Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Reconstructing industrial energy flows from fragmented statistics: A traceable accounting framework for Colombian manufacturing

Carlos A. Díaz González

cdiaz23@unab.edu.co

Universidad Autónoma de Bucaramanga

Research Article

Keywords: industrial energy flows, energy accounting, manufacturing, end-use disaggregation, data reconciliation, industrial ecology

Posted Date: November 26th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11653412/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Reconstructing industrial energy flows from fragmented statistics: A traceable accounting framework for Colombian manufacturing

Carlos A. Díaz González[a]
[a] *Facultad de Ingeniería, Universidad Autónoma de Bucaramanga – UNAB, Bucaramanga, Colombia*

Abstract
National energy balances conserve sectoral totals but often conceal the distribution of fuels and energy services across manufacturing activities. We develop a traceable, physically constrained reconstruction of industrial final-energy flows at the four-digit activity level, integrating Colombia's energy balance with annual manufacturing statistics, end-use survey references and process-specific feasibility rules. The framework preserves division-level carrier totals, distinguishes purchased, self-generated and cogenerated electricity, and avoids counting transformation inputs twice. For 2024, 85.259 terawatt-hours (TWh) are reconstructed across 105 manufacturing classes; direct and indirect process heat account for 80.20% and machine drive for 11.70%. Relative to division-level averages, energy-weighted class profiles diverge by 15.54% in carrier mix and 11.32% in end-use mix. Proxy-weight sensitivity leaves aggregate divergence broadly stable but redistributes 3.05–4.02 TWh across classes, highlighting the importance of evidence provenance. Divisional-average profiles also change illustrative coal, heat and electricity screening classifications for seven, ten and eight classes, respectively. A transferred-rule 2023 reconstruction supports temporal consistency rather than independent measurement validation. The results show how conservation-based industrial energy-flow accounting can reveal aggregation effects and support more differentiated resource and energy-system analyses in data-constrained settings.

Keywords: *industrial energy flows; energy accounting; manufacturing; end-use disaggregation; data reconciliation; industrial ecology*

1. Introduction

Industrial transitions depend on knowing how energy flows through heterogeneous manufacturing activities, not only how much is consumed in aggregate. Cement, metals, refining, food processing and assembly differ in fuels, thermal requirements and electricity use, with corresponding differences in plausible mitigation pathways. Industrial decarbonization research identifies industry-specific technologies and combined efficiency measures, while incomplete end-use statistics remain an obstacle to comparable energy indicators (Worrell & Boyd, 2022; International Energy Agency, 2014; Kim et al., 2024). For industrial ecology, this is also a resource-flow accounting problem: a national total may be correct while concealing the allocation of energy carriers to distinct production activities and services.

National energy balances establish conservation boundaries between transformation and final-energy flows (Eurostat, 2019). However, sector totals do not reveal whether an industrial fuel supplies a process furnace, steam generation or onsite electricity, nor whether electricity is purchased or generated at the facility. Evolving energy systems complicate those boundaries (Nagovnak et al., 2022), and energy-intensity comparisons can confound industrial structure with efficiency change (Herbeth et al., 2024). Thus, accounting closure and resolution are complementary requirements: a carrier total can reconcile at the divisional level yet obscure meaningful within-division differences.

Existing studies offer complementary methods for resolving these structures. Velasco-Fernández et al. (2018) linked national energy statistics to an end-use matrix across analytical scales. Saffer et al. (2025) allocated national industrial energy to conversion devices, while documenting the limits of transferring United States process evidence to other countries. Yu et al. (2025) reconstructed Chinese industrial heat demand by subsector and temperature range. Other contributions estimate industrial site-level consumption from national statistics (Bernelli Zazzera et al., 2025) or map energy demand across regions (Kerekeš et al., 2025). These works demonstrate the utility of hybrid statistical and technical information but differ in their allocation objects, boundaries and evidentiary constraints. None establishes a directly transferable four-digit carrier-by-end-use accounting scheme for Colombian manufacturing. Disaggregated material-flow accounting in industrial ecology has likewise addressed inconsistent

and incomplete data, although Wang et al. (2024) use a Bayesian rather than deterministic reconciliation framework.

This gap matters beyond data preparation. Reviews of bottom-up industrial energy models identify shortcomings in technology coverage, barriers and input transparency (Fleiter et al., 2011; Alamerew & Masanet, 2023). A broader synthesis finds persistent inconsistency in the definitions and resolutions used to analyze industrial energy efficiency (Andrijevskaja & Volkova, 2025). A reconstructed dataset is therefore more useful when each allocation can be traced to an observed quantity, an economic proxy or process evidence, and when sensitivity and aggregation effects are explicitly examined.

Within industrial ecology, physical energy-flow accounting supports the study of industrial metabolism and the construction of environmentally extended input–output (EEIO) tables, linking resource use in production activities to economy-wide supply chains. In Colombia, the National Administrative Department of Statistics (Departamento Administrativo Nacional de Estadística, DANE) publishes three complementary instruments: the Environmental–Economic Energy Flow Account (Cuenta Ambiental y Económica de Flujos de Energía, CAE-FE), the Environmental–Economic Air Emissions Account (Cuenta Ambiental y Económica de Flujos de Materiales de Emisiones al Aire, CAEFM-EA), and the Environmentally Extended Input–Output Matrix (Matriz Insumo-Producto Extendida Ambientalmente, MIP-EA) (DANE, 2025b, 2026a, 2026b). Research on EXIOBASE energy accounts and sectoral disaggregation shows why physical flows, activity classifications and accounting boundaries must be consistent (Rasul et al., 2024; Bakindi et al., 2026). The present study reconstructs a more detailed manufacturing final-energy layer that could inform these systems without itself constructing an input–output model.

Colombia's official datasets serve different accounting purposes. National demand and emissions scenarios operate at relatively broad sectoral scales (Nieves et al., 2019). The Colombian Energy Balance (Balance Energético Colombiano, BECO), maintained by the Mining and Energy Planning Unit (Unidad de Planeación Minero Energética, UPME), provides carrier totals by division (UPME, 2025), whereas the Annual Manufacturing Survey (Encuesta Anual Manufacturera, EAM) provides class-level electricity and economic indicators (DANE, 2026c). Earlier industrial process studies by the Energy and Environment Corporation (Corporación para la Energía y el Medio Ambiente, CORPOEMA) provide process information but not a current carrier-by-class inventory (CORPOEMA, 2014a). National efficiency policy reinforces the importance of differentiated industrial processes (UPME, 2022). Prior Colombian work on industrial efficiency determinants does not reconstruct the contemporary end-use balance (Pardo Martínez, 2010).

Reconciliation is not straightforward. Purchased electricity must be distinguished from self-generated and cogenerated electricity without counting transformation fuels twice. For direct fuels, the EAM often provides expenditure proxies rather than measured carrier quantities. End-use profiles transferred from historical or international surveys must be screened for suppressed observations, mapped across industrial classifications and constrained by physical feasibility. Assigning direct solid-fuel energy to mechanical drive, for example, would conflate primary-fuel input with conversion and final-use boundaries. Process-specific restrictions and provenance information are therefore as important as proportional closure. A related Colombian thesis used disaggregated energy indicators to examine subsector patterns, but the reconstruction and robustness of the balance are the focus here (Arias Torrado, 2026). Fuel-switching studies likewise show that thermal-service characteristics condition carrier choice (Rehfeldt et al., 2018).

This study reconstructs and tests manufacturing final-energy flows for 105 four-digit classes of Colombia's adaptation of the International Standard Industrial Classification (Clasificación Industrial Internacional Uniforme, CIIU) in 2024, with 2023 providing a consistency check. We combine BECO-preserving allocation, EAM physical and economic drivers, quality-screened end-use priors, Colombian process references, and explicit feasibility constraints. Five diagnostics test accounting closure, proxy sensitivity, carrier/end-use heterogeneity relative to divisional averages, temporal consistency and changes in indicative industrial screening. The contribution is a traceable, physically constrained resource-flow representation and a quantitative demonstration of the information lost through aggregation—not a new energy-accounting identity, measured class-level fuel inventories or calculated abatement potential.

2. Data sources and system boundaries

The reconstruction covers Colombian manufacturing divisions 10–31 under CIIU Rev. 4 A.C. (Adaptada para Colombia; 2022 update) (DANE, 2022). Division 32 was excluded because its heterogeneous activities and statistical aggregation prevent reliable matching to the corresponding energy-balance categories. The primary analytical year is 2024, comprising 105 observable four-digit CIIU classes (CIIU4); 2023 was reconstructed independently to examine temporal consistency and contains 106 classes, of which 105 are directly comparable. The statistical unit is therefore an industrial class rather than an individual establishment. Class-level fuel allocations should not be interpreted as directly metered consumption.

The Colombian Energy Balance BECO, maintained by UPME, provides the authoritative annual totals by industrial division and energy carrier (UPME, 2025; UPME, 2018). The EAM datasets for 2023 and 2024, published by DANE, supply class-level electricity consumption, purchased electricity, self-generation, cogeneration and relevant economic variables (DANE, 2025a; DANE, 2026c). BECO totals are retained as accounting constraints, while EAM observations determine their within-division allocation. Physical electricity data are distinguished from the EAM monetary expenditure on "other energy", which does not identify volumes by individual fuel and is used only as an allocation proxy.

Because the official balance and the manufacturing survey are constructed for different statistical purposes, matching activities and energy definitions is a substantive modelling step. We use common annual units of gigawatt-hours (GWh) and retain the BECO carrier nomenclature throughout the first-layer reconciliation. Electricity is distinguished from the primary fuels used to produce it, so that industrial fuel dependence and final electricity use are not conflated. This treatment is particularly relevant for sugar processing, refining and chemical activities that report their own electricity production.

End-use allocation draws primarily on the U.S. Manufacturing Energy Consumption Survey (MECS 2022), including its end-use tables and quality flags (U.S. Energy Information Administration, 2025; U.S. Energy Information Administration, 2026), and on the Colombian industrial characterization prepared by CORPOEMA for UPME (CORPOEMA, 2014a; CORPOEMA, 2014b). Official concordances between the North American Industry Classification System (NAICS) and the International Standard Industrial Classification (ISIC) guide the translation from U.S. activity categories to Colombian CIIU4 classes; sector-specific matching was reviewed against industrial process characteristics (U.S. Census Bureau, 2017). Spanish industrial energy statistics (2022) provide supplementary process-temperature references (Secretaría de Estado de Energía, 2024), whereas Colombia's industrial useful-energy balance supplies contextual efficiency benchmarks (CORPOEMA & IREES, 2019). Table S1 summarizes each dataset's distinct methodological function.

The accounting boundary comprises final energy consumed by these manufacturing classes, distinguished by carrier, electricity-supply mode and final end use. Purchased electricity, self-generated electricity and cogenerated electricity are separate supply modes; fuels entering their generation are recorded in transformation satellite accounts rather than counted again as final consumption. Energy recovery/residues remain distinct from bagasse and are not automatically classified as renewable. The reconstruction addresses final energy, not useful energy or non-energy feedstock flows; upstream electricity emissions and life-cycle effects fall outside this analysis (Eurostat, 2019; International Energy Agency, 2014). Where statistical disclosure prevents the attribution of a BECO residual to an observable CIIU4 class, the residual is retained explicitly rather than assigned arbitrarily.

3. Methodology

3.1. Energy-balance reconciliation and CIIU4 allocation

The accounting reconstruction has two linked layers. The first allocates carriers across four-digit industrial classes while preserving BECO division totals; the second distributes these flows across technologically admissible end uses without changing their energy magnitude. Confidential EAM identifiers were harmonized, and unsupported class values were not imputed (DANE, 2022; UPME, 2025; DANE, 2025a). The flow structure and accounting boundaries are shown in Fig. 1.

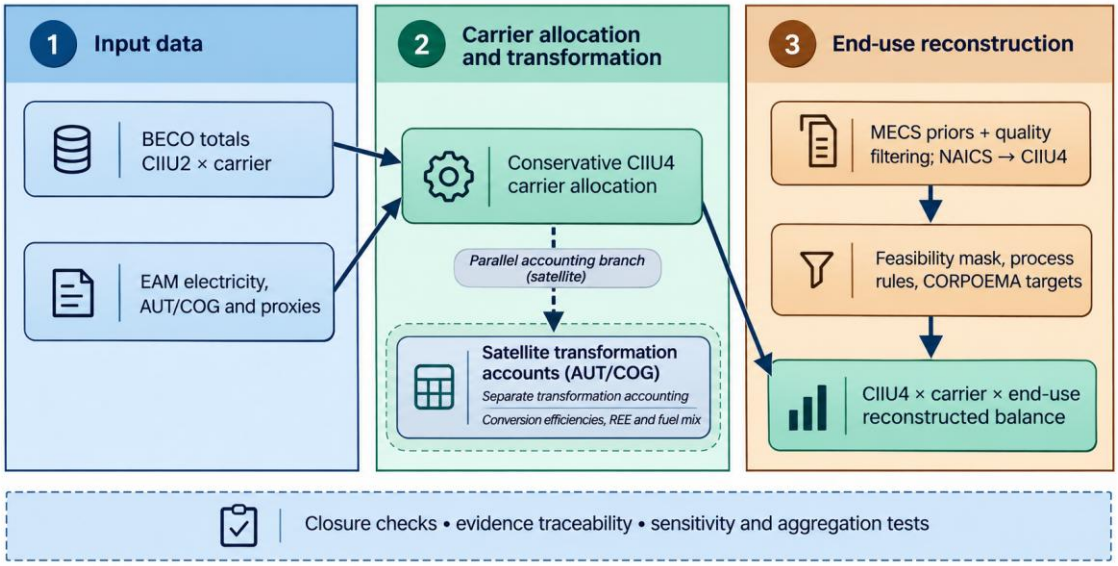


Fig. 1. Reconstruction workflow linking official energy totals, industrial allocation, transformation accounts, end-use priors and feasibility constraints.

For purchased electricity, the EAM physical consumption of each class is used as the intra-division driver. For class i in division d, the reconciled electricity amount is

$$E_{i,EE} = E_{d,EE}^{BECO} \frac{E_{i,EE}^{EAM}}{\sum_{j \in d} E_{j,EE}^{EAM}} \tag{1}$$

where the denominator sums the EAM electricity driver over the observable classes within d. Consequently, the class allocations sum to the BECO electricity total of that division. This preserves the official accounting magnitude while using physical industrial observations to recover the within-division structure (UPME, 2025; DANE, 2025a).

Direct-use fuels are reconstructed separately for each carrier f. The model applies a hierarchical weighting rule: explicit sector/process evidence where available; otherwise, the class share of EAM expenditure on other energy; and, only if this is insufficient, manufacturing sales or intermediate consumption. The corresponding reconciliation is

$$E_{i,f} = E_{d,f}^{BECO} \, w_{i,f} \tag{2}$$

$$\sum_{i \in d} w_{i,f} = 1 \quad \Rightarrow \quad \sum_{i \in d} E_{i,f} = E_{d,f}^{BECO} \tag{3}$$

The class-level weights are normalized only among the eligible classes of the same division and carrier. Accordingly, changes in weights redistribute a fixed quantity of fuel among eligible classes rather than modifying the reported division total. This distinction matters for interpretation: a high class-level value may be driven by a process-specific rule, whereas an otherwise similar value allocated through expenditure is a modelled estimate with weaker observational support.

Technology-based assignments take precedence over purely economic ratios. Examples include bagasse allocated to steam/boiler services in sugar production (1071), direct heat in panela production (1072), fuel use in cement kilns (2394) and ceramic firing (2392), and allowances for electric melting in basic metals (24xx). The BECO categories are retained without relabelling them as renewable sources; particularly, recovery/residues are not merged with biomass. The allocation is therefore conditional on identifiable process evidence where such evidence exists, whereas other carrier flows remain proxy-based estimates (CORPOEMA, 2014a; CORPOEMA, 2014b).

3.2. Electricity-supply modes and transformation boundaries

BECO reports a combined autogeneration–cogeneration electricity stream. The EAM provides their relative quantities and is used to separate the reconciled stream into self-generation (AUT) and cogeneration (COG) for each class. Before deriving the shares, reported electricity sales are deducted where applicable to prevent exported electricity from being mistaken for manufacturing self-consumption. The relative AUT share is

$$s_i^{AUT} = \frac{AUT_i^{EAM}}{AUT_i^{EAM} + COG_i^{EAM}} \tag{4}$$

with the complementary share assigned to COG. The two modes preserve the combined reconciled electricity total. Purchased electricity, AUT and COG subsequently receive the same technological end-use interpretation for a given class, because supply origin does not itself determine the function of electricity within production.

Inputs used to generate electricity are handled in separate satellite transformation accounts to avoid double counting with electrical final consumption. For thermal autogeneration, equivalent energy input is estimated from self-generated electricity, an assumed conversion efficiency and a class-specific or calibrated source mix:

$$E_{i,f}^{in,AUT} = \frac{E_i^{out,AUT}\, s_{i,f}}{\eta_{AUT}} \tag{5}$$

For cogeneration, the regulatory equivalent electrical efficiency (REE) is used rather than a simple electrical-conversion efficiency; under its definition, useful heat enters the denominator alongside primary energy. Equivalent fuel input assigned to electricity is an analytical attribution, not a complete plant-level combined heat and power (CHP) fuel balance (CREG, 2010). Specific fuel-mix rules for sugar (1071), refining (1921) and selected chemicals (2013) are retained; residual generic mixes are calibrated to accounting constraints. These satellite flows are reported separately and never added to final-energy totals.

3.3. Physically constrained carrier-to-end-use allocation

For each positive CIIU4 × carrier/supply-mode flow, MECS 2022 provides an initial conditional end-use distribution after mapping the nearest applicable NAICS process to the Colombian class. Where multiple NAICS categories correspond to a CIIU4 activity, their quantities are pooled before normalizing. Boiler consumption is mapped to indirect heat/steam, process heating to direct heat, machine drive to motive power, and other identified MECS services to corresponding end-use categories. CHP, conventional on-site generation and unreported end uses are removed from the normalization denominator so that transformation energy is not mistaken for final demand (U.S. Energy Information Administration, 2025; U.S. Census Bureau, 2017).

$$p^{MECS}(s,f,u) = \frac{E^{MECS}(s,f,u)}{\sum_{v \in U^*} E^{MECS}(s,f,v)} \tag{6}$$

MECS estimates flagged as censored or unreliable are not treated as precise process information. In particular, vectors supported only by censored cells are rejected as a basis for a complete end-use profile; other unresolved poor-quality vectors follow a documented hierarchy of robust profiles at the class–carrier, division–carrier, class thermal and division thermal levels. A neutral thermal fallback is used only where no more specific defensible profile exists. Allocating a non-electric carrier to heating, ventilation, and air conditioning (HVAC) requires explicit evidence of a suitable technology; categories cannot be inferred directly from the U.S. facility-heating definition (U.S. Energy Information Administration, 2026).

The source mapping is not a literal transfer of U.S. industrial technology. For example, sugar manufacturing is linked to the corresponding MECS sugar activity, petroleum refining to refineries, and cement/lime/gypsum to the combined relevant NAICS activities; the process interpretation is checked against Colombian evidence. For

electricity, a robust class-level distribution may be transferred across supply modes, because purchased, autogeneration and cogeneration electricity all serve the same final equipment.

A physical feasibility mask then classifies every carrier–end-use combination as allowed, conditional or structurally zero. Electricity may serve thermal, mechanical, refrigeration and building loads; solid fuels are assigned to admissible heat applications rather than direct machine drive or lighting; non-electric mechanical drive is conditional on an identified compatible technology. High-confidence rules for particular CIIU4 processes are binding, while medium-confidence rules inform conditional bounds. This prevents statistical normalization from creating physically incompatible uses (CORPOEMA, 2014a; CORPOEMA, 2014b), (Eurostat, 2019).

Reconciliation is a deterministic sequence of filtering, normalization and bounded proportional adjustments, not a numerical optimization. The sum of end-use allocations for every class and carrier remains fixed:

$$\sum_{u} E_{i,f,u} = E_{i,f}^{final} \tag{7}$$

For eligible gaseous and liquid fuels, the machine-drive allocation is capped by the corresponding cleaned prior. CORPOEMA historical shares then enter only as confidence-weighted divisional reference targets:

$$T_{d,g}^{soft} = (1 - \lambda_d)\, S_{d,g}^{clean} + \lambda_d\, S_{d,g}^{CORPOEMA} \tag{8}$$

The confidence weight λd takes values of 0.50, 0.35, 0.20 or 0, with a zero adjustment for divisions 19 and 24 where process-specific evidence prevails. Proportional updates operate exclusively on non-zero, technologically feasible support and are followed by row normalization and reapplication of conditional caps. A reference share is not imposed if reaching it would violate the mask or conservation requirement. Spanish temperature shares provide supplementary interpretation of thermal demand; useful-energy conversion is a separate, subsequent calculation and is not part of the final-energy allocation (Secretaría de Estado de Energía, 2024; CORPOEMA & IREES, 2019).

3.4. Accounting checks, uncertainty and comparative experiments

Internal verification comprises closure against BECO at division × carrier level, closure at class × carrier × end-use level, non-negativity, preservation of structural zeros, and separation of generation-input satellite accounts. Remaining unallocated energy is disclosed explicitly. Source provenance is documented for every positive carrier flow, distinguishing physical reconciliation, process-constrained assignments, EAM expenditure proxies and sales proxies. A non-probabilistic evidence score (0–100) summarizes support quality and can prioritize future field verification; it is not interpreted as a confidence interval or estimation-error distribution.

The tests distinguish conservation from empirical accuracy. A near-perfect closure is an accounting identity by construction; it cannot establish that class-level fuel quantities are measured correctly. Likewise, the evidence index ranks flows according to the strength of the underlying information, but no numerical interval of statistical uncertainty is inferred from it.

Five complementary experiments assess robustness and the decision relevance of disaggregation. First, economic allocation weights are perturbed within each division–fuel group using a power transform, keeping the carrier total and technology-constrained assignments fixed:

$$w_{i,f}^{(\alpha)} = \frac{w_{i,f}^{\alpha}}{\sum_{j \in d} w_{j,f}^{\alpha}} \tag{9}$$

Second, cleaned initial and reconciled final end-use allocations are compared under conservative interpolations of the observed CORPOEMA adjustment and bounded perturbations of weak-quality electricity priors. These experiments retain physical support and flow totals; importantly, interpolation is not interpreted as an exact rerun of the original reconciliation with altered CORPOEMA weights. Third, each CIIU4 energy-carrier and end-use profile

is compared with the energy-weighted mean profile of its two-digit CIIU (CIIU2) division. Divergence is quantified using total variation distance:

$$TV_i = \frac{1}{2}\sum_k \left| s_{i,k} - s_{d,k} \right| \tag{10}$$

where s denotes within-class or divisional shares across carriers or end uses. National means of these distances are weighted by class energy demand. Fourth, the 2024 rules are transferred to the independently reconciled 2023 balance without re-estimation, and temporal changes are examined for the 105 comparable classes; this assesses consistency under shared assumptions, not independent measurement accuracy. Finally, indicative priority classifications obtained from CIIU4 profiles are compared with those obtained by applying divisional-average profiles to the same class energy totals. Exploratory thresholds are 25% mineral coal, 80% combined direct/indirect heat and 25% electricity, limited to classes consuming at least 200 GWh/year. These are illustrative targeting rules, not official policy cutoffs or measured abatement potentials.

4. Results

4.1. Reconstructed manufacturing energy balance

The reconciled balance covers 105 manufacturing classes in 2024 and represents 85.259 terawatt-hours (TWh) of final energy. It differs from the BECO target for divisions 10-31 by only 0.200001 GWh (0.000235%), an explicitly retained statistical reserve in division 26. The corresponding 2023 reconstruction covers 106 classes and 87.540 TWh. These small residuals show accounting closure, not independent precision of every class-level fuel estimate. Table 1 presents the principal boundary and end-use indicators for both years.

Table 1. Coverage, reconciliation and principal energy indicators, 2023-2024.

Indicator	2023	2024
BECO target, CIIU 10-31 (GWh)	87,540.186	85,259.685
Reconstructed final energy (GWh)	87,539.986	85,259.485
Unallocated reserve (GWh)	0.200001	0.200001
Observable CIIU4 classes	106	105
Direct-use fuels (GWh)	72,288.389	70,416.860
Purchased electricity (GWh)	10,707.076	10,416.307
Autogenerated electricity (GWh)	1,720.899	1,711.926
Cogenerated electricity (GWh)	2,823.623	2,714.391
Direct + indirect process heat (%)	80.073	80.203
Machine drive (%)	11.666	11.698

Energy use is strongly concentrated. Food manufacturing (CIIU 10) accounts for 31.42 TWh (36.85%), other non-metallic mineral products (23) for 17.60 TWh (20.64%), and coke/refined petroleum products (19) for 13.22 TWh (15.50%). At class level, sugar manufacturing (1071), petroleum refining (1921) and cement/lime/plaster (2394) together account for 42.29% of reconstructed energy. This concentration coexists with sharp differences in carrier composition. Natural gas represents 31.66% of the total, mineral coal 24.75%, bagasse 18.49%, and electricity from all supply modes 17.41%. The carrier-to-division flows displayed in Fig. 2 reveal the pronounced association of residual biomass with food manufacturing, coal with mineral processing, and natural gas with refining and several other activities.

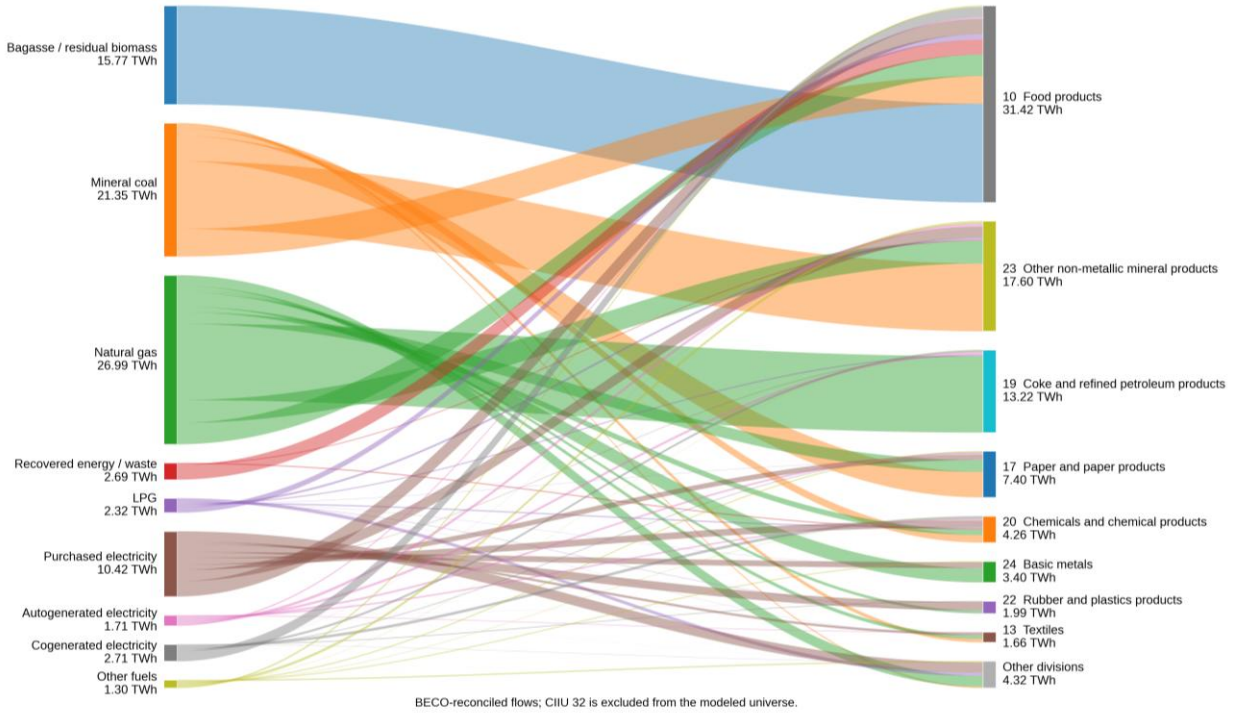


Fig. 2. Reconciled final-energy flows from carriers and electricity-supply modes to major manufacturing divisions, Colombia, 2024. Values are modelled allocations; electricity-supply modes are distinguished.

4.2. Carrier and end-use heterogeneity across manufacturing activities

Process heat dominates the reconstructed end-use balance. Direct process heat accounts for 40.595 TWh (47.61%) and steam/indirect heat for 27.786 TWh (32.59%), giving a combined thermal share of 80.20%; machine drive accounts for 9.973 TWh (11.70%). The other 8.10% comprises cooling and refrigeration, HVAC, lighting, internal transport, electrochemical activities and auxiliary/process uses. Figure S1 links the principal industrial divisions to these end uses and illustrates how thermal requirements differ markedly among manufacturing groups. These are carrier-constrained model allocations rather than metered end-use quantities.

The carrier perspective in Fig. 3 shows natural gas and coal dominating direct heat and residual biomass contributing strongly to indirect heat. Machine drive, HVAC and refrigeration are predominantly electric. These are physically constrained allocations, not metered equipment inventories; transformation fuels are not assigned directly to electricity-based final services.

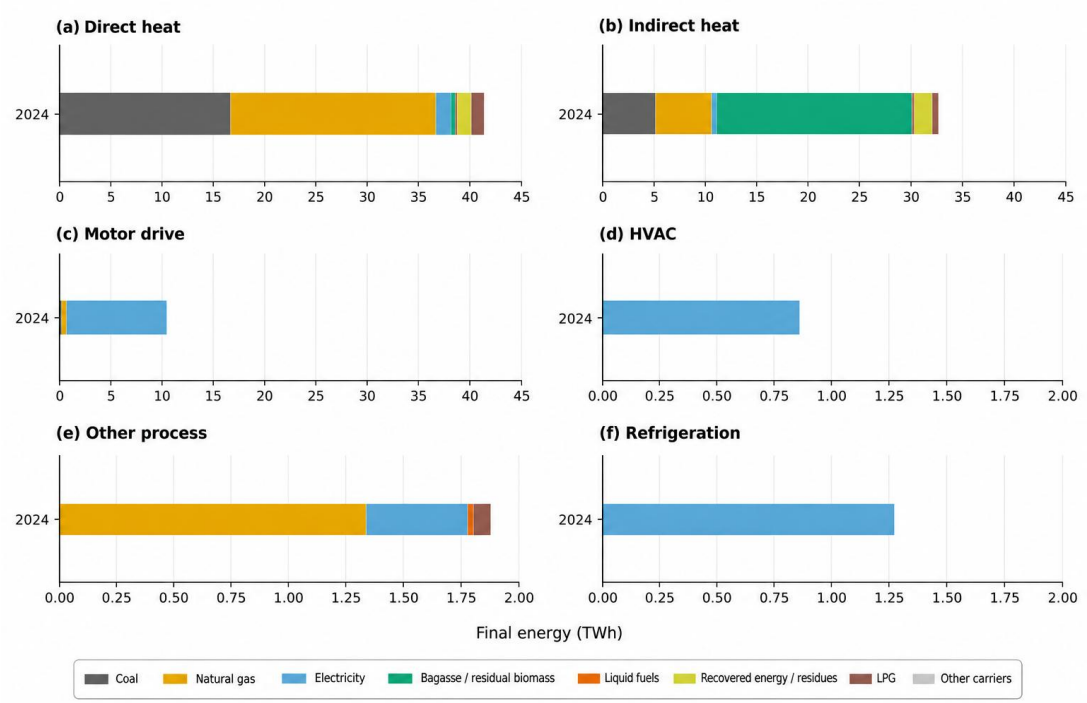


Fig. 3. Carrier composition within principal final-energy uses, 2024. Separate horizontal scales correspond to the absolute demand of each end use.

Division totals conceal substantial differences among constituent classes (Fig. S2). The carrier and end-use heat maps for the twenty largest classes (Fig. 4) show within-division variation. A particularly assumption-sensitive result is the 92.6% allocation of the BECO bagasse category to vegetable-oil extraction (1031): this is supported by a lower-confidence process rule, not directly measured fuel consumption, and requires field verification.

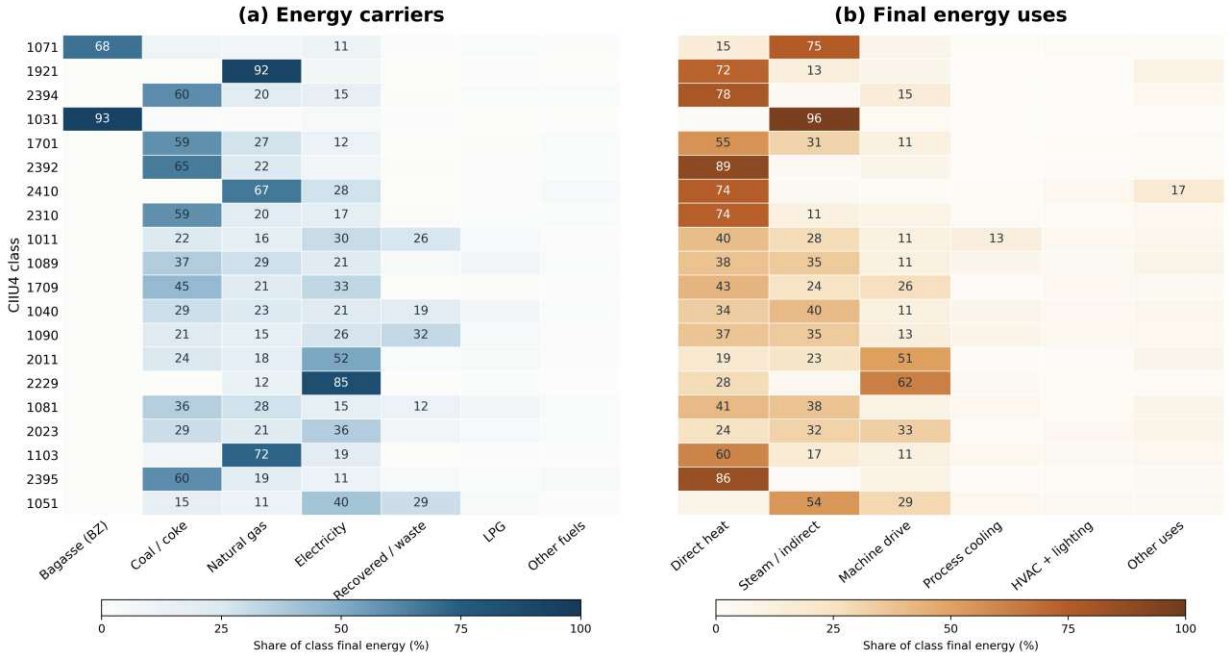
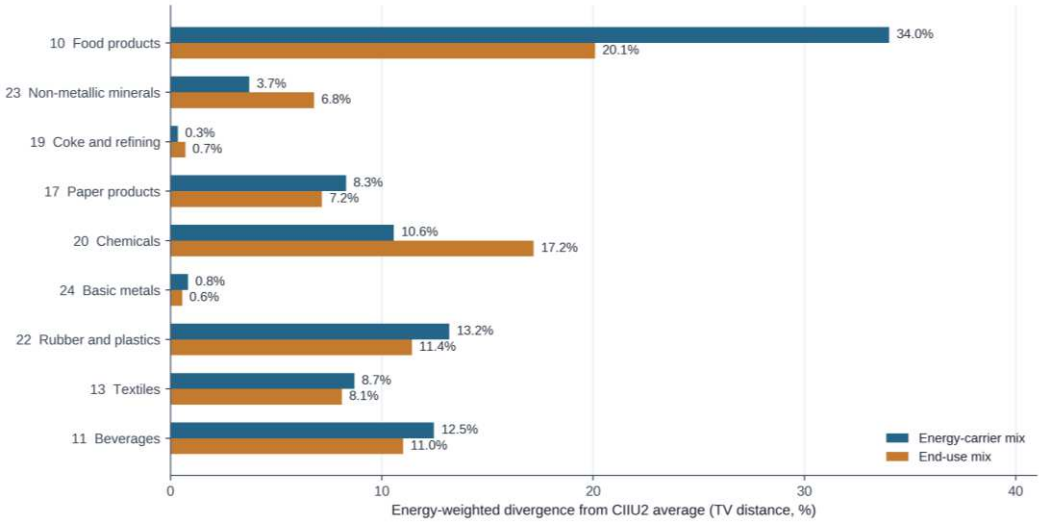


Fig. 4. Reconstructed carrier shares (a) and final-use shares (b) of the twenty largest CIIU4 manufacturing classes in 2024. Percentages are relative to each class total; the panels have separate colour keys on identical 0-100% scales. BZ denotes the BECO bagasse category; 'Other fuels' and 'Other uses' aggregate the residual categories.

4.3. Information concealed by divisional aggregation

To quantify the informational gain, each reconstructed CIIU4 profile was compared with a counterfactual in which all classes inherit the energy-weighted carrier and end-use shares of their parent CIIU2 division, while retaining their individual total energy demand. The counterfactual reproduces the divisional totals by construction but removes intradivisional heterogeneity. In 2024, the nationally energy-weighted total-variation distance between class-specific and divisional-average profiles is 15.54% for carriers and 11.32% for end uses; the corresponding 2023 distances are 15.46% and 10.31%. These metrics describe compositional divergence, not energy loss or statistical estimation errors.

Aggregation effects are highly uneven across divisions. In food manufacturing, the energy-weighted carrier divergence is 34.01% and end-use divergence 20.10%; the analogous carrier distance in refining and coke manufacturing is only 0.35%, largely because a single class dominates divisional energy. Figure 5 compares these intradivisional distances and illustrates the practical consequence for similarly sized food classes. Applying the divisional average to meat processing (1011) would assign approximately 899 GWh of bagasse even though the reconstructed class profile contains none, and would allocate around 244 GWh of electricity rather than the estimated 546 GWh. The contrast is a diagnostic of aggregation bias relative to the reconstructed baseline; it does not independently confirm that the class-level assignment is measured truth.



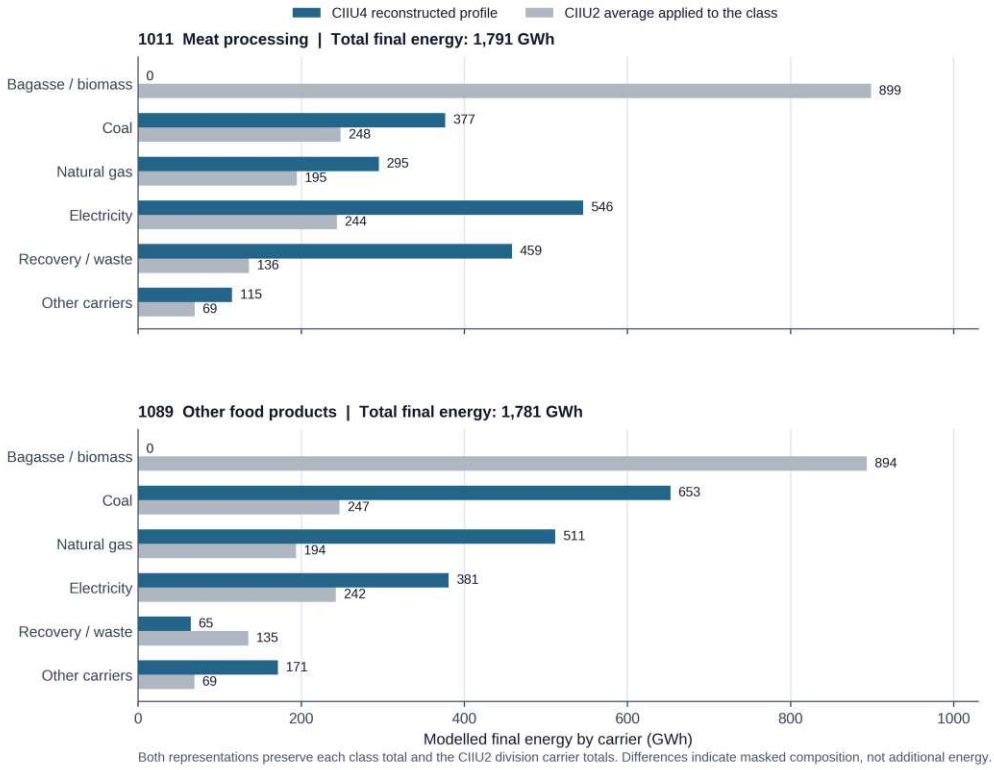


Fig. 5. Information concealed by CIIU2 averages: energy-weighted within-division divergence in carrier and end-use shares (upper panel), and reconstructed versus division-average carrier allocations for meat processing (1011) and other food products (1089) (lower panels), 2024. Divergence denotes total-variation distance, not a physical energy loss.

4.4. Sensitivity, evidence quality and temporal consistency

The carrier-allocation sensitivity experiment varied the concentration of EAM-derived intra-division proxy weights using exponents $\alpha = 0.75$, 1.00 and 1.25, without changing BECO division × carrier totals or class-specific hard technology rules. The nationally weighted carrier divergence remained between 14.97% and 16.30% in 2024, compared with 15.54% at the baseline; the corresponding 2023 range was 14.92-16.22%. Nevertheless, the alternative allocations redistributed 3,054-4,025 GWh among classes in 2024, exposing meaningful uncertainty for individual industrial activities. Cement, sugar, refining and pulp/paper were among the classes with the largest absolute changes.

End-use sensitivity was assessed through conservative perturbations of reconciled profiles, while retaining each CIIU4 × carrier total and the physically admitted support. Suppressing the observed CORPOEMA reconciliation adjustment after support projection increased the 2024 process-heat share by 0.29 percentage points (from 80.20% to 80.50%) and reduced the machine-drive share by 0.98 points. A 20% transfer of weak-prior electric drive energy to heat increased the thermal share by 1.29 points (to 81.49%); the reverse transfer reduced it by 0.26 points (to 79.94%). These are conditional, deterministic stress tests—not reruns of the original method at alternative CORPOEMA weights, probability intervals or independent validation. Figure 6b consequently displays deviations from the baseline in percentage points rather than absolute national shares, so that the size and asymmetry of these responses remain visible.

Table S2 summarizes these diagnostics. The baseline evidence ranking assigns 30.64% of 2024 energy to high confidence, 5.26% to medium-high and 60.26% to medium confidence, especially because direct fuels rely on EAM expenditure proxies. These labels reflect provenance, not quantitative uncertainty. Figure 6 compares carrier and thermal-share sensitivity.

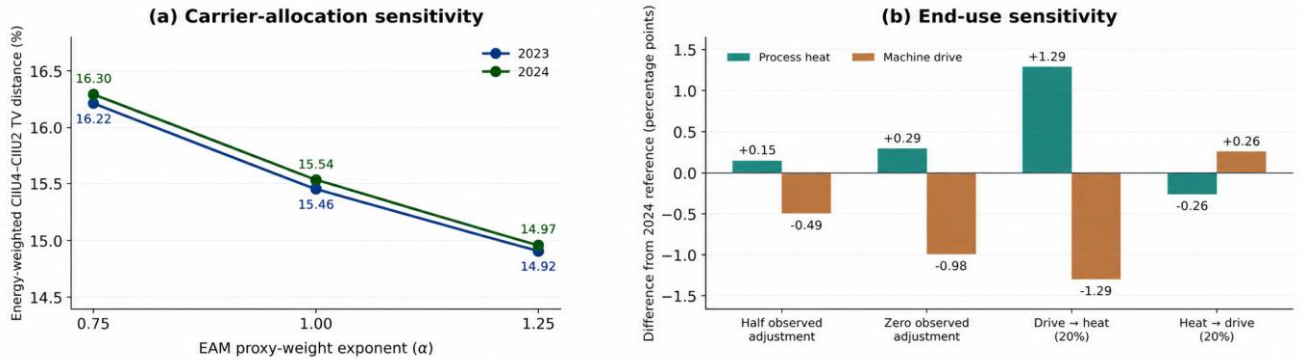


Fig. 6. Deterministic sensitivity diagnostics: (a) energy-weighted carrier divergence under alternative EAM proxy-weight exponents (2023-2024); (b) percentage-point deviations of process-heat and machine-drive shares from the 2024 reference under selected end-use perturbations. 'Half/zero observed adjustment' represents interpolation toward the cleaned initial allocation on the final physically admitted support, not a complete CORPOEMA recalibration.

The short longitudinal comparison further indicates internal consistency under rules transferred from 2024 to 2023. Total manufacturing energy declined by 2.61%, but national carrier shares changed by a total-variation distance of only 0.31% and end-use shares by 1.03%. The energy-demand rankings of the 105 comparable classes were highly concordant (Spearman $\rho = 0.9969$), and all ten of the largest classes remained in the top ten. Because the same technology rules and prior-treatment logic were applied across years, this stability should be interpreted as a consistency check, not independent validation of end-use accuracy or evidence of a structural energy transition.

4.5. Consequences for indicative industrial targeting

An illustrative screening experiment assessed whether model resolution affects the identification of energy-intensive activities for further technical appraisal. All 42 classes consuming at least 200 GWh in 2024 were assessed under three separate criteria: ≥25% mineral-coal share, ≥80% direct-plus-indirect process-heat share, and ≥25% electricity share. These arbitrary screening cut-offs are not official eligibility thresholds, efficiency potentials or retrofit feasibility measures. Compared with the reconstructed CIIU4 profiles, the CIIU2-average counterfactual altered the classifications of seven, ten and eight classes, respectively. Table 2 distinguishes classes selected only by the CIIU4 reconstruction from additional classes selected only by the aggregated representation.

Table 2. Illustrative differences in class-level priority screening (2024; classes ≥ 200 GWh).

Screening indicator	CIIU4 selected	CIIU2 avg. selected	CIIU4-only / CIIU2-only	Affected energy*
Coal share ≥ 25%	21	18	5 / 2	8.85%
Process heat ≥ 80%	18	24	2 / 8	12.95%
Electricity share ≥ 25%	19	17	5 / 3	8.93%

Table 2 note. Affected energy is the combined baseline consumption of classes whose selection changes, divided by the energy consumption of all screening-eligible classes (82.44 TWh). The three criteria were evaluated separately and should not be summed.

The model-based screening differences are asymmetric: divisional averages omit five and add two coal-dependent classes, omit two and add eight heat-dependent classes, and omit five and add three electricity-intensive classes (Fig. S3). Affected classes represent 8.85%, 12.95% and 8.93% of eligible energy, respectively; overlaps prevent summation. These are differences relative to the reconstructed baseline, not verified policy mistakes or emissions reductions. Existing electricity share is not additional electrification potential.

5. Discussion: industrial ecology and planning implications

This study contributes a traceable energy-flow reconstruction at four-digit industrial resolution, rather than a new physical accounting principle. Official division–carrier totals are conserved while class-level energy carriers, electricity supply modes and end uses are resolved using evidence-ranked rules. The 0.200001 GWh residual demonstrates accounting closure, not the measured accuracy of individual class estimates. For industrial ecology, the advance is the explicit connection between energy-flow boundaries, industrial activity detail and the consequences of aggregation.

The approach builds on, but differs from, existing disaggregation frameworks. Velasco-Fernández et al. (2018) combined top-down statistics with end-use information to analyse manufacturing across hierarchical scales; their framework also connects energy to labour and economic dimensions. Saffer et al. (2025) allocated national industrial energy to conversion devices and assessed the transferability of US end-use information, explicitly documenting the limitations of international proxies. Yu et al. (2025) reconstructed manufacturing heat demand in China by subsector and temperature range. Compared with those contributions, the present analysis places greater emphasis on a harmonised CIIU4 × carrier × end-use representation constrained by Colombian energy totals and technology-specific feasibility rules. Conversely, it does not provide the temperature resolution of Yu et al. or independently observed equipment-level consumption. Unlike probabilistic material-flow reconstruction (Wang et al., 2024), this study does not estimate a posterior error distribution; it explicitly separates closure, source provenance and deterministic robustness.

Separating the final-energy account from satellite transformation inputs is equally consequential. Autogeneration and cogeneration affect how electricity is supplied, but their attributed fuel inputs must not be added again to final demand. Nagovnak et al. (2022) showed why conventional balance boundaries require careful treatment as energy systems become more decentralised. Here, explicit accounting boundaries and physically admissible carrier–use combinations prevent transformations from being mistaken for final services. Importantly, the MECS and CORPOEMA profiles act as conditioned technological references rather than measured Colombian class-level distributions or compulsory divisional targets (U.S. Energy Information Administration, 2025; CORPOEMA, 2014a). This makes the procedure interpretable without implying that international priors are directly representative of every domestic process.

The empirical results show why additional industrial resolution is consequential. Although direct and indirect process heat together account for 80.20% of reconstructed 2024 final energy, carrier composition and end-use shares vary markedly among classes within the same division. The national energy-weighted divergence between CIIU4 carrier profiles and their CIIU2 averages is 15.54%; it reaches 34.01% for food manufacturing. Thus, an aggregate division can reproduce the official total while concealing the fuels associated with specific activities. The large modelled bagasse allocation to vegetable-oil extraction (CIIU 1031) nonetheless requires caution because it derives from a lower-confidence transferred process rule, not a class-level physical fuel observation.

The sensitivity experiments clarify the strength and the limits of that conclusion. Perturbing EAM proxy weights leaves the national carrier-divergence indicator within 14.97–16.30% in 2024, but moves approximately 3.05–4.02 TWh between classes; robustness of an aggregate finding therefore coexists with substantial uncertainty for individual allocations. Under the bounded end-use experiments, process-heat shares range from 79.94% to 81.49%, whereas the split between direct heat and steam is more sensitive to prior selection. These are deterministic stress-test outcomes, not statistical confidence intervals. Likewise, close agreement of reconstructed 2023 and 2024 profiles indicates longitudinal consistency under shared rules, not independent validation.

The comparison of indicative priority screens provides a practical interpretation of information loss. Among the 42 classes consuming at least 200 GWh in 2024, replacing CIIU4 profiles with CIIU2 averages changes seven coal-dependence selections, ten process-heat selections and eight electricity-share selections. These changes reveal potential mis-targeting when screening activities for further investigation, not verified savings or abatement opportunities. Colombia's PAI-PROURE identifies direct and indirect heat as major sources of industrial efficiency potential (UPME, 2022), while the IEA highlights technology opportunities for low-temperature industrial heat and steam (International Energy Agency, 2025). The reconstructed end-use mix can help locate candidates for detailed audits, but technology choice still depends on process temperature, fuel characteristics, useful-energy efficiency, costs and operating conditions; electricity share alone cannot measure further electrification potential. Bottom-up electrification studies and sector-coupled energy models further indicate that heat temperature, conversion technology and electricity-system assumptions are essential for evaluating options beyond such an initial screening (Madeddu et al., 2020; Lee et al., 2024).

These results offer a resource-flow baseline for Colombian industrial planning. The National Energy Plan 2022–2052 (UPME, 2024) and Just Energy Transition Roadmap (Ministerio de Minas y Energía, 2025) address future efficiency and fuel dependence at broader scales. CIIU4 carrier and end-use profiles can differentiate candidate activities for audits and subsequent process-heat or fuel-switching assessments, rather than assigning all classes

their divisional-average profile. They do not demonstrate retrofit feasibility, cost-effectiveness or policy performance; these require plant-level information and further modelling.

From an industrial ecology perspective, the reconstructed CIIU4 carrier–end-use matrix could complement Colombia's CAE-FE (physical energy flows), CAEFM-EA (air emissions by economic activity), and MIP-EA (interindustry transactions and environmental extensions) (DANE, 2025b, 2026a, 2026b). Together, these accounts provide complementary views of industrial metabolism: energy throughput, emissions to the environment, and impacts associated with production and consumption linkages. Our 105-class reconstruction resolves heterogeneity concealed by more aggregated activity groups; the 15.54% energy-weighted divergence between CIIU4 carrier profiles and CIIU2 averages shows why uniform sectoral energy coefficients may obscure differences among manufacturing activities. Direct integration would nonetheless require an explicit concordance between CIIU classes and national-accounts activities, as well as reconciliation of final-energy demand with intermediate energy products and transformation flows. Combustion emissions must also be distinguished from industrial-process emissions, biogenic CO_2 and upstream impacts. Thus, this study provides a potential physical basis for future energy-related EEIO extensions, but does not calculate input-output multipliers, embodied emissions or revised emissions inventories.

Three limitations constrain generalization. First, 60.26% of reconstructed 2024 energy carries medium-quality evidence, largely because the EAM's monetary 'other energy' variable does not reveal physical purchases by fuel; this traceability category is not a probabilistic error estimate. Second, international end-use priors, censored MECS cells, manual industrial concordances and technology-specific assumptions can affect individual process allocations despite conservation and zero-mask checks. Third, division 32 is excluded, the longitudinal assessment spans only two years, and the analysis does not independently resolve useful energy, process temperatures, life-cycle emissions or plant-level investment feasibility. As discussed in the industrial modelling literature, disaggregated representations alone do not capture technology adoption barriers (Fleiter et al., 2011).

The next priority is targeted empirical verification of sensitive allocations, particularly physical fuel quantities and thermal end uses for large consumers. Process temperatures and equipment data could connect these final-energy flows to subsequent technology assessments; longer time series could test stability beyond the 2023–2024 comparison. Transfer to other data-constrained countries requires new classification crosswalks and process constraints, rather than direct transplantation of Colombian rules.

6. Conclusions

This study developed a physically constrained and traceable framework for reconstructing manufacturing final-energy demand at the four-digit industrial classification level from heterogeneous national statistics. Its main contribution lies in integrating official energy-balance conservation, industrial activity data, technological feasibility rules, and end-use references into a consistent carrier–end-use representation, while explicitly assessing the robustness and practical value of industrial disaggregation.

The methodology combined BECO energy totals with EAM physical and economic allocation drivers, distinguishing purchased electricity, autogeneration, and cogeneration through separate accounting boundaries. MECS end-use priors, CORPOEMA references, and process-specific restrictions supported a hierarchical, deterministic allocation procedure. Sensitivity experiments, aggregation comparisons, and longitudinal consistency checks were subsequently employed to evaluate the reconstructed profiles.

The application to Colombia reconstructed 85.26 TWh of manufacturing final-energy demand across 105 CIIU4 classes in 2024, with a negligible accounting residual. Direct and indirect process heat represented 80.20% of total demand, while machine drive accounted for 11.70%. Compared with division-level averages, class-specific profiles exhibited energy-weighted divergences of 15.54% for energy carriers and 11.32% for end uses. These differences persisted under alternative EAM allocation weights, while selected end-use perturbations maintained the national thermal share between 79.94% and 81.49%. Importantly, replacing CIIU4 profiles with divisional averages changed the indicative classification of seven, ten, and eight industrial activities according to coal dependence, process-heat share, and electricity penetration, respectively.

These findings demonstrate that preserving national energy totals is insufficient to characterize the technological diversity of manufacturing activities. More disaggregated energy balances can provide a stronger analytical basis for differentiated industrial energy-efficiency measures, fuel-substitution assessments, and national energy planning. Future applications may integrate process-temperature information, establishment-level energy audits, and technology-specific assessments to connect reconstructed demand profiles with industrial decarbonization strategies.

Data availability

The original data used in this study are publicly available from the official sources cited in Section 2. The reconstructed manufacturing energy balance, including the disaggregated energy consumption matrices at the four-digit CIIU level, is available from the corresponding author under request.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Acknowledgements

This work was supported by Universidad Autónoma de Bucaramanga (UNAB) through the UNABCONVOCA 2023 internal research project No. 26598501. Carlos A. Diaz Gonzalez also acknowledges support from UNAB's 2026 Research Excellence Bonus Call.

CRediT authorship contribution statement

Carlos A. Díaz González: Conceptualization; Methodology; Investigation; Formal analysis; Data curation; Visualization; Writing - original draft; Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work the authors used IA tools in order to improve the redaction of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

References

Alamerew, Y. A., & Masanet, E. (2023). Evaluation of industrial decarbonization energy system models for policymaking: Literature gaps and research recommendations. *Procedia CIRP*, 116, 666–671. https://doi.org/10.1016/j.procir.2023.02.112

Andrijevskaja, J., & Volkova, A. (2025). Industrial energy use, efficiency, and savings: Methods for quantitative analysis. *Energy Efficiency*, 18, 76. https://doi.org/10.1007/s12053-025-10367-5

Arias Torrado, M. M. (2026). Análisis del sector manufacturero colombiano con base en sus balances energéticos desagregados [Master's thesis, Universidad Autónoma de Bucaramanga]. https://hdl.handle.net/20.500.12749/32948

Bakindi, A., Norman, J., Wiberg, A. H., & Allen, S. (2026). Streamlined column-based disaggregation method for carbon footprint quantification for multi-regional input–output (MRIO) models. *Journal of Industrial Ecology*, 30, 1535–1552. https://doi.org/10.1007/s44498-026-00102-3

Bernelli Zazzera, E., Prina, M. G., Marchetti, R., Misconel, S., Manzolini, G., & Sparber, W. (2025). Bridging the industrial data gap: Top-down approach from national statistics to site-level energy consumption data. *Data in Brief*, 59, 111365. https://doi.org/10.1016/j.dib.2025.111365

Comisión de Regulación de Energía y Gas (CREG). (2010). Resolución CREG 005 de 2010: Requisitos y condiciones técnicas que deben cumplir los procesos de cogeneración y regulación de esta actividad (art. 2). https://gestornormativo.creg.gov.co/gestor/entorno/docs/resolucion_creg_0005_2010.htm

CORPOEMA. (2014a). Determinación y priorización de alternativas de eficiencia energética para los subsectores manufactureros códigos CIIU 19 a 31 en Colombia a partir de la caracterización del consumo energético para sus diferentes procesos, usos y equipos de uso final (Vol. 1). CORPOEMA/UPME.

CORPOEMA. (2014b). Determinación y priorización de alternativas de eficiencia energética para los subsectores manufactureros códigos CIIU 19 a 31 en Colombia a partir de la caracterización del consumo energético para sus diferentes procesos, usos y equipos de uso final (Vol. 2). CORPOEMA/UPME.

CORPOEMA, & IREES. (2019). Primer balance de energía útil para Colombia y cuantificación de las pérdidas energéticas relacionadas y la brecha de eficiencia energética: Resumen Ejecutivo BEU Sector Industrial. UPME/CORPOEMA/IREES.

Departamento Administrativo Nacional de Estadística (DANE). (2022). Clasificación Industrial Internacional Uniforme de Todas las Actividades Económicas, Revisión 4 Adaptada para Colombia (CIIU Rev. 4 A.C.), actualización 2022. DANE.

Departamento Administrativo Nacional de Estadística (DANE). (2025a). Encuesta Anual Manufacturera (EAM) 2023: Microdatos, metodología y anexos. https://microdatos.dane.gov.co/index.php/catalog/871

Departamento Administrativo Nacional de Estadística (DANE). (2025b). Matriz insumo producto - extendida ambientalmente (MIP-EA) y huella de carbono (HC): Cuenta de economía circular (CECI). DANE. https://www.dane.gov.co/files/operaciones/CECI/doc-MIP-CECI-2024pr.pdf

Departamento Administrativo Nacional de Estadística (DANE). (2026a). Cuenta Ambiental y Económica de Flujos de Energía (CAE-FE): Cuadro de oferta y utilización, 2024 provisional [Data set]. DANE. https://www.dane.gov.co/files/operaciones/CAE-FE/anex-CAE-FE-2024p.xlsx

Departamento Administrativo Nacional de Estadística (DANE). (2026b). Cuenta Ambiental y Económica de Flujos de Materiales de Emisiones al Aire (CAEFM-EA): Cuadro de oferta y utilización, 2005–2024 provisional [Data set]. DANE. https://www.dane.gov.co/files/operaciones/CAEFM-EA/anex-CAEFM-EA-2024p.xlsx

Departamento Administrativo Nacional de Estadística (DANE). (2026c). Encuesta Anual Manufacturera (EAM) 2024: Metodología general, ficha metodológica, anexos y microdatos publicados. https://microdatos.dane.gov.co/index.php/catalog/888

Eurostat. (2019). Energy balance guide: Methodology guide for the construction of energy balances and operational guide for the energy balance builder tool. European Commission. https://ec.europa.eu/eurostat/documents/38154/4956218/ENERGY-BALANCE-GUIDE.pdf

Fleiter, T., Worrell, E., & Eichhammer, W. (2011). Barriers to energy efficiency in industrial bottom-up energy demand models—A review. *Renewable and Sustainable Energy Reviews*, 15(6), 3099–3111. https://doi.org/10.1016/j.rser.2011.03.025

Herbeth, S., Coënt, L., Lazarou, S., & Mahovsky, M. (2024). Energy consumption decomposition analysis using European official statistics: Methodology and input data. *Statistical Journal of the IAOS*, 40(3), 659–684. https://doi.org/10.3233/SJI-230059

International Energy Agency. (2014). Energy efficiency indicators: Fundamentals on statistics. International Energy Agency. https://doi.org/10.1787/9789264215672-en

International Energy Agency. (2025). Renewables for industry: Electrification of low-temperature heat and steam. IEA. https://www.iea.org/reports/renewables-for-industry

Kerekeš, A., Burdack, A., Rupakula, G. D., Lippkau, F., Heinrichs, H., Kuhn, P., Stolten, D., Linßen, J., Blesl, M., & Hamacher, T. (2025). Regional patterns of global industrial energy demands as a foundation for modelling decarbonization pathways. *Scientific Data*, 12, 1745. https://doi.org/10.1038/s41597-025-06206-y

Kim, J., Sovacool, B. K., Bazilian, M., Griffiths, S., & Yang, M. (2024). Energy, material, and resource efficiency for industrial decarbonization: A systematic review of sociotechnical systems, technological innovations, and policy options. *Energy Research & Social Science*, 112, 103521. https://doi.org/10.1016/j.erss.2024.103521

Lee, H., Lee, J., Kang, S. W., Kim, D., Kim, I., & Koo, Y. (2024). Effects of sector coupling on the decarbonization potential of the manufacturing sector—An integration of the power, hydrogen, and manufacturing sectors. *Energy Strategy Reviews*, 53, 101425. https://doi.org/10.1016/j.esr.2024.101425

Madeddu, S., Ueckerdt, F., Pehl, M., Peterseim, J., Lord, M., Kumar, K. A., Krüger, C., & Luderer, G. (2020). The CO_2 reduction potential for the European industry via direct electrification of heat supply (power-to-heat). *Environmental Research Letters*, 15(12), 124004. https://doi.org/10.1088/1748-9326/abbd02

Ministerio de Minas y Energía. (2025). Hoja de ruta para la transición energética justa de Colombia: Resumen ejecutivo. https://minenergia.gov.co/documents/13272/Hoja_de_ruta_transicion_energetica_justa_TEJ_2025.pdf

Nagovnak, P., Kienberger, T., Baumann, M., Binderbauer, P., & Vouk, T. (2022). Improving the methodology of national energy balances to adapt to the energy transition. *Energy Strategy Reviews*, 44, 100994. https://doi.org/10.1016/j.esr.2022.100994

Nieves, J. A., Aristizábal, A. J., Dyner, I., Báez, O., & Ospina, D. H. (2019). Energy demand and greenhouse gas emissions analysis in Colombia: A LEAP model application. *Energy*, 169, 380–397. https://doi.org/10.1016/j.energy.2018.12.051

Pardo Martínez, C. I. (2010). Investments and energy efficiency in Colombian manufacturing industries. *Energy & Environment*, 21(6), 545–562. https://doi.org/10.1260/0958-305X.21.6.545

Rasul, K., Schmidt, S., Hertwich, E. G., & Wood, R. (2024). EXIOBASE energy accounts: Improving precision in an open-sourced procedure applicable to any MRIO database. *Journal of Industrial Ecology*, 28(6), 1771–1785. https://doi.org/10.1111/jiec.13563

Rehfeldt, M., Fleiter, T., & Worrell, E. (2018). Inter-fuel substitution in European industry: A random utility approach on industrial heat demand. *Journal of Cleaner Production*, 187, 98–110. https://doi.org/10.1016/j.jclepro.2018.03.179

Saffer, J. J., Bolson, N., & Cullen, J. (2025). Allocation of national energy use to the industrial sector. *Applied Energy*, 397, 126388. https://doi.org/10.1016/j.apenergy.2025.126388

Secretaría de Estado de Energía. (2024). Estadística Anual de Consumo Energético en la Industria 2022. Ministerio para la Transición Ecológica y el Reto Demográfico. https://www.miteco.gob.es/content/dam/miteco/es/energia/files-1/balances/Estadisticas/industria/Estad%C3%ADstica%20Anual%20Consumo%20Energ%C3%A9tico%20Industrial%202022.pdf

Unidad de Planeación Minero Energética (UPME). (2018). Balance energético colombiano: Documento metodológico. UPME.

Unidad de Planeación Minero Energética (UPME). (2022). Plan de Acción Indicativo del Programa de Uso Racional y Eficiente de la Energía (PAI-PROURE) 2022–2030. https://www.upme.gov.co/simec/planeacion-energetica/proure/

Unidad de Planeación Minero Energética (UPME). (2024). Plan Energético Nacional 2022–2052: Resumen ejecutivo. https://docs.upme.gov.co/DemandayEficiencia/Documents/PEN_2022_2052/Resumen_ejecutivo_PEN_2022_2052.pdf

Unidad de Planeación Minero Energética (UPME). (2025). Balance Energético Colombiano (BECO): revisión 2023–preliminar 2024 [Serie histórica 1975–2024, versión 01, con presentación técnica de diciembre de 2025]. https://www.upme.gov.co/simec/oferta-y-demanda/balance-minero-energetico-colombiano/

U.S. Census Bureau. (2017). 2017 NAICS to ISIC Rev. 4 concordance [Classification correspondence table]. https://www.census.gov/naics/concordances/concordances.html

U.S. Energy Information Administration. (2025). 2022 Manufacturing Energy Consumption Survey (MECS), Table 5.4: End uses of fuel consumption [Released August 2025]. U.S. EIA.

U.S. Energy Information Administration. (2026). 2022 Manufacturing Energy Consumption Survey methodology and data quality: Survey design, implementation, and estimates. https://www.eia.gov/consumption/manufacturing/data/2022/pdf/Survey%20Methodology_2022.pdf

Velasco-Fernández, R., Giampietro, M., & Bukkens, S. G. F. (2018). Analyzing the energy performance of manufacturing across levels using the end-use matrix. *Energy*, 161, 559–572. https://doi.org/10.1016/j.energy.2018.07.122

Wang, J., Ray, K., Brito-Parada, P., Plancherel, Y., Bide, T., Mankelow, J., Morley, J., Stegemann, J. A., & Myers, R. (2024). Bayesian material flow analysis for systems with multiple levels of disaggregation and high dimensional data. *Journal of Industrial Ecology*, 28(6), 1409–1421. https://doi.org/10.1111/jiec.13550

Worrell, E., & Boyd, G. (2022). Bottom-up estimates of deep decarbonization of U.S. manufacturing in 2050. *Journal of Cleaner Production*, 330, 129758. https://doi.org/10.1016/j.jclepro.2021.129758

Yu, E. H., Yuan, Y., Chong, C., Arras, M., Ma, L., Li, Z., & Ni, W. (2025). Quantifying heat demand of China's manufacturing by sub-sectors and temperature zones: A four-step accounting method. *Cleaner Energy Systems*, 11, 100190. https://doi.org/10.1016/j.cles.2025.100190