

Committed emissions from U.S. meatpacking plants

Supplementary Material

Methods

1.0 Compiling list of cattle meatpacking plants

The Food Safety and Inspection Service (FSIS) within the USDA publishes a weekly dataset of every meatpacking plant in the U.S., its parent company, its latitude and longitude and which species it slaughters and/or processes¹. The dataset distinguishes between plants that (1) slaughter but do not do secondary processing, the output of which is a cattle carcass and the by-products of the slaughter, (2) exclusively do secondary processing - turn into secondary cuts (i.e. steaks, ground beef, etc.) or flavored items (i.e. beef jerky, seasoned hamburgers) or (3) both slaughter and process in the same facility. The FSIS also provides an indication of size by grouping meatpacking plants into buckets by slaughter volume from the previous 360 days: Group 1 - less than 1,000; Group 2 - 1,000 to 10,000; Group 3 - 10,000 to 100,000; and Group 4 - 100,000 to 10 million.

As of 3 December 2025, there were 7,159 meatpacking plants in the U.S. Of these, 932 are slaughtering or slaughtering and processing cattle. This study does not include plants that only do secondary processing of cattle carcasses, but only those that slaughter or slaughter and process.

Of the 932 plants that slaughter or slaughter and process cattle, 667 also slaughter swine, 35 slaughter poultry and 678 slaughter other meat such as lamb, goats, deer, etc. While it is not possible to isolate what portion of their capacity is dedicated to which types of animals, when looking only at Group 4 plants, the largest plants of which there are 47 in total, only four of these

Company	# of plants
JBS	9
Tyson	4
Cargill	5
American Foods Group	4
Central Valley Meat Co., Inc.	3
National Beef Packing Co. LLC	3
Caviness	2
Agri Beef Co.	2
Nicholas Meat LLC	1
Creekstone Farms Premium Beef	1
STX Beef Company, LLC	1
Brown Packing Co., Inc.	1
Nebraska Beef Ltd.	1
Greater Omaha Packing Co., Inc.	1
One World Beef Packers	1
American Food Group	1
Lone Star Beef Processors	1
DemKota Ranch Beef	1
FPL Food	1
Sustainable Beef LLC	1

Table 1: List of companies in the dataset and the number of plants they own

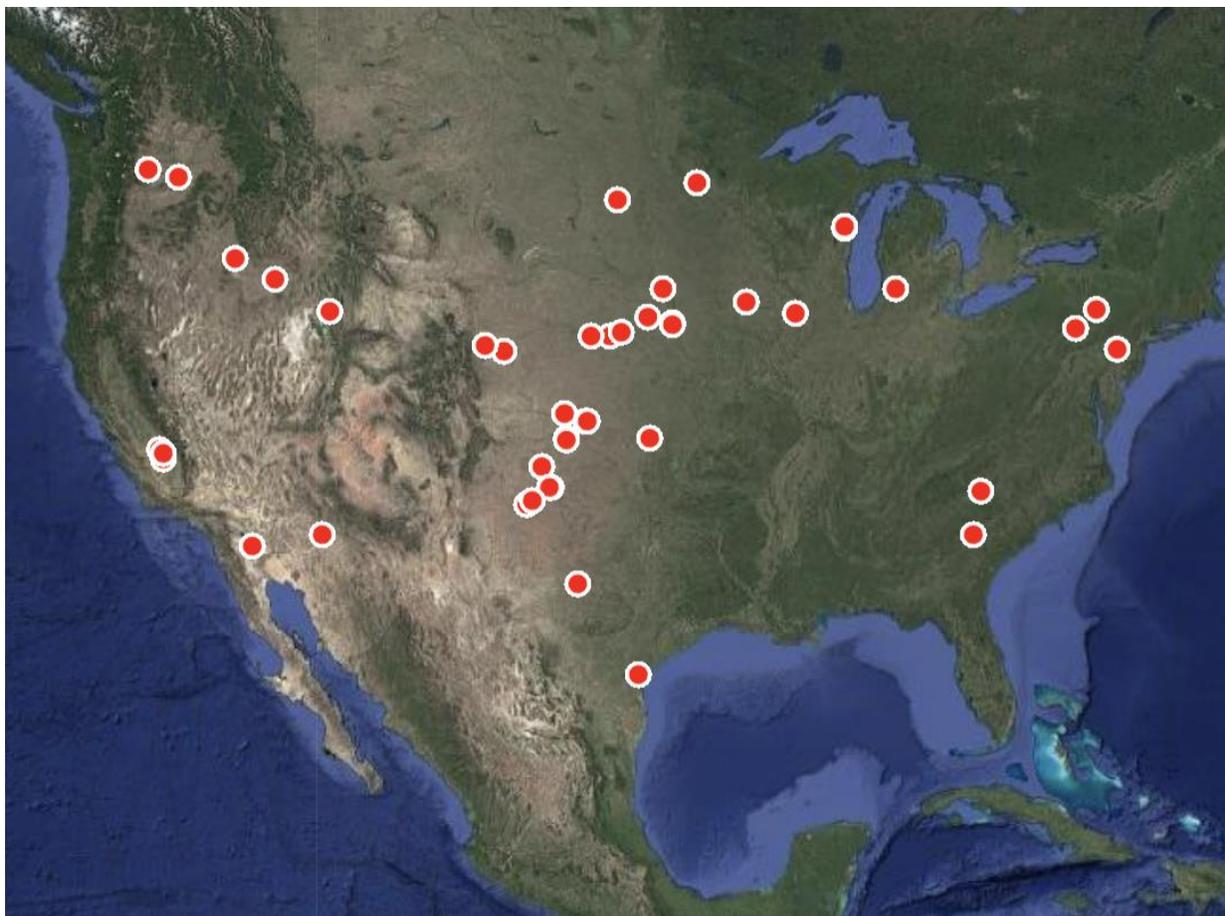


Figure 1: The location of the 44 plants included in the dataset

are listed as slaughtering other animals in addition to cattle. These plants were removed from the data, leaving 43 Group 4 plants that exclusively slaughter or slaughter and process cattle. Of these 43, one plant (Tyson in Lexington, NE) announced closure in in later 2025 and was removed from the list. Additionally, two new mid-sized plants (American Heartland Packing in Wright City, MO and Sustainable Beef LLC in North Platte, NE) were opened in 2025 and incorporated into the sample. The final plant sample is 44 plants owned by 20 companies (*Table 1, Figure 1*).

Together, these plants account for an outsized portion of slaughter capacity in the U.S. The four largest meatpacking firms – Tyson, Cargill, National Beef (Marfrig) and JBS – alone account for 85% of cattle purchases in the U.S.² By including the remaining Group 4 plants, owned by 14 companies, most of the cattle processing in the US is covered by these plants.

2.0 Compiling measurements of the spatial footprint of plants

2.1 Taking measurements from satellite imagery

Using the latitudes and longitudes for each meatpacking plant in the FSIS dataset, we built a longitudinal dataset of the spatial footprint of each meatpacking plant. We used historical satellite imagery available through Google Earth Pro, which provides intermittent high-resolution imagery of U.S. sites from approximately 1992 onward. This imagery is not available for every year, but a measurement was taken for every year that imagery was available.

For each plant and each year in which a high-resolution image was available, we manually digitized polygons over the facility footprint. These polygons were drawn around three key spatial features for each year: (1) the buildings on the plant site, (2) employee parking areas, and (3) transport truck zones. Polygons were then aggregated to produce a single measurement for each of the three spatial components per establishment for each year a high-resolution image was available.

2.2 Filling in missing measurements

Measurements from satellite imagery were compiled into a panel dataset with one row per plant per year, beginning with the first high-resolution measurement year for each plant and extending through 2025. On average, coverage of measured years per plant was 46.4%.

To fill in missing measurements values, we began by implementing a simple deterministic rule-based interpolation procedure. A moving-window or statistical smoothing model was intentionally avoided to preserve the discrete, event-like nature of physical plant expansions. The aim was to reconstruct plausible annual footprints while maintaining the ability to identify any sudden substantial footprint changes that could be linked to investment events.

Each observation was classified into one of three states: stable, noise, or jump, based on the magnitude of the spatial change relative to the previous observation.

- **Jumps** were large changes, indicative of substantial structural additions to the plant

- **Noise** represented small, likely inconsequential changes in footprint that could arise from operational adjustments (e.g., a new storage shed) rather than new capital investment.
- **Stable** states were years with no change between the measurements surrounding a time gap in the satellite imagery; the intervening years were filled with the same value

States were assigned as follows. For each consecutive observed pair (year A with measurement m_A , year B with measurement m_B): compute the absolute change $|m_B - m_A|$. If $|m_B - m_A| = 0$, classify as stable and fill the years between year A and year B with m . Then, if $0 < |m_B - m_A| \leq 1000$, m_B was flagged as ‘noise’ and the intervening years between year A and year B were filled in by linear interpolation between m_A and m_B . The noise threshold was set at 1000 m² because visual inspection of multiple plants across several years confirmed that additions below 1000 m² corresponded to minor additions rather than major expansion events. This process is also illustrated in *Table 2*. This procedure increased average measurement coverage from 44% to 66.6% for building footprints, 70.2% for parking and 66% for trucks.

For all *jump* cases ($|m_B - m_A| > 1000 \text{ m}^2$), the year of change was estimated using annual Landsat time-series analysis. The polygon representing the spatial difference between m_B and m_A was extracted, and median composite images were compiled for each year of the gap (inclusive of the bounding years). From each annual composite we derived seven spectral bands—red, green, blue, near-infrared (NIR), short-wave infrared 1 and 2 (SWIR1, SWIR2)—and two indices: the Normalized Difference Vegetation Index (NDVI) and the SWIR-to-red reflectance ratio. NDVI and SWIR-to-red were selected because they respond strongly to the conversion of vegetated or bare surfaces to impervious materials. Diagnostic checks ensured that each gap was covered entirely by a single Landsat collection (5, 7, or 8), avoiding cross-sensor harmonization; for example, a 2012–2015 gap was analysed solely with Landsat 7 data.

A multi-stage change-detection procedure was then applied to identify the year of a sustained and substantial shift in the spectral or index values:

Year	Building (m ²)	Difference (v)	Flag	Fill
2014	19,942			19,942
2015				20,081
2016				20,081
2017	20,219	277	noise	20,219
2018				20,219
2019	20,219	0	stable	20,219
2020				
2021				
2022	23,584	3,365	jump	23,584

Table 2: An example of the interpolation procedure used to fill in missing measurements using noise/stable/jump flags

- **Primary step:** multivariate PELT (Pruned Exact Linear Time) applied jointly to NDVI and SWIR-to-red for gaps ≥ 4 years.
- **Secondary step:** univariate PELT applied separately to NDVI or SWIR-to-red for gaps ≥ 4 years.
- **Primary fallback:** multivariate maximum-sum-difference method for gaps < 4 years.
- **Secondary fallback:** univariate maximum-sum-difference method for gaps ≤ 4 years.
- **None assigned:** if no meaningful discontinuity was detected.

PELT was implemented in its least-squares configuration, which identifies changepoints that minimize the total sum of squared residuals of piecewise-constant segments—that is, breaks in segment means. To control sensitivity, we used the penalty formulation

$$pen = pen_{mult} \times \log(N) \times \sigma,$$

where N is the number of years in the gap and σ is the empirical standard deviation of the signal. The default multiplier was $pen_{mult} = 3.0$. We required at least four years of complete annual data (no missing values) to attempt PELT on a given signal. We tested minimum-year thresholds

of 4, 5, and 6 and penalty multipliers $pen_mult \in \{2,3,4,5\}$. Results were robust: changing pen_mult from 2 to 5 altered the consensus year in $\approx 0.9\%$ of cases.

For gaps shorter than four years where PELT cannot reliably resolve step changes, the year-over-year difference in each metric was calculated directly. The year with the largest aggregate positive difference was assigned as the change year. The result was flagged as *multivariate* if both indices shifted concurrently or *univariate* if only one did.

Landsat's spatial resolution ($30\text{ m} \times 30\text{ m} = 900\text{ m}^2$ per pixel) supports the 1000 m^2 threshold used to distinguish *jumps* from *noise* but also limits the stability of results for smaller changes ($\approx 1000\text{--}3000\text{ m}^2$) with few valid pixels. To reflect this, each detected *jump year* was assigned a confidence class:

- **High confidence:**
 - Change detected by the PELT changepoint algorithm (both multivariable and single variable), and
 - At least 20 valid pixels within the change polygon in that year.
- **Medium confidence:**
 - Change detected by PELT with fewer than 20 pixels, or
 - Change identified by the maximum-jump with ≥ 20 pixels of valid data.
- **Low confidence:**
 - Change detected by the maximum-jump with < 20 pixels of valid data.

Of 363 remaining *jump* gaps after filling *stable* and *noise* cases, the procedure identified a jump year for 288 (79 %): 154 high-confidence, 98 medium-confidence, and 36 low-confidence detections. Low-confidence cases were typically short gaps with small area changes (mean 3.6 years; $\approx 1237\text{ m}^2$). Because short gaps constrain the timing error to $\pm 1\text{--}2$ years and involve minor structural additions, their influence on downstream capital-investment inference is limited. Conversely, the longest and largest changes are resolved with the highest confidence.

$$m_B - m_A$$

Once a jump year j was identified, the pre- and post-change measurements were propagated to complete the annual series: m_A was forward-filled from year A to $j - 1$ and m_B was back-filled from year B to j . This increased overall data coverage to 92.1 % for building footprints, 92.8 % for truck areas and 93.0 % for parking areas.

After this process, the remaining gaps were imputed by forward-filling m_A . This was the case for 22 plants for which the most recent measurement was between 2023-2024. These were gaps where the last measurement from high-resolution satellite imagery was before 2025. These could not be filled through Landsat change detection because of the lack of a m_B by which to identify any potential change in spatial footprint.

3.0 Compiling plant slaughter capacity

Daily slaughter capacity—the maximum number of cattle a facility is physically equipped to process—was used as the measure of plant scale. Capacity was selected over throughput because throughput varies with cattle supply, prices, and operational conditions, whereas capacity reflects the technical and financial commitment a plant makes to the upper bound of slaughter under favourable market conditions.

Capacity data were compiled from *Cattle Buyer's Weekly*, an industry publication that has reported U.S. meatpacking capacity annually since 1999. The dataset is primarily company-level, with plant-level figures available only in 2003 and 2024. As a result, plant-level capacity is complete for single-plant companies but missing for multi-plant firms (e.g., Tyson, JBS, Cargill) in most years. For these multi-plant firms, the publication reports the total company capacity and the number of plants operating in each year.

To reconstruct plant-level capacity for multi-plant firms, we first rebuilt each company's plant portfolio from 2003–2024, identifying the year in which each establishment was acquired. When company-level capacity and the number of plants remained constant before or after the 2003 and 2024 plant-level benchmark years, these values were forward- and back-filled to the surrounding years.

To fill in remaining gaps, a similar process was followed as was done for spatial measurements. The difference in capacity C between Year A and Year B was calculated as $|C_B - C_A|$ and temporal gaps flagged as either ‘stable’, ‘noise’ or ‘jumps.’ Stable gaps, where $|C_B - C_A| = 0$ were filled in with C_A . A noise threshold of 50 cattle per day—chosen because changes below this level correspond to minor operational adjustments rather than structural expansions—was used to identify ‘noise.’ Where $|C_B - C_A| < 50$, gap years were filled in with the mean of C . This increased the average data coverage for each plant from 61% to 79%.

For ‘jump’ cases in which $|C_B - C_A| > 50$ but the year of the jump was unknown, we conducted a systematic online archival search of news articles, company announcements, industry reports, and regulatory filings to identify investment events, upgrades, or ownership changes occurring during the gap years. For every jump except one, documentary evidence was found that aligned with the observed capacity increase (listed in the *Supplementary Material*). Incorporating these events increased average coverage to 98.94%. There was only one capacity jump for which no reports could be found - American Foods Group’s plant in Green Bay, WI, for which there is minimal company or press coverage. For this plant, C_A was forward filled up to Year B, resulting in a capacity observation for every plant for every year it was open from 2003-2024.

4.0 Identifying capital investment events and their depreciation period

4.1 Types of investments

To identify investments, a framework was used that distinguishes between four mutually exclusive types of investments based on whether they involved (a) changes to the spatial footprint and (b) changes in plant capacity. This is shown in *Table 3*.

Spatial investments can be determined through observations of satellite imagery and changes in spatial measurement. Capacity increases can be determined through changes in the daily slaughter capacity. The only type of investment not able to be identified through this process is non-spatial/non-capacity investments. However, such investments may be more likely to be

	Capacity Increase	Non-Capacity Increase
Spatial	Spatial/Capacity CAPEX events marked by an increase in building footprint <i>and</i> a corresponding jump in plant capacity (e.g., expansion of slaughtering floor)	Spatial/Non-Capacity CAPEX events with a footprint increase but no associated capacity change (e.g., additions for cold storage, offices or secondary processing)
Non-Spatial	Non-Spatial/Capacity CAPEX events not linked to spatial changes but associated with an increase in capacity (e.g., automation or process streamlining)	Non-Spatial/Non-Capacity CAPEX events with neither a footprint nor capacity increase (e.g., maintenance, food safety upgrades, wastewater improvements)

Table 3: A framework of types of CAPEX investment events

general maintenance and may be more likely to be expensed and paid for with cash rather than be capitalized and so therefore are not a concern for this research.

4.2 Identifying CAPEX investments

To identify capital investments at meat-processing plants, we detected substantial and sustained increases in either (a) building footprint or (b) slaughter capacity. We computed year-on-year deltas and deltas over a 2-year running timespan to account for longer projects:

- **1-year change:** $\Delta C_t = C_t^{log} - C_{t-1}^{log}$ and $\Delta B_t = B_t - B_{t-1}$
- **2-year change:** $\Delta C_t = C_t^{log} - C_{t-2}^{log}$ and $\Delta B_t = B_t - B_{t-2}$

where C_t is daily slaughter capacity and B_t is total building area.

To determine what constitutes a “substantial” increase, we used a robust threshold based on the median absolute deviation (MAD) of the distribution of *positive* deltas pooled across all plants (Figure 3).

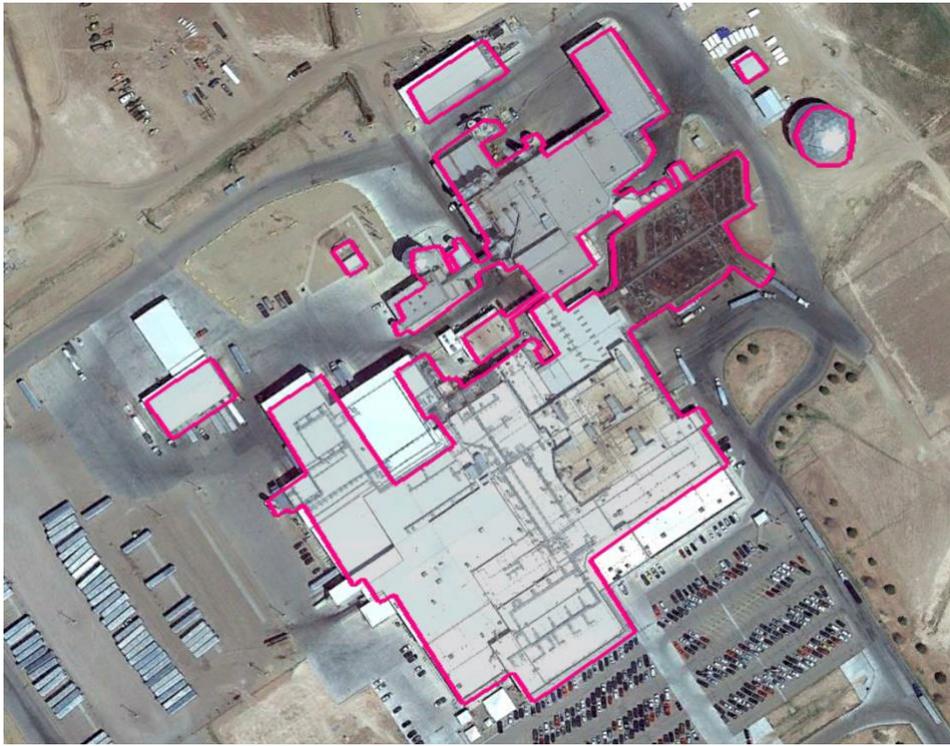


Figure 2: The Caviness plant in Hereford, TX in April 2022. The pink outline is the building footprint from the previous year, against which new building additions can be seen.

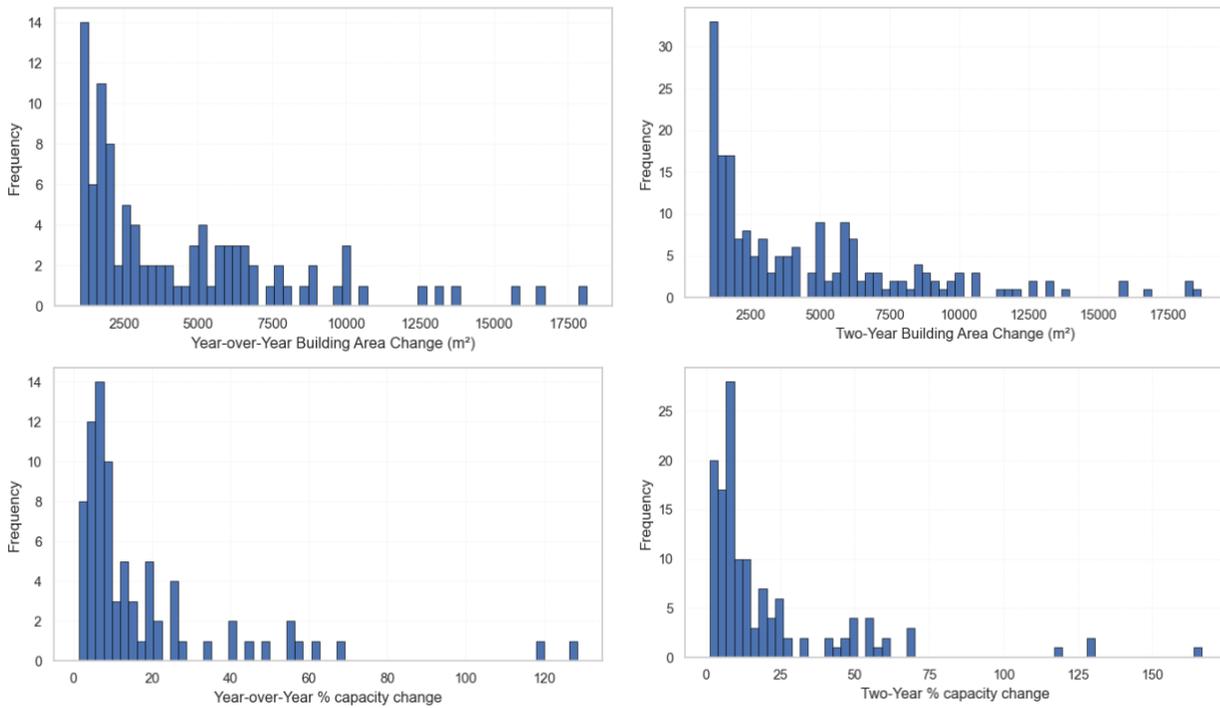


Figure 3: The distribution of the one-year and two-year deltas of plant buildings and capacity

The threshold was:

$$T = \text{median}(X) + \text{MAD}(X) \cdot k \cdot 1.4826$$

where:

- X_+ denotes the pooled positive deltas,
- $1.4826 \cdot \text{MAD}$ is the standard SD-consistent scaling for MAD,
- k is a sensitivity multiplier.

We tested values of $k \in [0.1, 3]$ and validated each setting against known expansions identified from industry news reports and satellite imagery (see *Supplementary Material*). A value of $k = 0.1$ provided the best balance of sensitivity and specificity for our dataset, which exhibits a heavy right tail due to large one-time expansions at a subset of plants. Under this threshold, the year-over-year change required to signal a substantive event was approximately 3,300 m² for building footprint and 0.09 in log-capacity. For two-year changes, the corresponding thresholds were approximately 3,500 m² for buildings and 0.11 for the log-capacity metric. *Figure 2-3* show the distribution of the deltas and a sample of the change in the building size that was flagged.

We required that any flagged increase be sustained for at least three consecutive years or until the final available observation in 2024. Specifically, for a hit at year t , capacity or building footprint at years $t, t + 1, \dots$ had to remain at or above the newly elevated level. A given C_t^{\log} or ΔB_t was flagged as a magnitude hit if it exceeded the threshold for that metric and met the persistence requirement. Results hits were then classified into one of the four investment categories from *Table 2* based on whether either $\Delta C_t, \Delta B_t$ or both hit their respective plant threshold.

Capital investments often unfold over multiple years. To avoid counting multi-year projects as separate events, we grouped persistent hits into episodes. Within each plant, events were merged into a single episode when they (1) were of the same CAPEX type, and (2) occurred within a two-year window of each other. If either condition failed—e.g., a capacity-only signal followed by a year with both spatial and capacity growth—a new episode was started.

CAPEX type	Number of episodes (2003-2023)
Spatial / Non-Capacity	36
Non-Spatial / Capacity	22
Spatial / Capacity	8
Opening	6

Table 4: Number of identified CAPEX investment events by type

After this, the construction of four new plants since 2003 was manually added to the list of investments and given an ‘opening’ label. In addition, two new builds that have taken place in the last year were manually added. These could not be added through spatial measurements because satellite imagery of their full building is not available yet. However, their daily capacity was pulled from media reports.

The resulting dataset contains 72 plant-level CAPEX episodes occurring between 2003-2024. The count of each type is in *Table 4*. The higher number of spatial events rather than capacity events is consistent with industry reports that capacity expansions have been less frequent due to contractions in herd sizes and underutilization, especially over the past decade. The consistency of spatial events also points to the ‘drip-feed’ of maintenance capex that continues into plants even while capacity stays relatively constant.

4.3 Calculating depreciation periods

After identifying investment episodes, we assigned each a depreciation period. We first quantified the scale of each investment by converting the magnitude of the underlying change - building expansions for spatial events and capacity increases for capacity events - into a normalized intensity score using the percent rank of all events of the same type. This mapped investment magnitudes onto a continuous 0–1 scale within each category.

We then defined a plausible range of depreciation lifetimes for each investment type, using accounting standards for capital assets and reference lifetimes reported in publicly available financial filings from major meatpacking firms:³⁻⁵

Spatial / Non-Capacity: 12-18 years

Although Tyson and National Beef report building and property improvements with upper useful lives of 25–33 years, those upper bounds likely include entire new buildings. Because the events in this category represent additions to existing structures, we use a slightly shorter upper bound and reserve longer lifetimes for new-facility openings.

Non-Spatial / Capacity: 7-15 years

Companies report very short useful lives (lower bound of 2–3 years) for small office equipment under “machinery,” but these include machinery not associated with plant-scale processing upgrades that change slaughter capacity (e.g. office supplies). Capacity-relevant machinery (e.g., fabrication-line upgrades, new chilling or deboning systems) typically falls in the intermediate 7–15 year class-life range under tax rules and industry filings.

Spatial / Capacity: 12-22 years

These events involve both structural expansion and machinery upgrades. We therefore align the lower bound with other spatial investments (12 years) and extend the upper bound to reflect the combined structural and equipment components that typically give such projects a longer composite useful life.

New Build / Opening: 25 years

Although accounting “useful life” is not strictly proportional to the physical scale of a project, scale is a practical proxy for relative cost in this context. Larger building expansions are generally more expensive than smaller ones; similarly, capacity-only upgrades can be costly even without added square footage (e.g., installation of new machinery).

For each investment, the final depreciation period d was determined by interpolating within its category-specific range according to its intensity score I :

$$d = low_y + I(hi_y - low_y)$$

where y_{low} and y_{high} are the lower and upper bounds of the depreciation window for that investment type. This assigns shorter lifetimes to small-scale investments and longer lifetimes to larger ones, while remaining consistent with accepted depreciation practices.

5.0 Calculating emissions

5.1 Calculating unmitigated emissions factors

We estimated lifetime, per-head methane and nitrous oxide emissions for each type of cattle supplied into plants in the USA. Following Pelton et al. (2025)⁶ and the EPA's GHG emissions inventory⁷, animals were modelled through their life stages:

- beef steers and heifers (calf → stocker/not-on-feed → feedlot/on-feed or calf-fed → feedlot)
- dairy steers (calf-fed → feedlot)
- dairy cows (calf → replacement 7–11 months → replacement 12–23 months → mature/reproductive)
- beef cows
- bulls.

Stage lengths and cattle weights in pounds are taken from Pelton et al. (2025 – SI, Tables 8-10).

CH₄ from enteric fermentation:

Emissions factors for enteric fermentation at the various life stages for each type of cattle were taken from the EPA (2024 – Annex 3, A-143) and used to calculate the following:

$$\text{Lifetime } CH_{4,t} = \sum_s \frac{D_s \cdot EF_{s,t}}{365}$$

where EF is the emissions factor in kg CH₄ per head per year for cattle type t at life stage s and D is the number of days in life stage.

CH₄ from manure:

To calculate methane emissions from manure at each life stage for each cattle type, we used the EPA Tier-2 formula (2024 – Equation A-35):

$$CH_{4,t} = VS_s \cdot B_0 \cdot \rho_{CH_4} \cdot \sum_w (p_w \cdot MCF_w \cdot (1 - capture_w \cdot destr_w))$$

Volatile solids (kg) for each animal type (t) for each stage (VS_s) are from Pelton et al. (2025 – Tables 17-20). A national value was derived by taking the median across all states. Maximum methane potential (B_0) for each cattle type is from EPA (2022 – Annex 3, A-156) and .662 was used as the density of CH₄ at 25° C (kg CH₄/m³ CH₄) (ρ_{CH_4}) (EPA, 2024 - A-317).

Emissions from 8 different waste management systems (w) were modelled – pasture, dry lot, liquid slurry, anaerobic digestors, daily spread, storage pits, solid storage, uncovered anaerobic digestors. The national percentage of waste managed by each strategy (p_w) at each life stage was derived from state-level percentages from the EPA (2024) and Pelton et al. (2025). Total cattle populations by type were taken from the EPA (2024 - Annex 3, A-124) and distributed by type and state using EPA state-level distributions (2024 – Annex 3, Tables A-159 and A-160).

Median methane conversion factors (MCF) for each waste management systems from across temperature distributions were taken from Pelton et al. (2025 – SI, Table 21). Methane capture (.99) and destruction (.98) for anaerobic digestion also follow Pelton et al. (2025).

N₂O from manure:

We follow EPA Tier-1 for direct N₂O (EPA, 2024 – Equation A-40) and indirect N₂O (EPA, 2024 – Equation A-41) from managed manure nitrogen. Direct nitrogen was calculated as:

$$N_2O - N_{direct} = Nex_s \sum_w s_w EF_{N_2O,w}$$

Indirect volatilization and leaching were calculated:

$$N_2O - N_{vol} = Nex_s EF_{vol} \sum_w s_w f_w^{vol}$$

$$N_2O - N_{leach} = Nex_s EF_{leach} \sum_w s_w f_w^{leach}$$

Total nitrogen excretion (Nex) for all animals and all stages (s) excluding calves were taken from the EPA (2024, Annex 3, A-158). The EPA does not provide this unit for calves, so a nitrogen excretion rate of .45 was taken from Pelton et al. (2025 – SI, Table 24) and combined with bodyweight (Table 9-10) to calculate total excretion for calves. N_2O emissions factors by manure management system was taken from Pelton et al. (2025 – SI, Table 25). Nitrogen volatilization rates and runoff/leaching rates for both beef and dairy manure management systems were taken from Pelton et al. (2025 – SI, Table 26). Emissions factors for volatilization (.01), runoff/leaching (.0075) and molar mass conversion ratio (44 kg N_2O /28 kg N) were used by Pelton et al. (2025 – SI:37).

For all emissions, AR6 100-year GWPs were used ($CH_4 = 27.2$; $N_2O = 273$) to convert all amounts to CO₂eq.

5.2 Calculating emissions factors after mitigation

To determine the impact of the adoption of mitigation scenarios, we again drew on Pelton et al. (2025) who calculated the potential emissions savings from individual measures for cattle in the USA. As the boundary of our focus-area is on CH_4 and N_2O from the cattle themselves, we modelled the potential savings from the two mitigation options they model that would affect CH_4 and N_2O emissions – (1) feed additives in feedlots and dairies and (2) moving from uncovered lagoons to anaerobic digestors for dairies and solids separation for dairies.

For CH_4 reductions from feed additives, we applied a 22% emissions reduction in methane from enteric fermentation across cattle types (Pelton et al., 2025, SI, p. 53). This percent reduction was applied to life stages where cattle are grain-fed rather than grass-fed. For emissions from manure, Pelton et al. (2025) does not report a specific emissions reduction percentage at the head of cattle level specifically for manure management strategies so we estimate a 20% reduction in CH_4 from

Cattle Type	Lifetime GHGe (tons CO₂eq) - Unmitigated	Lifetime GHGe (tons CO₂eq) - Mitigated
Steer – Stocker	1.452	1.353
Steer – Calf-Fed	1.284	1.143
Steer – Dairy	1.933	1.730
Heifers – Stocker	1.405	1.297
Heifers – Calf-Fed	1.102	0.955
Dairy Cows	26.098	18.927
Beef Cows	14.821	14.821
Bulls	9.133	9.133

Table 5: Unmitigated and mitigated emissions factors for the lifetime of each cattle type

manure from dairy cattle as they are the primary users of anaerobic digestors and solid separators. No reductions in N₂O emissions were calculated.

The final unmitigated and mitigated emissions factors are in *Table 5*.

6.0 Calculating investment- and plant-level committed cattle and emissions

6.1 Calculating committed cattle

We quantify committed cattle and associated committed emissions at two levels: (1) plant-level capacity, representing the structural emissions locked in by the existence and scale of each slaughter facility; and (2) the investment-level CAPEX commitments, representing emissions locked in once capital expenditure has been made and remains on the balance sheet.

To estimate committed cattle at the structural plant level, we construct three utilization scenarios that span the operating range of U.S. beef-packing facilities as found in industry reports:^{8,9}

- **Low utilization:** 85%
- **Average utilization:** 92%
- **High utilization:** 105%

These values reflect industry data on the range of capacity utilization during the cattle herd cycle. Utilization above 100% occurs when plants add overtime shifts or Saturday operations during periods of abundant cattle supply; conversely, 85% utilization reflects conditions in periods of herd contraction.

For each utilization scenario, we multiply the total daily capacity by the utilization rate and by 260 operating days, the standard U.S. working days assuming a 5-day work week.

$$H_{total,b} = u_b \cdot D \cdot \sum_i C_i$$

where H is the total annual head of cattle slaughtered at plant i based on its daily capacity C at utilization rate u_b and operating D days per year.

To quantify committed cattle from deployed CAPEX, we identify all investments with depreciation schedules that extend beyond 2025 then compute committed cattle by summing annual capacity by the remaining years in the depreciation lifetime. 51 investments were still active as of 2025. Where multiple investments overlap for a single plant, we used the capacity and the remaining depreciation period associated with the later investment to avoid double-counting cattle.

6.2 Calculating total committed unmitigated emissions

Percentage distributions by cattle type (*Table 6*) were based on USDA commercial slaughter statistics as compiled by Pelton et al. (2025 – SI:Table 1)⁶. These data tell us how many dairy

Cattle Type	% of total cattle slaughtered
Steer – Stocker	16%
Steer – Calf-Fed	11%
Steer – Dairy	26%
Heifers – Stocker	16%
Heifers – Calf-Fed	11%
Dairy Cows	9.4%
Beef Cows	8.8%
Bulls	1.7%

Table 6: The percentage of cattle by type slaughtered

cows, beef cows, bulls, and fed cattle are slaughtered each year, and how the fed cattle are split among dairy-origin animals, beef calves sent straight to feedlots, and beef calves that go through a stocker phase. We assumed a 50/50 split among the beef-fed animals as half males (steers) and half females (heifers). We then used Pelton et al.'s (2025) national proportions to divide each of those groups into stocker animals and calf-fed animals (about 60% stocker and 40% calf-fed).

For each utilization scenario b , we allocate a plant's total annual head H_b across cattle types using fixed slaughter shares p_t from *Table 5*. The number of cattle of type t processed for utilization band b is

$$h_{b,t} = H_b \cdot p_t$$

Total unmitigated emissions for cattle type t under band b are then calculated as:

$$\text{tonnes } CO_2e_{b,t} = h_{b,t} \cdot EF_t$$

where EF_t is the type-specific emission factor in tonnes of CO₂eq. Total annual emissions for utilization band b was then

$$\text{tonnes CO}_2e_{\text{total},b} = \sum_t \text{CO}_2e_{b,t}$$

This same process was followed for the total head of cattle associated with the 51 CAPEX investments currently in depreciation.

6.3 Calculating the transition to mitigated emissions

Mitigated emissions were modelled by assuming that per-head, per-type mitigation measures are fully adopted by 2050, with a linear transition from 2025 to 2050.

To calculate total capacity for each plant and utilization band, emissions in 2025 were calculated using the unmitigated emission factors, and emissions in 2050 were calculated using the fully mitigated factors. A linear interpolation between these two endpoints provided annual emissions factors for each cattle type over the transition period.

For emissions associated with capital investments, emission factors were likewise interpolated linearly from unmitigated values in 2025 to mitigated values in 2050. For each year, these time-varying emission factors were multiplied by the number of cattle of each type committed by investments still within their depreciation period.

7.0 Developing emissions budgets and transition scenarios

We calculated two non-CO₂ emissions budget scenarios for US beef from 2025-2050 as follows:

7.1 EAT-Lancet Relative Share:

First, we constructed a “relative share” emissions budget based on the recommended 5 Gt CO₂e yr⁻¹ global food systems budget¹⁰. This budget assumes that the United States maintains its current share of global beef-sector non-CO₂ emissions through 2050, with total emissions downscaled to fit within the 5 Gt CO₂e yr⁻¹ budget.

We estimated the present global total non-CO₂ emissions from food systems using FAOSTAT “Emissions from Livestock” and “Emissions from Crops” farm-gate inventories from 2022¹¹. Reported CH₄ and N₂O quantities were converted to CO₂-equivalents using IPCC AR6 100-year GWP values (CH₄ = 27.2; N₂O = 273). These data yield 5,440 Mt CO_{2e} in global food-system non-CO₂ emissions for 2022. The beef-sector contribution to emissions were then calculated from FAOSTAT livestock data by summing global emissions from beef cattle and 30% of dairy-cattle emissions. This was derived by dividing total cattle slaughtered in 2024 (31.8 million head),¹² of which 8.7% were dairy cows, equating to 2.76 million head, which accounts for ~30% of the national dairy herd¹³. We then divided U.S. emissions by this total, indicating total 176.8 Mt CO_{2e} or 3.25% of global food systems emissions comes from US beef.

Under the assumption that this 3.25% share remains constant, the U.S. beef-sector allocation within a 5 Gt non-CO₂ global cap in 2050 is 162.4 Mt CO_{2e} yr⁻¹.

7.2 EAT-Lancet Dietary Share:

The second budget is based on the adoption of the EAT-Lancet dietary recommendation of a maximum of 15g of red meat per capita p/ day, under the assumption that 50% of this allocation would come from beef and 50% come from pork and lamb. From this, a per capita consumption of 7.5g per day was calculated. To translate this to a national emissions transition pathway, we calculated national beef consumption for 2019 from the USDA’s Food Availability (Per Capacity) Data System¹⁴ from 2021 – 52.5 g/ per day or 19.16 kg per year. We then calculate the emissions from total national consumption based on the distribution of cattle types (*Table 8*) and their lifetime emissions factors (*Table 7*) above and multiplied that by the population, resulting in 157.934 MtCO_{2e} from beef consumption nationally. We then applied the same emissions factors to 7.5g of beef per capita per day and by the projected population in 2050 to calculate total emissions from a transition to the EAT-Lancet diet, which resulted in 24.073 MtCO_{2e} per year nationally.

7.3 IPCC Transition Scenarios:

We compiled all transition pathways from IIASA’s IPCC Scenario Explorer¹⁵ that report CH₄ and N₂O emissions from livestock for the United States. Four models provide emissions at this

level of sectoral detail: AIM/CGE 2.2, IMAGE 3.2, MESSAGEix-GLOBIOM 1.1, and REMIND-MAgPIE 2.1–4.3. Each model offers multiple economic and policy pathways based on differing assumptions about energy systems, land use, and the deployment of bioenergy with carbon capture and storage (BECCS) and other sequestration strategies.

We downscaled each scenario’s agricultural CH₄ and N₂O emissions to the beef sector. For every scenario, we identified the reported emissions from livestock and applied attribution factors derived from U.S. EPA emissions data^{16-Tables 5-3 and 5-6}. Over 2018–2022, beef cattle accounted for 44% of national livestock CH₄ emissions (72% from enteric fermentation and 3.2% from manure) and 36% of N₂O emissions; dairy cattle accounted for 23% of CH₄ (25% from enteric fermentation and 26% from manure) and 37% of N₂O. We again modelled 30% of dairy cattle slaughtered for beef (see above). Combining these contributions yields attribution rates of 51.5% of CH₄ and 47.1% of N₂O emissions assignable to beef. We multiplied each scenario's livestock emissions by these fractions and converted resulting CH₄ and N₂O emissions to CO₂-equivalent units using AR6 100-year GWP values (CH₄ = 27.2; N₂O = 273).

An analysis of the emissions pathways across warming scenarios (1.5-3°C, C1-C6) showed that pathways were relatively equivalent across models (*Figure 4*), indicating that, for most models, emissions from livestock are not sensitive to the mitigation cost inputs these models use to change warming outcomes. The exception is the IMAGE 3.2 model which explicitly models ‘lifestyle change’ and ‘no lifestyle change’ scenarios where beef consumption decreases in the former or grows along with socioeconomic outcomes in the latter. For this model, these two sets of scenarios were broken out into separate budgets. The IMAGE 3.2 default scenarios were removed so as to focus on only those scenarios that adjusted livestock outputs. The resulting set of model scenarios was:

- IMAGE 3.2 – Dietary Change
- IMAGE 3.2 – No Dietary Change
- AIM/CGE 2.2
- MESSAGEix-GLOBIOM 1.1
- REMIND-MAgPIE 2.1-4.3

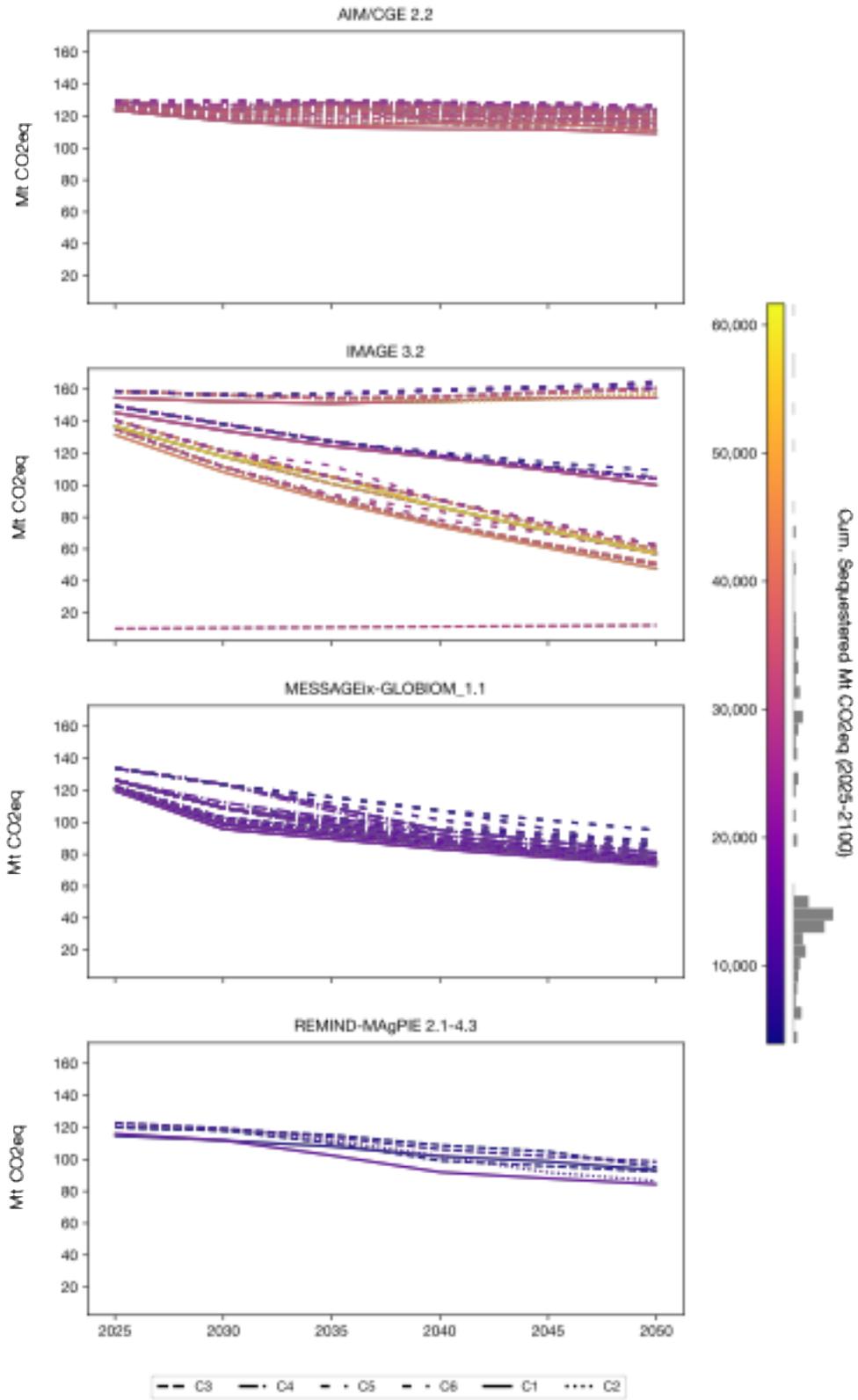


Figure 4: Compilation of each IAM's emissions pathways (2025-2050) across all C1-C6 warming scenarios, along with the amount of emissions sequestered over the full length of the scenario.

Scenarios were grouped accordingly to these model categories and the median of MT CO₂eq p/year from been emissions was taken for each set of scenarios to determine the budget.

To group scenarios by their reliance on sequestration measures, we extracted each scenario's reported sequestered emissions and summed the cumulative CO₂ sequestered between 2025-2100. The following model variables were used to account for sequestration:

'Emissions | CO₂ | AFOLU' and 'Emissions | CO₂ | AFOLU | Land'

Some models reported CO₂ emissions from land in the first variable or the latter of both. To guard against double counting, we instituted a rule where, if the amount sequestered was equivalent for both variables, we retained only one. If the amount sequestered was zero for one and greater than zero for another, we took the sum.

AFOLU emissions are reported as negative number in model outputs to signify land as a carbon sink. Where the total from 2025-2100 was a positive number, signifying that, for that scenario, land was a net carbon source, the amount sequestered was entered as zero. Then the negative signs were converted to positive to make them equivalent to other sequestration model outputs.)

'Carbon Sequestration | Land Use' and 'Carbon Sequestration | Land Use | Afforestation'

Some models reported these cumulatively, 'Carbon Sequestration | Land Use' > 'Carbon Sequestration | Land Use.' In these instances, we took the difference between the two and created 'Carbon Sequestration | Land Use | Non-Afforestation.'

'Carbon Sequestration | CSS | Biomass'

This signifies models' reporting of bioenergy with carbon capture and storage (BECCS)

The other sequestration model variables included were:

- 'Carbon Sequestration | CSS | Fossil'
- 'Carbon Sequestration | CSS | Industrial Processes'
- 'Carbon Sequestration | CSS | Direct Air Capture'
- 'Carbon Sequestration | CSS | Enhanced Weathering'

- ‘Carbon Sequestration | CSS | Feedstocks’
- ‘Carbon Sequestration | CSS | Other’

For each set model-scenario budgets mentioned above, the median GT CO₂ sequestered between 2025-2100 was taken.

	IMAGE3.2 (Dietary Change)	AIM/CGE 2.2	IMAGE3.2 (No Dietary Change)	MESSAGEix- GLOBIOM_1.1	REMIND- MAgPIE 2.1-4.3
CO2_AFOLU	11,326	2,394	3,005	2,982	1.2
BECCS	4,411	13,294	3,950	3,740	4,924
CSS Fossil	4,235	8,461	6,521	1,738	1,017
CSS Industrial	371	161	638	260	442
CSS Direct Air Capture	0	0	0	0	210
CSS Enhanced Weathering	0	0	0	0	0
CSS Feedstocks	2,081	0	2,923	0	0
CSS Afforestation	10,654	5,947	3,387	2,440	85
CSS Land Use (Non-Afforestation)	0	0	0	1,121	0
Total MtCO2	38,824	31,136	28,632	13,066	67,47

References

1. FSIS. Meat, Poultry and Egg Product Inspection Directory. <http://www.fsis.usda.gov/inspection/establishments/meat-poultry-and-egg-product-inspection-directory> (2025).
2. MacDonald, J. M. *Concentration in U.S. Meatpacking Industry and How It Affects Competition and Cattle Prices*. <https://www.ers.usda.gov/amber-waves/2024/january/concentration-in-u-s-meatpacking-industry-and-how-it-affects-competition-and-cattle-prices> (2024).
3. U.S. Premium Beef, LLC. *Form 10-K, F-28*. https://www.sec.gov/Archives/edgar/data/1289237/000168316825001699/uspb_i10ka-122824.htm (2025).
4. Tyson. *Form 10-K*. <https://ir.tyson.com/reports/annual-reports/default.aspx> (2025).
5. IRS. Publication 946, How To Depreciate Property - Appendix B. <https://www.irs.gov/publications/p946> (2024).
6. Pelton, R. E. O. *et al.* Greenhouse gas emissions in US beef production can be reduced by up to 30% with the adoption of selected mitigation measures. *Nat. Food* **5**, 787–797 (2024).
7. EPA. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2022 U.S.* <https://www.epa.gov/ghgemissions/draft-inventory-us-greenhouse-gas-emissions-and-sinks-1990-2022> (2024).
8. Coburn, K. & Hurst, C. *Scenario Analysis of US Beef Plant Closures*. (2025).
9. Beef Magazine. Beef packing capacity update. *Beef Magazine* (2022).
10. Rockström, J. *et al.* The EAT–Lancet Commission on healthy, sustainable, and just food systems. *The Lancet* **406**, 1625–1700 (2025).
11. FAOSTAT. Crops and livestock products. (2023).
12. USDA. *Livestock Slaughter - 2024 Summary*. <https://esmis.nal.usda.gov/sites/default/release-files/r207tp32d/k930dv029/1v53mt52h/lsan0425.pdf> (2025).
13. USDA. *Milk Production, Disposition, and Income - 2024 Summary*. <https://esmis.nal.usda.gov/sites/default/release-files/4b29b5974/79409w163/2z10zn413/mlkpdi25.pdf> (2025).
14. USDA. Food Availability (Per Capita) Data System. (2025).
15. Byers, E. *et al.* AR6 Scenarios Database. Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis <https://doi.org/10.5281/zenodo.7197970> (2022).
16. EPA. *Global Non-CO2 Greenhouse Gas Emission Projections & Mitigation, 2015-2050*. (2019).