector**	**technology**	**minicam.non.energy.input**	**1971**	**2010**	**2050**	**2100**
process heat food processing	biomass	biomass	non-energy	2.7	2.7	2.7	2.7
process heat food processing	biomass	biomass cogen	non-energy	6.88	6.88	6.88	6.88
process heat food processing	gas	gas	non-energy	1.08	1.08	1.08	1.08
process heat food processing	gas	gas cogen	non-energy	2.75	2.75	2.75	2.75
process heat food processing	gas	gas with solar	non-energy	1.5	1.5	1.5	1.5
process heat food processing	refined liquids	refined liquids	non-energy	1.08	1.08	1.08	1.08
process heat food processing	refined liquids	refined liquids cogen	non-energy	2.75	2.75	2.75	2.75
process heat food processing	heat	heat	non-energy	1.08	1.08	1.08	1.08
process heat food processing	coal	coal	non-energy	2.7	2.7	2.7	2.7
process heat food processing	coal	coal cogen	non-energy	6.88	6.88	6.88	6.88
process heat food processing	electricity	electricity	non-energy	0.7	0.7	0.7	0.7

process heat food processing	electricity	electric heat pump	non-energy	2.67	2.67	2.67	2.67
process heat food processing	electricity	electricity with solar	non-energy	1.12	1.12	1.12	1.12
food processing	food processing	food processing	non-energy	0.1051	0.1051	0.1051	0.1051

Table S3 Regional food processing overall supplysector non-energy costs. Units are 1975$/Mcal. For any region not specified explicitly here, the global value from the global technology database will be used by default.

Region	**Cost (1975$/Mcal)**
Africa_Eastern	0.0293
Africa_Northern	0.0633
Africa_Southern	0.0705
Africa_Western	0.0198
Argentina	0.1261
Australia_NZ	0.515
Brazil	0.0955
Canada	0.3881
Central America and Caribbean	0.1209
Central Asia	0.0632
China	0.0616
Colombia	0.0879
EU-12	0.2039
EU-15	0.3718
Europe_Eastern	0.0334
Europe_Non_EU	0.116
European Free Trade Association	0.3691
India	0.0145
Indonesia	0.0522
Japan	0.4934
Mexico	0.2154

Middle East	0.0941
Pakistan	0.0134
Russia	0.1226
South Africa	0.1243
South America_Northern	0.2655
South America_Southern	0.118
South Asia	0.0196
South Korea	0.1815
Southeast Asia	0.0633
Taiwan	0.1128
USA	0.3258

Table S4 Process heat food processing technology coefficients. Values are unitless (EJ energy input per EJ heat output).

supplysector	subsector	technology	minicam.energy.input	secondary.output	1975	2100
process heat food processing	biomass	biomass	delivered biomass		1.43	1.43
process heat food processing	biomass	biomass cogen	delivered biomass	electricity	1.82	1.82
process heat food processing	gas	gas	wholesale gas		1.25	1.25
process heat food processing	gas	gas cogen	wholesale gas	electricity	1.67	1.67
process heat food processing	gas	gas with solar	wholesale gas		1	1
process heat food processing	gas	gas with solar	global solar resource		0.33	0.33
process heat food processing	refined liquids	refined liquids	refined liquids industrial		1.25	1.25
process heat food processing	refined liquids	refined liquids cogen	refined liquids industrial	electricity	1.67	1.67
process heat food processing	heat	heat	district heat		1	1
process heat food processing	coal	coal	delivered coal		1.25	1.25
process heat food processing	coal	coal cogen	delivered coal	electricity	1.67	1.67

process heat food processing	electricity	electricity	elect_td_ind		1	1
process heat food processing	electricity	electric heat pump	elect_td_ind		0.45	0.45
process heat food processing	electricity	electricity with solar	elect_td_ind		0.8	0.8
process heat food processing	electricity	electricity with solar	global solar resource		0.33	0.33

Table S5 Food processing technology vintage and retirement assumptions.

technology	lifetime	shutdown.rate	half.life	steepness	median.shutdown.point	profit.shutdown.steepness
electric heat pump	25		13	0.3	-0.5	6
electricity with solar	25		13	0.3	-0.5	6
gas with solar	25		13	0.3	-0.5	6
all other technologies	40		20	0.3	-0.5	6

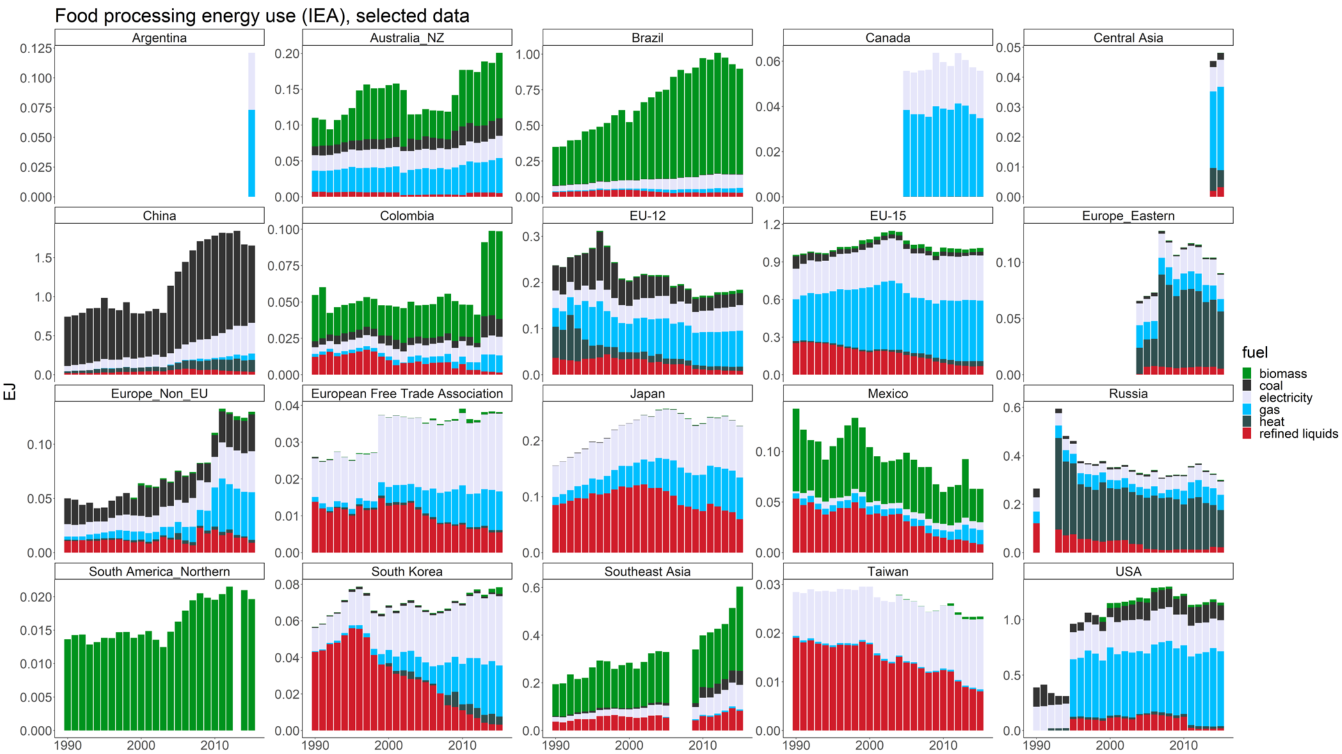


Fig. S1: Food processing sector energy use by fuel from the IEA Energy Balances raw data, only for regions and years that meet the criteria for sufficient data detailed above. These data are those that are used to obtain the linear model between food processing energy use and calorie consumption.

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