

Review

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Review

Life-Cycle Assessment of Innovative Industrial Processes for Photovoltaic Production: Process-Level LCIs, Scale-Up Dynamics and Recycling Implications

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Featured Application

The compiled process-level LCIs and scale-up insights can support sustainable manufacturing design, recycling strategies, and policy development for next-generation photovoltaic technologies.

Abstract

The rapid commercialization of next-generation photovoltaic (PV) technologies, particularly perovskite, thin-film roll-to-roll (R2R) architectures and tandem devices, necessitates the environmental performance, not only at cell or module level, but also in industrial manufacturing. Existing reviews and life cycle assessment (LCA) studies have compared device-level metrics, e.g., energy payback time and global warming potential, for silicon, cadmium telluride (CdTe), copper indium gallium selenide (CIGS) and perovskite technologies. Most syntheses yet remain limited to cradle-to-grave outcomes at technology level and rely heavily on aggregated inventory databases. They do not systematically compile or harmonize process-level life-cycle inventories (LCIs) for manufacturing steps that distinguish the industrial routes that include R2R coating, solution deposition, atomic layer deposition, low-temperature processing and novel encapsulation-metallization methods. These LCIs assess essentially how environmental impacts evolve across scale-up stages (lab-pilot-industrial), evaluating trade-offs in manufacturing, recyclability and critical material recovery, simultaneously providing standardized LCI templates for future studies. Motivated by gaps in inventory detail and methodological quince for emergent PV processes, this review: (1) compiles and critically analyses process-level LCIs for innovative PV manufacturing routes; (2) quantifies sensitivity to scale, yield, and energy mix; (3) proposes standardized methodological rules and open-access LCI templates to improve comparability, reproducibility, and techno-environmental modelling.

Keywords: life cycle assessment; photovoltaics; sustainable manufacturing processes; roll-to-roll; perovskite; scale-up; life cycle inventory; recycling; material criticality

1. Introduction

The rapid expansion of global PV manufacturing marks a decisive phase in the clean-energy transition. By 2024, global installed PV capacity exceeded 1.6 TW, with annual production surpassing 400 GWp and a compound growth rate near 25% yr⁻¹ [1–3]. This surge has been driven by efficiency improvements, cost declines following a 20% learning rate per cumulative doubling of production [4–6], and increasing policy alignment with net-zero roadmaps [7,8]. As industrial production scales to the multi-gigawatt and terawatt levels, understanding the environmental performance of PV technologies is no longer limited to device physics or module-level metrics; it must encompass the manufacturing processes themselves that enable large-scale deployment.

Although PV technologies differ in materials, device structures, and manufacturing routes, most modern modules follow a broadly similar production sequence. Manufacturing typically begins with substrate or wafer preparation, such as cutting, texturing, or cleaning glass and silicon surfaces, followed by thin-film or wafer processing, which may involve coating, printing, chemical solution deposition, vapor deposition, or high-vacuum sputtering [3]. These layers are then consolidated through annealing or other thermal treatments to form the functional semiconductor stack. Metallization establishes the electrical contacts needed for charge extraction, while encapsulation and lamination protect the device from moisture, oxygen, and mechanical stress [8]. Finally, module assembly integrates the laminated cell stack with the frame, junction box, and wiring to produce the finished PV module. Each of these steps is associated with specific energy and material flows, which together determine the overall manufacturing footprint of PV technologies [3,8].

Previous comparative LCA studies of PV technologies have mainly evaluated different device classes, such as crystalline silicon, CdTe, CIGS, and perovskite, using high-level indicators. These indicators often include cradle-to-gate impacts, which cover environmental burdens from raw-material extraction ('cradle') to the point the product leaves the factory ('gate'), and cradle-to-grave impacts, which additionally include use and end-of-life stages. Another commonly used indicator is energy payback time (EPBT), which measures how long a PV system must operate to generate the amount of energy that was required to produce it and global-warming potential (GWP), which expresses climate impacts in terms of CO₂-equivalent emissions over a specified time horizon [9–12].

Several studies, including Muteri et al. [9], Milousi et al. [10], and the ReCiPe-based assessment of Rashedi and Khanam [11], consistently report that thin-film technologies generally exhibit lower embodied energy and greenhouse-gas (GHG) emissions than conventional wafer-based silicon modules, largely due to lower material consumption and lower-temperature processing. ReCiPe is a widely used life cycle impact assessment (LCIA) method that converts emissions and resource flows into midpoint indicators, such as climate change, toxicity and endpoint indicators like human health, ecosystem quality, allowing for consistent comparison of environmental burdens [11]. However, these comparative assessments typically rely on aggregated LCIs datasets (e.g., Ecoinvent [10]) and therefore do not fully resolve the underlying unit-process data that describe coating, deposition, annealing, encapsulation, and metallization steps that dominate manufacturing impacts [12–14].

As next-generation PV technologies, particularly perovskite, tandem, and roll-to-roll (R2R) flexible architectures, move closer to commercialization, the need for process-specific environmental data becomes more urgent. Recent studies of pilot and industrial production lines show that steps such as drying/annealing, substrate preparation, and encapsulation can each contribute more than 60% of total cradle-to-gate GWP [12–14]. Detailed inventories covering R2R slot-die coating [15,16], atomic layer deposition (ALD) [17], low-temperature solution processing [18], and vacuum sputtering [19] further demonstrate strong sensitivity to operational conditions, including throughput, yield losses, and the carbon intensity of the electricity mix [20,21]. Yet few evaluations harmonize these datasets or examine how environmental indicators evolve as manufacturing scales from laboratory to pilot to industrial production levels [22,23].

Alongside these developments, new prospective and dynamic LCA frameworks have emerged to integrate technological learning rates and electricity-grid decarbonization with manufacturing LCIs [4,24,25]. These methods show that environmental learning curves can reduce the projected cradle-to-gate footprints of monocrystalline-Si and perovskite PV by 20–80% toward 2050 [24,26]. This aligns with techno-economic scaling models that link production capacity (MWp yr⁻¹) to both cost and embodied-energy reductions [2,13]. Together, these insights indicate that scale itself is an environmental variable, not only an economic one.

End-of-life (EoL) management has also gained prominence as global PV deployment expands. European industrial initiatives have demonstrated high-efficiency recovery of glass, aluminum, silver, and silicon from retired modules [27,28], while newer industrial trials report Ag and Si recovery rates above 90% [29,30]. Process-integrated LCAs show that closed-loop recycling can reduce cradle-to-grave GHG emissions by 40–80% [31,32], and policy analyses estimate more than 60

million tonnes of PV waste by 2045 in the EU alone [33]. Integrating these EoL pathways into manufacturing LCAs is therefore essential for circular-economy planning and assessing material criticality [6,34].

Despite this progress, no existing review systematically compiles and harmonizes process-level LCIs across the diverse manufacturing routes now emerging, from R2R coating and solution deposition to ALD, sputtering, and low-temperature encapsulation. Moreover, guidance on scaling rules, uncertainty treatment, and functional-unit normalization for such process inventories remains fragmented. Addressing these gaps is essential for consistent techno-environmental modeling and for designing the next generation of sustainable PV production lines.

This review therefore aims to: (i) compile and critically analyze process-level LCIs reported for innovative PV manufacturing routes, including R2R, vacuum, and solution-processed lines; (ii) quantify scale-up dynamics (lab->pilot->industrial) and sensitivity to yield, throughput, and electricity carbon intensity; (iii) propose standardized methodological rules and open-access LCI templates to enhance comparability, reproducibility and integration with techno-economic assessments. By shifting the analytical focus from technology class to manufacturing process, this work contributes a harmonized evidence base for evaluating environmental trade-offs at industrial scale and supports the transition toward circular, low-carbon PV production.

2. Methodology

2.1. Literature Search Strategy

A structured literature search was carried out in Web of Science, ScienceDirect, and Google Scholar to identify peer-reviewed LCA studies relevant to PV manufacturing. The search covered publications from January 2015 to November 2025. The following exact search terms were used, both individually and in paired Boolean combinations:

- 'life cycle assessment',
- 'LCA',
- 'photovoltaic',
- 'solar cell',
- 'perovskite',
- 'thin-film',
- 'roll-to-roll',
- 'tandem',
- 'manufacturing process',
- 'recycling'.

The Boolean structure followed the format: (life cycle assessment OR LCA) AND (photovoltaic OR solar cell) AND (manufacturing process OR recycling OR perovskite OR thin-film OR roll-to-roll OR tandem).

Using this exact search string ensured reproducibility and eliminated ambiguity in the retrieval procedure. A total of 1,824 articles were initially identified (889 from ScienceDirect, 543 from Web of Science, and 392 from Google Scholar), consistent with the screening summary shown in Figure 1.

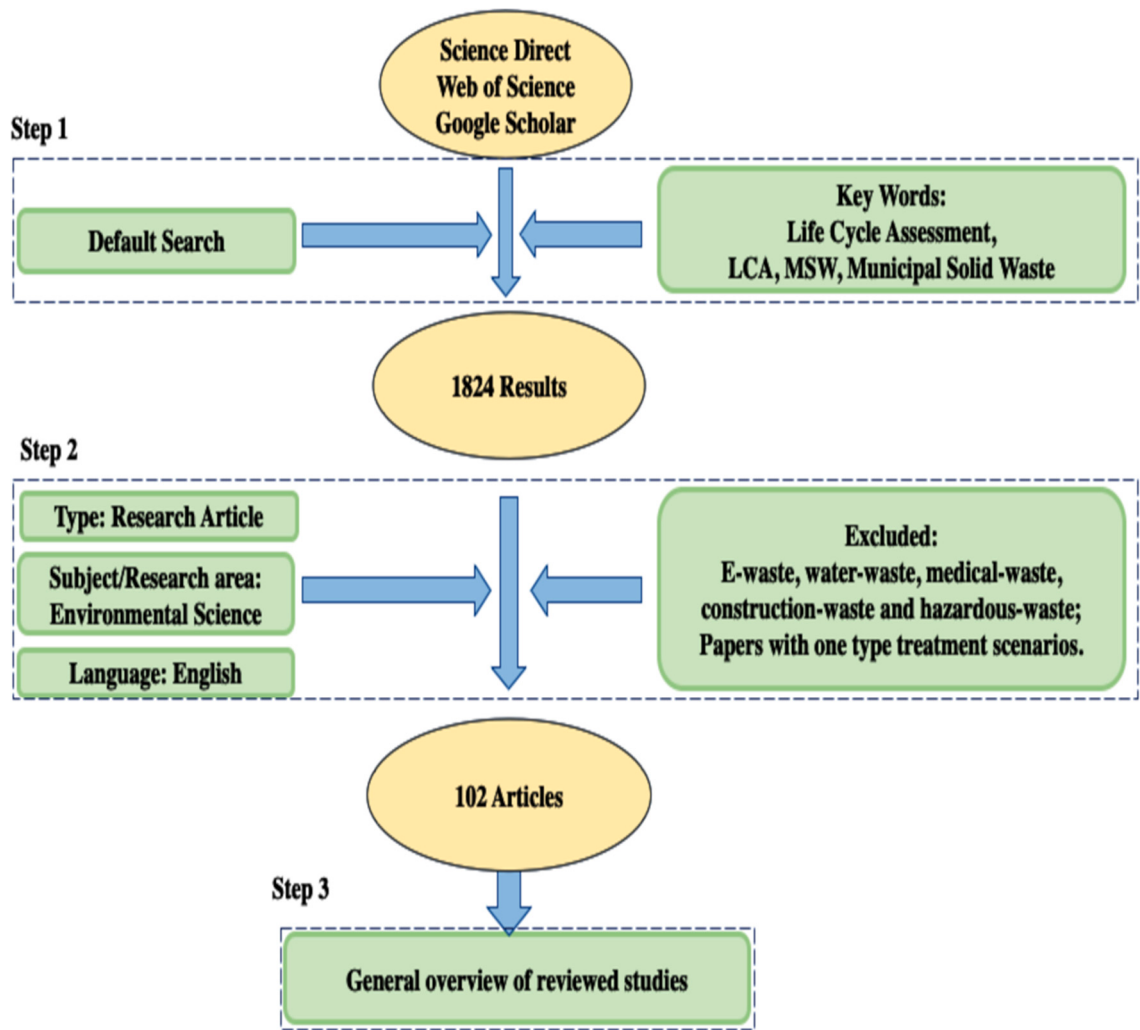


Figure 1. Search and selection criteria of reviewed studies.

2.2. Selection Criteria

To achieve consistency with the filtering steps shown in Figure 1, the inclusion and exclusion criteria were translated directly from the figure’s structure.

Inclusion filters (Figure 1, Step 2):

Articles were retained only if they met the following explicit criteria:

- Publication type: Review and Research article
- Research area: Environmental Science or directly related subfields
- Language: English

Exclusion filters (Figure 1, Step 2):

Articles were excluded if they focused on:

- E-waste
- Water-waste
- Medical-waste
- Construction-waste
- Hazardous-waste

or if they presented only one treatment scenario, making them unsuitable for comparative environmental analysis.

Applying these transparent filters reduced the dataset from 1,824 records to 102 articles, which were then included in the review.

2.3. Review Framework

Following the flow presented in Figure 1, the final set of 102 articles was examined to provide a general overview of the reviewed studies (Figure 1, Step 3). The analysis focused on identifying recurring themes in PV-related LCA research, including the types of manufacturing processes assessed, the system boundaries employed (cradle-to-gate or cradle-to-grave), and the methodological approaches used within Environmental Science research.

The selected studies were systematically analyzed based on:

1. Technology focus: crystalline silicon, CdTe, CIGS, perovskite, tandem, or hybrid thin-film.;
2. Manufacturing process coverage: deposition/coating, encapsulation, substrate preparation, metallization, and recycling;
3. Scale and system boundary: laboratory, pilot, or industrial scale;
4. Functional unit (FU) and impact categories (e.g., GWP, Cumulative Energy Demand (CED), Acidification Potential (AP), Eutrophication Potential (EP));
1. The FU is the quantified reference that defines what exactly is being compared in an LCA. It provides a consistent basis for calculating and normalizing environmental impacts across different technologies, processes, or scales.
5. Data source type: experimental, modeled, or hybrid;
6. LCA methodology: attributional vs. consequential, LCI data transparency, and software tools used;
7. Treatment of end-of-life (EoL) and circularity: recycling scenarios, recovery of critical materials, and reuse routes.

3. Technology and Process Landscape

Industrial PV manufacturing has diversified beyond conventional crystalline-silicon (c-Si) wafer routes toward perovskite, tandem, and thin-film architectures, bringing new materials, unit operations, and production configurations that reshape both environmental and techno-economic performance.

3.1. Perovskite, Tandem, and Thin-Film Routes: Technical Primer

Perovskite PVs have advanced from laboratory cells to pre-industrial modules exceeding 800 cm² and certified efficiency above 25% [1,14,18,35]. Two dominant device stacks, such as mesoporous n-i-p and inverted p-i-n, impose distinct sequences of deposition, annealing, and encapsulation with measurable differences in embodied impacts at the mini-module scale [14]. Tandem configurations that pair perovskite top cells with silicon or CIGS bottom cells provide a practical route beyond single-junction limits and are now a focal point of sustainability reviews and prospective LCAs [21,22]. Across technology families (Si, CdTe, CIGS, perovskite), comparative reviews consistently show that absorber chemistry governs toxicity/criticality profiles while substrates and encapsulants dominate energy use, particularly for flexible or building-integrated photovoltaics (BIPV) applications [19,36]. Low-temperature, carbon-electrode perovskites reduce both thermal budgets and metal intensity relative to noble-metal stacks, with recent cradle-to-gate LCAs confirming meaningful GWP reductions at process scale [18,35]. Taken together, these findings highlight perovskite and tandem platforms as strong candidates for high-efficiency, lower-temperature manufacturing with clear pathways toward flexible and integrated PV products [1,14,21,22,36].

3.2 Unit Operations and Equipment Classes

Process-level environmental burdens in next-generation lines are concentrated in a few unit operations: substrate preparation/clean, solution or vacuum deposition, drying/annealing, contact

formation and encapsulation/lamination [8,12,37]. For solution-processed routes, slot-die and related scalable coaters enable continuous wet deposition with solvent choice and recovery as first-order levers; comparative studies show that switching to greener solvents and continuous coating cuts electricity and solvent burdens versus batch doctor-blading [15,16]. ALD and related vacuum steps remain essential for barrier layers and TCOs; recent assessments quantify their strong non-linear sensitivity to throughput and grid carbon intensity and outline mitigation pathways at the recipe and tool levels [17]. Thermal/photonic annealing frequently dominates step-level energy, reinforcing the need for furnace/oven ecodesign and heat-management strategies in industrial lines [12,38]. For device reliability and circularity, encapsulation choices (glass-glass vs. polymer-metal foils, barrier performance, curing routes) can shift cradle-to-gate GWP by double-digit percentages and determine feasible EoL pathways [12,39,40]. Complementary developments in thermal management and peripheral equipment (e.g., heat sinks, power electronics) round out the equipment landscape and hotspot profile for process-resolved LCIs [40,41]. Harmonizing these unit operations into wet/thermal/vacuum/ambient classes provides a consistent scaffold for cross-technology LCI reporting and later scale-up modelling [8,12,17].

3.3 Typical Line Configurations

Manufacturing architectures cluster into batch, continuous R2R, and hybrid flows. Batch toolsets (common in wafer-based lines) offer tight control but limited throughput scalability; in contrast, R2R integrates sequential coating, drying, and barrier formation on moving webs to maximize material utilization and line uptime [15,16]. Hybrid lines that combine continuous solution coating of functional stacks with batch vacuum finishing or encapsulation are increasingly used on pilot and pre-industrial perovskite/OPV lines and have demonstrated competitive energy use and yield trajectories [42,43]. System-level integrations (e.g., PV/Thermal (PV/T) hybrids) highlight additional layout choices and thermal constraints that influence both product design and line configuration [44]. As Figure 2 illustrates, the choice of batch vs. R2R vs. hybrid determines the frequency and intensity of energy-intensive steps (dry/anneal, vacuum modules) and therefore the dominant contributions to cradle-to-gate GWP and throughput-dependent learning.

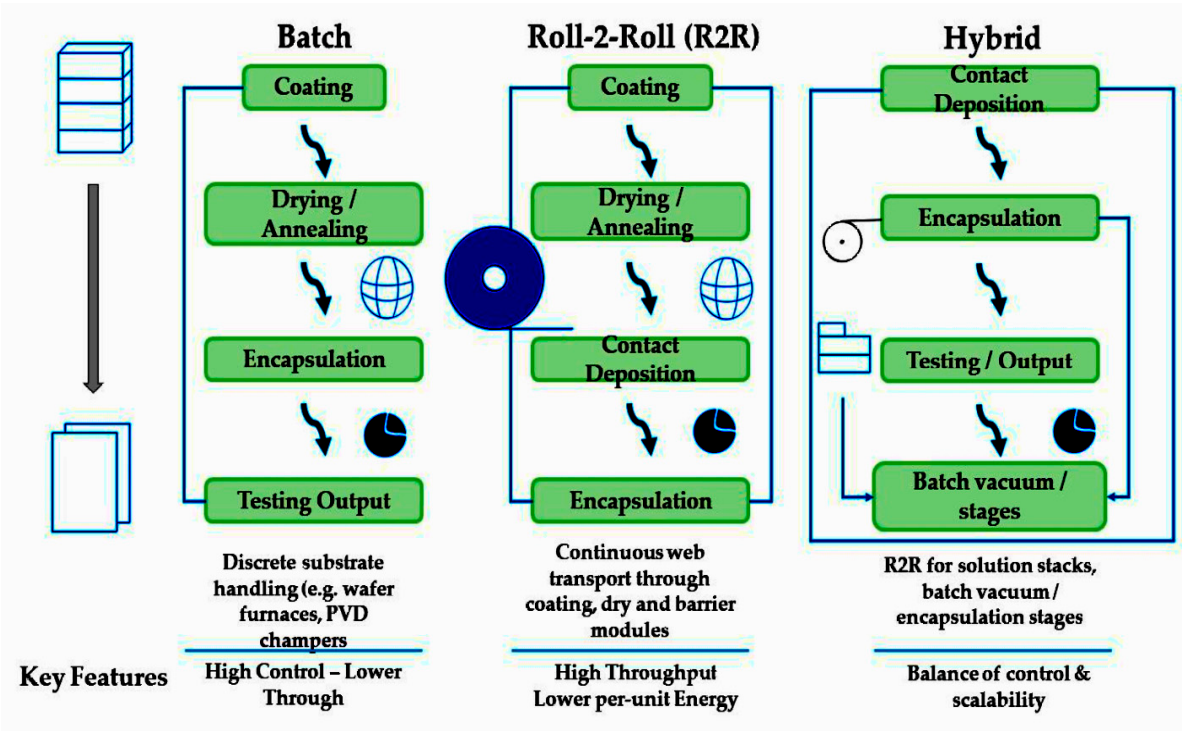


Figure 2. Schematic overview of representative manufacturing line configurations for next-generation photovoltaic technologies.

4. Process-Level LCI Compilation and Harmonization

4.1. Normalization Rules (FU, Boundaries, Electricity)

Harmonized LCIs for next-generation PV processes require normalization of FUs, system boundaries, and energy inputs to ensure comparability across studies and technology readiness levels. Most cradle-to-gate studies adopt 1 m² of module area or 1 kWp of rated capacity as FU, yet results can diverge by more than an order of magnitude if yield, lifetime, or active-area ratios are not consistently applied [3,8,12,26,45]. A transparent reference FU anchored to 1 m² active layer and expressed in MJ/primary/kWp or g CO₂-eq/Wp allows consistent scaling between lab-scale device data and industrial throughput scenarios [46–48].

Boundary harmonization similarly requires clear distinction between foreground process modeling (substrate, deposition, annealing, encapsulation) and background datasets (upstream electricity, gases, solvents). International Energy Agency (IEA) guidance [3] and recent prospective frameworks [23,24,26] recommend aligning cut-offs and material inclusions with ISO 14044 [49] while explicitly reporting excluded utilities (vacuum pumps, clean-room HVAC). Grid electricity normalization remains a dominant factor; its contribution to total GWP varies from <20% in low-carbon grids to >60% in coal-intensive systems [2,24,50]. Recent process-level LCAs show that electricity carbon intensity, tool idle times, and heating method (furnace vs. photonic) can explain 70–80% of cross-study variability in impact results [17,51].

To facilitate meta-analysis, all process inventories in this work are expressed using a unified reference of EU-27 grid (2023) [1] for baseline scenarios and a normalized FU of 1 m² active absorber equivalent, unless otherwise specified.

4.2 LCIs by Process Family

Process LCIs were grouped into solution-based, vacuum-based, and hybrid thin-film families according to dominant energy and material drivers [8,12,17,32,42,52]. For each, per-step data (solvent mass, energy use, emission factors) were harmonized following the functional-unit and boundary normalization rules given in Section 4.1. Solution processes (slot-die, blade, inkjet): Step LCIs are dominated by solvent use, drying/annealing, and substrate handling. Data from [12,15,16,42,48] indicate embodied energy between 200–400 MJ m⁻², with solvent recovery efficiency as the main uncertainty lever. Vacuum processes, ALD, sputtering, evaporation): Process LCIs from references [17,37,38,53] show strong throughput dependence. When normalized per m², chamber heating and pumping contribute ≈ 60% of process energy. Advanced pulsed-ALD and low-temperature sputter recipes can halve GWP if throughput is doubled [17,52,54].

Hybrid tandem and encapsulation flows: Integrated lines combining wet and dry steps show intermediate energy intensities (250–350 MJ m⁻²) and greater sensitivity to encapsulation and substrate mass [12,32,40,42,55]. For all process families, common equipment utilities, air handling, vacuum pumps, chillers, and dryers, were separately inventoried using scaling factors derived from [27,37,39,53]. Harmonized process tables (Figures 3 and 4) present the mean, standard deviation, and range of energy and mass flows per step. These datasets span perovskite, silicon (Si), organic solar cells (OSC), and balance of system (BOS) inventories across regional and multi-technology contexts [52–59].

4.3 Data-Quality Tiers and Uncertainty Characterization

To capture data representativeness across technology readiness levels, we introduce a three-tier data-quality scheme:

Tier 1: Primary industrial data or verified pilot-line measurements.

Tier 2: Laboratory or pre-industrial LCIs adjusted via throughput and yield scaling.

Tier 3: Literature averages or modeled estimates without direct measurement.

Following [23,24,26,48,56,60,61], parameter uncertainty for each process was represented by log-normal distributions fitted to reported min-max values. Monte Carlo propagation (10^4 samples) quantified uncertainty in aggregated cradle-to-gate GWP, showing coefficients of variation between 20-60% for lab-scale data and <15% for industrial references.

A cross-cutting finding from [17,24,26,48,56,57] is that energy intensity and solvent recovery efficiency dominate overall variance, while material yield and uptime become secondary at industrial scale. To enable transparent meta-analysis, all LCIs in this work are annotated with data-quality flags (Tier 1-3) and uncertainty ranges (95% CI) following the pedigree-matrix structure in Table 1.

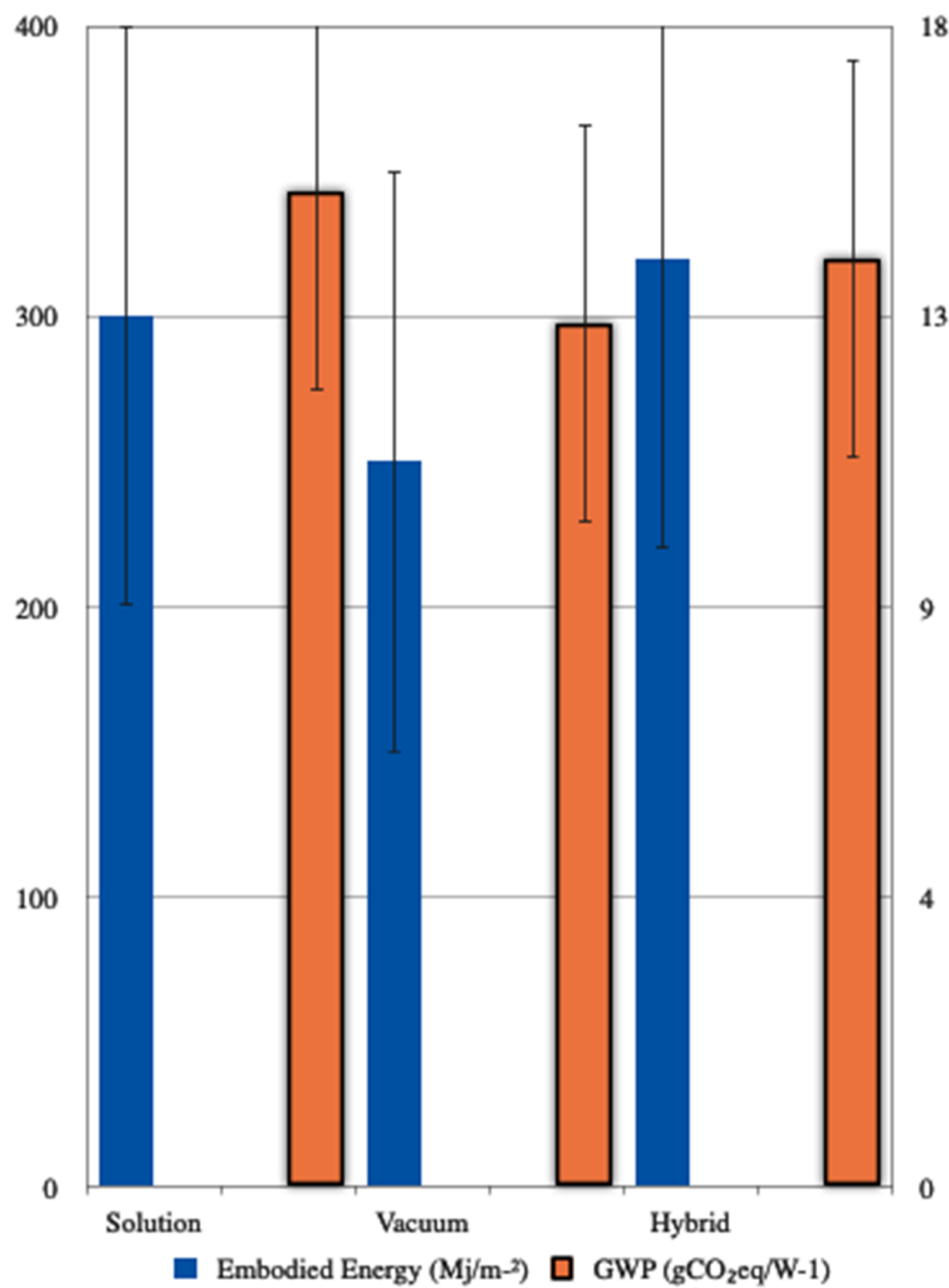


Figure 3. Mean embodied energy and global-warming potential (GWP) intensities of solution-processed, vacuum-processed, and hybrid photovoltaic process families. Error bars denote one-sigma uncertainty derived from Tier 2-3 data (Table 1).

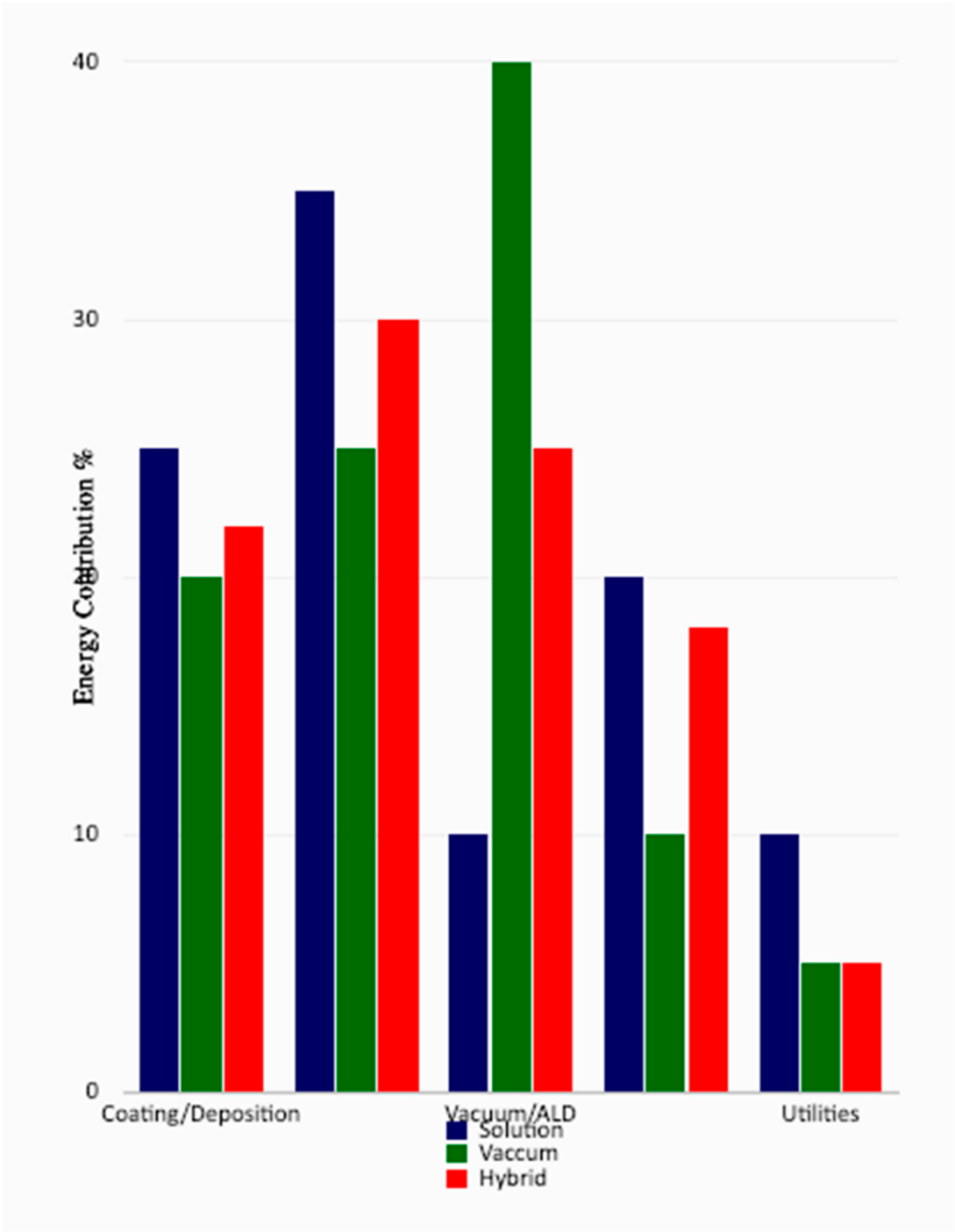


Figure 4. Relative contributions of main unit operations to total process energy for representative solution, vacuum, and hybrid photovoltaic manufacturing lines. Data synthesized from [12,15–17,38–43,53–55] after normalization per m² active area (Section 4.1).

Table 1. Data-quality classification and uncertainty ranges for process-level photovoltaic LCIs. Tiers 1-3 correspond respectively to measured industrial/pilot data, scaled laboratory inventories, and modeled or averaged literature data. Values represent energy intensity (MJ m⁻²) ranges after normalization (Section 4.1). Coefficients of variation (CoV) reflect propagated Monte Carlo uncertainty following [23,24,26,48,56,57].

Process family	Data-quality Tier 1(industrial/pilot)	Tier 2(lab→pilot scaled)	Tier 3(literature/model)	Dominant uncertainty drivers	Typical CoV (%)	Representative data sources
Solution-processed(slot-die, blade, inkjet)	Measured energy ≈ 200-250 MJ m ⁻²	250-400 MJ m ⁻²	300-500 MJ m ⁻²	Solvent recovery η, annealing temperature, substrate mass	30-60%	[12,15,16,42,45,52]
Vacuum-processed(ALD, sputter, evaporation)	150-200 MJ m ⁻²	200-350 MJ m ⁻²	250-400 MJ m ⁻²	Chamber heating, pump idle power, throughput	20-50%	[17,37,38,53,54]
Hybrid thin-film / tandem	220-280 MJ m ⁻²	300-380 MJ m ⁻²	350-450 MJ m ⁻²	Encapsulation mass, yield, interface recombination losses	25-45%	[12,32,40,42,55]
Encapsulation / lamination	40-70 MJ m ⁻²	60-100 MJ m ⁻²	80-120 MJ m ⁻²	Curing route, barrier foil, curing temperature	15-30%	[12,38,39,44]
Ancillary / utilities (HVAC, vacuum, power electronics)	10-20% of total energy	15-25%	20-30%	Grid mix, duty cycle, maintenance schedule	10-25%	[26,37,39,54,56,57]

5. Scale-Up Dynamics and Sensitivity Analysis

5.1. Scaling from Laboratory to Pilot and Industrial Production

Transitions from laboratory fabrication to pilot and industrial production introduce scale-dependent changes in energy intensity, solvent consumption, throughput and yield, all of which strongly influence cradle-to-gate impacts. Systematic scale-up reviews highlight that deposition uniformity, tool idle power and stabilization of continuous-line operation determine whether environmental improvements follow technological learning curves or remain constrained by equipment limitations [23,26]. Pre-industrial perovskite module lines show that drying/annealing, substrate preparation and encapsulation dominate laboratory footprints but decline markedly with increasing line speed, coating width, and stabilized uptime at pilot scale [12]. Perovskite fabrication studies consistently confirm that burdens shift from annealing and solvent losses toward utilities, substrate handling and equipment stabilization as scale increases [15,53].

Empirical learning-curve studies for silicon, thin-film, polysilicon feedstock and metallization demonstrate persistent 15-25% reductions in energy and material intensity per cumulative doubling of production [6], aligning with broader evidence from industrial learning in the energy sector [4,25]. Prospective LCA frameworks formalize how technology readiness level (TRL) progression, upscaling, and scenario design interact with manufacturing configuration to generate non-linear environmental improvements [23]. Pilot-to-industrial transitions also introduce new system-level interactions: thermal-management components such as heat sinks and phase-change materials, inverter and power-

electronics integration, and utilities for heating, ventilation, and air conditioning (HVAC) and cooling begin to account for 10-25% of total process energy [41]. Scale-up demonstrations of titanium dioxide (TiO₂)-nanorod architectures show co-evolution between design, deposition method, and yield, with multi-fold improvements reported when transitioning from small-area lab devices to stabilized pilot lines [13]. Likewise, hybrid PV/T integrations reveal how thermal layout, substrate design, and throughput influence uptime and material efficiency during scale-up [44].

Process-resolved prospective LCAs confirm that industrial routes can reduce cradle-to-gate GWP by 30-70% relative to laboratory baselines once throughput normalization, tool loading, equipment duty cycles, and downtime optimization are incorporated, underscoring that environmental impacts evolve as functions of both scale and process architecture rather than device efficiency alone.

5.2 Parameterized Scenarios

Scenario-based modelling demonstrates that electricity carbon intensity is the dominant driver of cradle-to-gate GWP for emerging PV manufacturing routes. Carbon-aware optimization frameworks show strong GWP sensitivity to grid mix, duty cycles, and equipment-loading assumptions [62,63], while regional LCAs for perovskite, Si, and OPV systems consistently report 2-4× variation in impacts when identical processes are evaluated under different grid carbon intensities [35,60,64]. These findings are reinforced by studies in building-integrated and storage-integrated PV systems, which highlight the additional influence of BOS configurations and thermal-management pathways [43,65].

For solution-processed lines, scenario levers such as solvent-recovery efficiency, coating method and annealing route remain first-order determinants of environmental intensity [53]. Material-substitution scenarios, including carbon-electrode perovskites and reduced-Ag metallization, demonstrate significant GWP reductions relative to Au-based or high-Ag baselines, especially under low-carbon electricity [18,35,55]. Similar sensitivities appear in national-scale LCAs for Chinese PV production, where electricity mix, yield, and material efficiency jointly shape environmental outcomes [57].

Forward projections for South and North Italy and EU-wide electricity systems indicate substantial manufacturing-footprint reductions under 2030-2050 decarbonization trajectories [66–68]. Prospective LCA frameworks incorporating learning curves and TRL-based upscaling show that declining grid carbon intensity interacts strongly with yield and throughput improvements, producing non-linear environmental gains [24,69]. Consequential scenario modelling for distributed PV reaches similar conclusions: operational context and regional electricity mix dominate future-footprint estimates [46].

Dynamic LCA-LCC models further confirm the central role of electricity carbon intensity, while also capturing system-level cost-impact interactions relevant for industrial planning [10,56,61]. Prospective tandem-module assessments extend these insights to multi-junction architectures, revealing combined sensitivities to absorber choice, metallization strategy, and electricity mix [70]. Collectively, these scenario analyses show that grid decarbonization, solvent recovery, and material substitution, especially silver reduction, remain the most effective levers for lowering cradle-to-gate impacts across next-generation PV manufacturing.

5.3 Comparative Cradle-to-Gate Results Across Routes

Comparative LCAs across crystalline-Si, thin-film, perovskite, tandem, and perovskite-Si hybrid modules consistently show that electricity carbon intensity, manufacturing geography, and module design dominate cross-technology variance. Regional assessments report multi-fold differences (typically 2-4×) in cradle-to-gate GWP for identical module designs due solely to grid mix and upstream supply-chain characteristics, demonstrated in case studies for Burkina Faso, China, and Italy [2,64,67]. Similar patterns appear in national and sub-national assessments, where hydropower- or nuclear-dominated regions achieve substantially lower embodied GHG footprints than coal-based grids [58,67].

Supply-chain and geopolitical analyses indicate that upstream manufacturing pathways, especially ingot/wafer production for Si and vacuum deposition for thin films, drive large regional carbon-intensity disparities; relocating stages or shifting regional electricity mixes can therefore change technology rankings [7,48]. Multi-regional comparisons also show that encapsulation choice, module architecture,

and substrate mass modulate these geographic sensitivities [32,67]. Prospective tandem and perovskite-Si hybrid studies suggest that future grid decarbonization and absorber-stack evolution can shift comparative rankings, with tandems surpassing mono- and multi-Si in several 2030-2050 scenarios [70]. Findings align with updated U.S. inventories: lower-temperature thin films and optimized tandems generally exhibit lower embodied GWP than mono-Si under low-carbon electricity [48]. Complementary national-scale LCAs confirm contexts where hydropower-linked Si chains can outperform thin films, depending on metallization and transparent conductive oxide (TCO) burdens [2,58].

EoL comparisons show that closed-loop recovery and high-yield recycling can reduce cradle-to-gate GWP by ~40-60% for perovskite/Si tandems and by similar margins for crystalline-Si modules when Ag and Si recovery exceed industrial benchmarks [32,58]. Overall, regional electricity mix, module architecture, and recovery efficiency remain the primary determinants of comparative environmental performance across current and next-generation PV technologies [2,64,67].

6. Recycling, Circularity, and Material Criticality

6.1 EoL Pathways, Recycling and Logistics

The environmental profile of PV manufacturing extends beyond the production phase into EoL systems. Studies analysing panel recovery show that demanufacturing, material separation, and logistics significantly influence cradle-to-grave impacts. For instance, recovery processes for c-Si modules show major GHG reductions when silver and silicon are recycled at high rates [34]. Research by Ansanelli et al. [28] evaluates detailed mechanical and chemical recovery pathways for polymer, glass, and metal fractions and shows that treatment-stage energy and chemical use dominate impacts when waste volumes are low, with transport contributing only marginally [28]. Celik et al. [71] demonstrate through logistics modelling that EoL transport distance, consolidation strategy, and fragmentation steps influence energy use and emissions across recovery systems.

Closed-loop recycling scenarios for crystalline-Si modules, evaluated through full grave-to-cradle modelling, show that loop-closure is feasible when high recovery efficiencies for Si, glass, Ag and Al are achieved, with performance strongly dependent on collection volumes and module-quality entering the recycling stream [72]. Laboratory-scale studies of polymer pyrolysis and delamination processes show how thermal treatment conditions and reactor design influence energy demand during polymer-layer removal, providing insight into how advanced separation steps may integrate into future EoL pathways [73]. Prospective assessments using advanced physical separation technologies indicate that future recycling systems could obtain higher recovery efficiencies and lower impacts as throughput increases and processes become more integrated [30]. Overall, effective EoL system design, including logistics, high-efficiency separation technologies, and high-yield recovery pathways, is pivotal for achieving circular PV supply chains.

6.2 Allocation, Credits and EoL Accounting

Allocation of recycled flows, crediting of recovered materials, and boundary settings strongly shape the environmental outcomes of PV EoL modelling. Ali et al. [74] show that adopting avoided-production credits for recovered materials (e.g., Si, Al) can substantially improve the performance of distributed PV systems when displacement factors are realistically defined. Allocation choices within mechanical-chemical recovery of c-Si modules, particularly for glass and metal fractions, can alter GWP results because different output streams inherit different portions of the energy and chemical burdens Closed-loop modelling confirms that material-reuse credits, particularly for Si and Al, can significantly reduce cradle-to-module impacts when loop-closure efficiency and sorting quality are sufficiently high [72]. Nevala et al. [75] show that allocation in physical-separation systems (e.g., liberation, optical sorting) determines how burdens are distributed between recyclable fractions, especially when comparing mechanical versus more chemically intensive processes. For perovskite modules, hydrometallurgical recycling studies show that credits for recovered Pb, Au, or Ag depend strongly on assumed substitution ratios and on whether the recovered material meets virgin-grade quality specifications [76].

Collectively, these studies underline that transparent allocation rules (mass, economic, system-expansion), consistent substitution assumptions, and clearly defined credits are essential for interpreting PV EoL LCAs across technologies.

6.3 Critical Materials, Scarcity and Substitution

Material criticality remains a central concern for long-term PV sustainability, especially for elements such as Ag, In, Sn, Pb, and Au. High-efficiency recovery of Ag and Si from c-Si modules has been shown to substantially reduce resource-scarcity indicators, underscoring the importance of metal-recovery yields in circular strategies [35]. Global, technology-spanning assessments of critical-material risks identify distinct vulnerability profiles for Si, thin-film, and tandem architectures, emphasizing that recycling and substitution strategies must be technology-specific [77]. Analyses of silver-use trajectories under net-zero scenarios show that reductions in Ag intensity, combined with robust recycling loops, are necessary to avoid future supply constraints [5]. Comparisons of upcycling and downcycling end-of-life pathways indicate that upcycling, where recovered materials displace high-value inputs, significantly improves material-criticality metrics relative to downcycling into low-grade applications [78].

Substitution pathways also provide relief: evaluations of biobased and fluorine-free encapsulants demonstrate reduced toxicity, lower dependence on fluoropolymers, and improved circularity potential for next-generation PV modules [79,80]. Prospective assessments of tandem supply chains further indicate that critical-material dependence can intensify if substitution and recycling strategies are not integrated early, highlighting the need for coordinated material-management planning. Taken together, these studies show that mitigating critical-material risks requires a combination of high-yield recycling, credible substitution strategies, and tighter material-loop closure, particularly for Ag, In/Sn, Pb, and specialty polymers. Figure 5 summarizes critical-material risk profiles for next-generation PV technologies, combining supply-risk indices, environmental-impact scores, recycling efficiency trajectories, and viable substitution pathways across Ag, In/Sn, Pb, and Au.

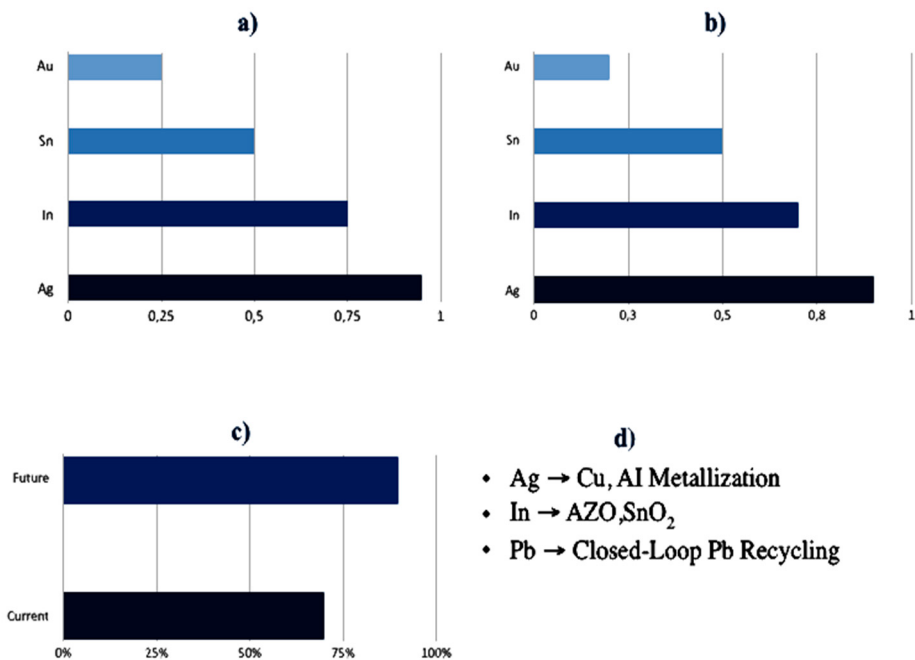


Figure 5. Critical materials risk and substitution map for next-generation PV technologies. Panels summarize: (a) supply-risk indices for Ag, In, Sn, and Au; (b) environmental-impact scores including mineral scarcity and toxicity; (c) current versus future recycling/recovery efficiencies; and (d) substitution pathways including Ag→Cu/Al metallization, In→AZO/SnO₂ TCOs, and closed-loop Pb recovery. The figure integrates evidence

from criticality analyses, recycling studies, and prospective assessments across crystalline-Si, thin-film, and perovskite PV systems [5,19,21,22,27–32,54,70,76–80].

7. Methodological Guidance for Transparent Process-level LCAs

To enable transparent, comparable, and reproducible process-resolved LCAs of PV manufacturing, a minimum set of core methodological and inventory elements are reported. These factors directly influence cradle-to-gate impacts and determine the robustness of scale-up assessments across solution-processed, vacuum-processed, hybrid thin-film, tandem, and crystalline-silicon technologies [3,8,12,24,26,48]. Recent supply-chain assessments further show that manufacturing geography and upstream routing can materially shift embodied emissions, making explicit disclosure of electricity sources and sourcing locations essential [81,82]. Agile LCA approaches in the built environment underline that inconsistent system boundaries and missing energy-flow metadata limit comparability and hinder integration with ecodesign and building-scale modelling [83], while façade-integrated PV decision tools demonstrate the need to co-report functional-unit assumptions, area-to-power conversions, and BOS dependencies when coupling LCA with cost/performance metrics [84].

For emerging PVs (e.g., OSC and perovskites), framework studies emphasize that inconsistent boundaries and incomplete process metadata undermine cross-technology comparisons, reinforcing strict reporting rules [49]. Multi-objective PV ecodesign also shows that optimization outcomes are highly sensitive to transparent background LCIs, energy flows, and declared sensitivity parameters [85]; regional EPBT/LCA case studies further highlight that electricity-mix metadata must be disclosed explicitly [86], and hydropower-linked silicon chains illustrate how supply-chain electricity choices affect foreground emissions and must be documented with spatial/temporal precision [87].

Because current PV LCA studies differ widely in their treatment of FUs, system boundaries, equipment-level energy accounting, solvent and gas flows, and uncertainty characterization, a structured reporting framework is essential. Table 2 summarizes the recommended reporting requirements for transparent and reproducible process-level inventories, including functional-unit specification, boundary definition, foreground/background separation, per-step energy and material flows, data-quality tier assignment, and uncertainty documentation.

To support practical adoption of these recommendations, Appendix A provides a complete standardized data template, including metadata, process maps, foreground inventories, background dataset links, electricity scenarios, data-quality structures, end-of-life modelling, and validation checks. The appendix tables serve both as reproducible documentation for the worked example and as a reusable template for future PV LCA studies.

Rather than prescribing a rigid format, the reporting checklist offers a harmonized minimum standard that all future process-resolved PV LCAs should meet. Consistent application of these elements will enable meaningful comparison across different manufacturing routes, geographical contexts, and technology-readiness levels, supporting integration with techno-economic analyses and prospective LCA models.

Table 2. Required reporting requirements for transparent, reproducible, and comparable process-level PV LCAs.

Category	Required reporting items	Why it matters	Applies to	Sources
Functional unit (FU)	1 m ² active area and 1 kWp; module efficiency, active/total area ratio; yield to FU	Misaligned FUs can shift results by >×10; active-area normalization enables lab→pilot translation	All	[3,8,12,48]
System boundary	Foreground steps (substrate prep, deposition/coating, drying/anneal, metallization, encapsulation) vs. background (electricity mix, gases, solvents); explicit exclusions (HVAC, vacuum idle)	Boundary gaps drive hidden variance; explicit foreground/back-ground splits enable harmonization	All	[3,24,26]
Electricity	Grid mix (region, year), carbon intensity, on-site generation; tool idle vs. loaded power; duty cycles	Top driver of GWP; 2-4× swings across regions; idle time is a frequent hotspot	All	[2,24,48,66,67,81,82,86,87]
Process LCIs (per step)	Energy (MJ/m ²), gases/solvents (kg/m ²), consumables, rejects/yield, tool setpoints (T, t, P)	Enables step-wise attribution and meta-analysis	Solution, vacuum, hybrid lines	[12,17,42,85]
Solvent management	Solvent identity, recovery efficiency (%), losses, abatement	Major driver in wet lines; recovery is a first-order lever	Solution lines	[12,15,16,42]
Vacuum equipment	Pumping scheme, chamber volume, base pressure, cycle times, idle energy	Throughput-sensitive; chamber/pump energy dominates per m ²	Vacuum lines	[17,56]
Annealing/drying	Heating method (furnace vs. photonic), setpoints, line speed, thermal losses	Often the single largest energy step; ecodesign is essential	All	[12,38]
Encapsulation & substrates	Glass/foil types, barrier performance, curing route (UV/thermal), mass per m ²	Shifts GWP by double digits; constrains EoL options	All	[12,32,40,42]
Data tier & pedigree	Tier (1-3), measurement vs. model, TRL, vintage; uncertainty ranges	Enables uncertainty propagation and fair weighting	All	[24,26,60]
Scenario levers	Grid-carbon pathways, solvent recovery, Ag reduction, yield/throughput	Transparent sensitivity; supports prospective results	All	[24,48,69,70,81,82,86,87]
BOS and power electronics	Inverter rating, lifetime, replacement, efficiency	BOS can be non-trivial in system LCAs	Systems	[37,48,84]
EoL modeling	Collection, transport, process flows, recovery yields (Si, Ag, glass, Al), credits/allocation	Determines circularity benefits; can reduce GWP by ~40-60%	All	[30,32,71–75,88–92]

8. Conclusions

Achieving genuinely low-impact next-generation PV technologies ultimately depends on understanding and optimizing the manufacturing processes that enable their industrial deployment, rather than focusing solely on device-level performance. Across perovskite, tandem, thin-film, and crystalline-silicon routes, the dominant contributors to cradle-to-gate impacts are consistently found in energy-intensive steps such as drying and annealing, substrate preparation, vacuum pumping and heating, and encapsulation, all of which exhibit strong sensitivity to electricity carbon intensity, duty cycles, throughput, and idle power. Evidence from pilot and industrial lines shows that scale-up is itself a major environmental lever: as production shifts from laboratory conditions to continuous, high-uptime industrial operation, improved tool loading, higher line speeds, and stabilized solvent and heat-management systems typically reduce environmental footprints by 30-70%, tracking established industrial learning rates. Comparative LCAs make clear that technology rankings are highly context-dependent, with regional electricity mix, encapsulation and substrate choices, and supply-chain configurations exerting stronger influence than absorber chemistry alone. Circularity emerges as essential for future PV manufacturing, as high-yield recovery of silver, silicon, glass, and other critical materials can reduce cradle-to-grave GHG emissions by roughly 40-60%, provided that allocation rules and material-substitution assumptions are consistently defined. Despite methodological progress, uncertainty remains concentrated in vacuum-tool energy use, solvent balances, heating profiles, encapsulation data, and end-of-life modeling for emerging stacks, highlighting the need for improved metrology and transparent reporting. By harmonizing process-level LCIs, clarifying functional units and system boundaries, and providing standardized, open templates, this work supports reproducibility, comparability, and integration with prospective and techno-economic models, ultimately enabling more reliable assessments and more sustainable industrial pathways for next-generation PV technologies.

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Abbreviations

The following abbreviations are used in this manuscript:

ALD	Atomic Layer Deposition
AP	Acidification Potential (acidifying emissions, e.g., SO ₂ -eq)
BIPV	Building-Integrated Photovoltaic
BOS	Balance of System
CdTe	Cadmium Telluride

CED	Cumulative Energy Demand (total primary energy required)
CI	Confidence Interval
CIGS	Copper Indium Gallium Selenide
CoV	Coefficients of Variation
Cradle-to-gate	Assessment boundary that includes all life-cycle stages from resource extraction ('cradle') up to the point where the product leaves the manufacturing facility ('gate'), excluding use and end-of-life phases.
Cradle-to-grave	Assessment boundary that includes the full life cycle of a product, from resource extraction ('cradle') through manufacturing, use, and end-of-life treatment ('grave').
c-Si	Crystalline-silicon
EoL	End-of-life
EP	Eutrophication Potential (nutrient enrichment impacts, e.g., PO ₄ ³⁻ -eq)
EPBT	Energy Payback Time
FU	Functional Unit
GHG	Greenhouse-gas
GWP	Global Warming Potential
HVAC	Heating, Ventilation, and Air Conditioning
IEA	International Energy Agency
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LCI	Life Cycle Inventory
OSC	Organic Solar Cells
PV	Photovoltaic
PVPS	Photovoltaic Power Systems Programme
PV/T	Photovoltaic/Thermal Hybrid System
R2R	Roll-to-Roll (R2R)
Si	Silicon
TCO	Transparent Conductive Oxide
TiO ₂	Titanium Dioxide
TRL	Technology Readiness Level

Appendix A

Appendix A.1: Standardized LCI Data Templates (How to Use)

To make process-resolved PV LCIs interoperable across studies and reproducible across TRLs, a standardized multi-tab template has been developed. Because the full file cannot be provided, the eight worksheet tables from this template are included as Tables A1–A8. The structure uses consistent

terminology, units, metadata fields, and data-quality criteria aligned with best practice in the IEA PV Power Systems Programme (IEA PVPS) Task 12 and recent prospective LCA frameworks [3,8,12,24,26,48]. The worksheets are designed for straightforward transfer into standard LCA software environments (e.g., Brightway [93], openLCA [48], SimaPro [64]) and for use in meta-analysis, scale-up modeling, and scenario exploration.

Template structure (tabs and roles)

- README: Defines the FU, system boundary, grid mix (region and year), background database versions, TRL, and citation/DOI metadata. Provides instructions and assumptions required for reproducibility [3,8,24].
- PROCESS_MAP: A line diagram of all unit operations (e.g., substrate clean → wet/vacuum deposition → annealing → contacts → encapsulation). Each row includes equipment class (wet/thermal/vacuum/ambient), tool ID, and alternative routing (batch / R2R / hybrid) [8,12,15,17,42].
- FOREGROUND_LCI: Per-step measurements or modeled flows: energy (MJ), electricity (kWh), thermal energy, substrate/encapsulant mass, solvents and recovery efficiency, precursor gases, idle power, uptime, throughput, and yield [12,15–17,42].
- BACKGROUND_LINKS: Explicit mapping to background processes (Ecoinvent/GaBi), including dataset name, region, year, transport distances, and database version numbers to guarantee reproducibility [3,48].
- ELECTRICITY_SCENARIOS: Baseline grid (e.g., EU-27, 2023) and prospective mixes (2030/2050) with carbon intensities used for sensitivity runs and scenario modelling [2,24,48,67].
- DATA_QUALITY: Tier classification (1-3), pedigree scores, distribution type, min/max, and uncertainty notes (measured vs. modelled). This aligns with prospective LCA requirements [23,24,26,56].
- EOL_SCENARIOS: Mechanistic description of EoL pathways (mechanical, thermal, hydrometallurgical) with recovery efficiencies for metals, silicon, glass, and encapsulant; allocation rules (mass, economic, system expansion) [27–34,88–92].
- VALIDATION: Automated checks for unit consistency, mass/energy balancing, solvent in-out consistency, and flagging of out-of-range values; includes a QA audit log for publication.

The FOREGROUND_LCI sheet uses fixed units and standardized field names to ensure interoperability across studies. Core columns include: Process_Step, Equipment_Class, TRL, Area_Pass (m²), Throughput, Uptime (%), Yield (%), Active_Time (min), Idle_Power (kW), Active_Power (kW), Electricity (kWh), Thermal_Energy (MJ), Solvent_i (kg), Recovery_Eff (%), Gases_i (kg), Substrate (kg), Encapsulant (kg), Waste (kg), Notes, Tier, Dist_Type, Mean, SD, Min, Max. Units are fixed, and the default functional unit is 1 m² active area, with embedded formulas enabling conversion to kWp or kWh based on user-defined device efficiency and STC assumptions [3,24,45–48].

The complete standardized template is released as Supplementary File S1 (PV_LCI_Template_Pervoskite.xlsx). This file contains the full multi-tab structure (README, PROCESS_MAP, FOREGROUND_LCI, BACKGROUND_LINKS, ELECTRICITY_SCENARIOS, DATA_QUALITY, EoL_SCENARIOS, VALIDATION), pre-populated with a worked example for a pre-industrial perovskite PV device. The perovskite example demonstrates the intended use of the template, how to map process routes, populate per-step LCIs, assign background links, and conduct validation checks, while preserving flexibility for adaptation to other PV technologies.

How to use the template (workflow)

The template is intended for both reproducible reporting and direct integration into LCA software. The recommended workflow is:

1. Define FU and system boundary in the README tab; choose the baseline electricity mix and background database versions [3,8,24,48].
2. Map the process sequence in PROCESS_MAP, selecting batch, R2R, or hybrid configurations [15–17,42].
3. Input step-level measurements or modeled values into FOREGROUND_LCI, including idle power, active power, solvent recovery efficiencies, and heating/curing mode [12,15–17].
4. Link each flow to background datasets and specify baseline and scenario electricity mixes in ELECTRICITY_SCENARIOS [2,3,24,48,67].
5. Assign data-quality metadata (Tier, pedigree, distributions) in DATA_QUALITY following prospective LCA guidelines [23,24,26,56].
6. Add end-of-life pathways with material-specific recovery yields and allocation choices in EoL_SCENARIOS [27–34,80–92,94].
7. Run consistency checks in VALIDATION, then export machine-readable CSV/JSON and archive the versioned dataset with a DOI.

Good practices embedded in the template

- Clear, enforced separation of foreground (measured/modelled) vs. background (database-derived) flows [3,8].
- Mandatory reporting of electricity carbon intensity, region, and year for baseline and scenario conditions [2,24,48,67].
- Explicit reporting of idle power, uptime, solvent balances, and heating method, which drive most uncertainty in process-level PV LCAs [12,15–17,24,26].
- Fully versioned background datasets, grid datasets, and template versioning to ensure reproducibility.
- Built-in uncertainty structure using Tiers + stochastic ranges (mean/SD/min/max).

Appendix A.2: Priority Data Gaps and Measurement Needs

Despite rapid methodological progress, several high-leverage uncertainties limit comparability and forward-looking modeling of next-generation PV manufacturing.

1. Electricity and temporal dynamics: Grid-mix year/region, marginal vs. average carbon intensity, and idle-power duty cycles are unevenly reported; studies should publish time-stamped electricity data and line-speed dependencies [2,3,12,17,24,48,56,57,67].
2. Thermal steps and annealing physics: Ramp/soak schedules, thermal-mass corrections, photonic-curing profiles, and heat-recovery efficiencies are poorly measured on pilot lines; standardized logging would narrow uncertainty bounds significantly [12,17,38,42,56].
3. Vacuum processes (ALD, sputtering): Pump curves, chamber leakage rates, gas-purge flows, precursor utilization fractions, and cycle-time dependencies are rarely disclosed; process-normalized reporting would enable realistic scaling [17,24,26].
4. Solvent systems and emissions: Solvent balances, fugitive losses, and abatement efficiency remain largely assumption-based; mass-balance tests and closed-loop recovery data (η by solvent) are urgently needed for scalable wet coating [12,15,16,24,26,42,48].
5. Encapsulation and substrate specificity: Barrier foils, adhesives, and curing data (including fluorine-free and bio-based systems) remain sparse, with large impact on GWP and recyclability [12,38–40,44,69,79,80,95].

6. EoL for emerging stacks: Pb/Ag/Au recovery yields, hydrometallurgical routes, and system-expansion allocation rules differ widely; consistent reporting is essential for perovskite and tandem modules [27,69,96–99].
7. Critical-materials trajectories and substitution: Ag, In/Sn, Pb, and rare materials require linked supply-risk + LCA modeling tied to realistic manufacturing and regional supply chains [5,19–22,32,48,70,77,78]. Emission and release-potential studies for third-generation PVs should inform parameterization [100].
8. Consequential and prospective coupling: Learning curves, TRL scaling, and regional decarbonization should be embedded in transparent scenario files (CSV/JSON) accompanying each LCA [4,23–26,48,60,61,67,69,70].
9. Cross-domain linkages: Water footprinting, urban deployment, circular-materials, and hydrogen-coupling LCAs require synchronized FUs, grid data, and background versions to avoid double counting [10,50,61,65,85,89,99,101,102].

Appendix A.3

Appendix A3 provides the complete process-LCI template developed and used in this work for a representative pre-industrial perovskite (p-i-n) single-junction module produced on a hybrid solution-vacuum line. The eight tables document, in a machine-readable but publication-ready format, all metadata, unit operations, foreground inventories, background dataset links, electricity scenarios, data-quality pedigree, EoL assumptions, and internal validation checks that underpin the cradle-to-gate assessment. Together, they illustrate how the proposed reporting framework can be implemented in practice: Table A1 summarizes project-level definitions and functional-unit conventions; Table A2 maps the manufacturing route into discrete unit operations; Table A3 reports the step-resolved foreground LCIs; Table A4 links each flow to specific background processes; Table A5 defines baseline and prospective electricity-mix scenarios; Table A6 describes data tiers, sources, and uncertainties; Table A7 outlines end-of-life and recycling scenarios; and Table A8 aggregates energy and solvent balances and calculates consistency indicators. These appendix tables are intended both as transparent documentation for the case study and as a reusable template that other researchers can adapt to different PV technologies, scales, and regional contexts.

Table A1. README - Metadata and system description.

Field	Value
Project_Title	Perovskite (p-i-n) single-junction module - hybrid line (solution + vacuum)
Version	1.0 (2025-11-10)
DOI_or_Repo_Link	
Authors	K. Kiskira; N. Gerolimos; G. Priniotakis; D. Nikolopoulos
Functional_Unit	1 m ² active area (default) and 1 kWp reported via conversion formulas
Active_to_Total_Area_Ratio	0.9
Module_Efficiency_STC_%	20
FU_Conversion_Notes	Conversions to kWp use user-specified efficiency (20%) and STC 1000 W/m ² .

System_Boundary	Cradle-to-gate (substrate → coating/deposition → anneal/dry → metallization → encapsulation).
Foreground_Included	Substrate cleaning; TCO sputter; ALD barrier; ETL coat; Perovskite coat; HTL coat; Metallization; Encapsulation; QA.
Background_Included	Electricity mix; gases; solvents; precursors; transport (default 200 km truck) mapped via BACKGROUND_LINKS.
Explicit_Exclusions	Clean-room HVAC (if site-wide), building works, spare parts outside scheduled maintenance, R&D scrap.
Baseline_Grid_Region	EU-27
Baseline_Grid_Year	2023
Background_DB	Ecoinvent / GaBi (placeholder names)
DB_Version	v3.x / 2024 equivalent
TRL	Pre-industrial / pilot (Tier 1-2 blend)
Geography_of_Manufacturing	EU (pilot line)
Citation_Primary	See manuscript bibliography IDs [12,15–17,33,41,43,49]
Notes	Numbers are representative within literature ranges; replace with site data when available.
HEAT_RECOVERY_FACTOR	0.2
GLASS_MASS_kg_per_m2	12
ENCAPSULANT_kg_per_m2	0.6

Table A2. PROCESS_MAP - Unit operations and routing.

Unit_Operation	Equipment_Class	Tool_ID	Routing	Notes
Substrate wash and prep	wet	SUB-CLN-01	batch	Glass soda-lime 3.2 mm; DI water; detergents
TCO sputter (ITO/AZO)	vacuum	TCO-SPT-01	batch	DC sputter; Ar
ALD barrier (optional)	vacuum	ALD-BAR-01	batch	Al ₂ O ₃ / HfO ₂ ; H ₂ O
ETL slot-die coat	wet	ETL-SD-01	R2R	SnO ₂ dispersion; low-tox solvent
Perovskite slot-die coat	wet	PVK-SD-01	R2R	p-i-n inks; greener solvent mix
Anneal/dry (IR/air)	thermal	ANN-OVN-01	R2R	IR + air knife; heat recovery

HTL slot-die coat	wet	HTL-SD-01	R2R	Polymer HTL ink
Metallization (screen/ink)	ambient	MET-PRT-01	batch	Ag or Cu grid; low Ag route
Encapsulation and lamination	thermal	ENC-LAM-01	batch	Glass-glass; POE/EVA
End-of-line test and QA	ambient	QA-VIS-01	batch	EL test; visual

Table A3. FOREGROUND_LCI - Process inventory (calculated).

Process_Step	Substrate wash & prep	TCO sputter (ITO/AZO)	ALD barrier (optional)	ETL slot-die coat	Perovskite slot-die coat	Anneal/dry (IR/air)	HTL slot-die coat	Metallization (screen/ink)	Encapsulation & lamination	End-of-line test & QA
Equipment_Class	wet	vacuum	vacuum	wet	wet	thermal	wet	ambient	thermal	ambient
TRL	Pilot	Pilot	Pilot	Pilot	Pilot	Pilot	Pilot	Pilot	Pilot	Pilot
Area_Pass_m2	1.0	1.0	0.7	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Throughput_m2_h	20	15	10	30	30	30	30	20	15	15
Uptime_%	90	92	92	90	90	92	92	93	95	95
Yield_%	95	95	95	97	95	96	97	98	99	99
Active_Time_min	6	12	10	5	8	15	5	4	12	3
Idle_Power_kW	1	2.5	1.8	0.6	1.2	1.5	0.5	0.3	1	0.1
Active_Power_kW	2	5	3	1.2	3	4	1	0.8	3.5	0.3
Electricity_kWh	0.2	1	0.5	0.1	0.4	1	0.083333333	0.053333333	0.7	0.016666667
Electricity_GWP_Gco2	540	1350	810	324	810	1080	270	216	945	81
Thermal_Energy_MJ	0	0.648550725	0.251086957	0.389	0.948	1.229347826	0.318448068	0.168309677	0.505964912	0.046896199
Solvent_kg	0.18	0.94	0.47	0.10	0.41	0.97	0.08	0.05	0.66	0.02

Recovery_Eff_%	0.00	5.14	2.39	7.55	11.25	7.86	6.18	4.12	4.18	1.55
Gases_kg	1.096842105	4.553240643	2.628931501	0.869647508	2.880373614	9.87740078	0.861910737	0.706690932	7.954427786	0.485529374
Substrate_kg	0.003644662	2.560429861	1.43419999	3.762090367	4.444846327	2.98151514	3.081433262	1.543336947	1.234734021	0.515569574
Encapsulant_kg	10.96840995	22.59551223	15.72605532	10.79954858	21.89624214	38.60583249	10.57144961	10.65786226	39.30444687	8.740303549
Waste_kg	#DIV/0! !	5.468334561	3.482187809	1.069120146	2.713238252	8.289876321	0.913962715	0.596399308	6.755294886	0.249786594
Notes	DI water recirc; mild detergent	Ar purge ~0.05 kg/m²	Al2O3 ~30 nm equiv.	Low-tox carrier; recovery 80%	Greene r solvent blend; 85% recovery	IR anneal ; heat recovery factor ~0.2	Polym er HTL; 80% recovery	Low-Ag formula tion ~1.5 g/m²	Glass-glass; POE/EV A ~0.6 kg/m²	EL imagin g; visual
Tier	2	2	2	2	2	2	2	2	1	1
Dist_Type	lognormal	lognormal	lognormal	lognormal	lognormal	lognormal	lognormal	lognormal	lognormal	lognormal
Mean										
SD										
Min	0.8	0.7	0.7	0.8	0.7	0.7	0.8	0.8	0.8	0.9
Max	1.2	1.3	1.4	1.3	1.4	1.3	1.3	1.2	1.2	1.1
Time_Check	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	CHECK ACTIVE TIME	

Calculations for Table A3:
HEAT_RECOVERY_FACTOR = README!\$B\$22
GLASS_MASS_kg_per_m2 = README!\$B\$23
ENCAPSULANT_kg_per_m2 = README!\$B\$24
Electricity CO2 factor = VALIDATION!\$B\$11

$$\text{Electricity_kWh} = (\text{Active_Time_min}/60) * \text{Active_Power_kW} + (\text{Active_Time_min}/60) * (1 - \text{Uptime_}\% / 100) * \text{Idle_Power_kW},$$

(1)

If columns are:
Active_Time_min = H2
Active_Power_kW = K2
Idle_Power_kW = I2
Uptime_% = F2
Then:

$$\text{Electricity_kWh} = (H2/60) * K2 + (H2/60) * (1 - F2/100) * I2, \tag{2}$$

$$\text{Electricity_GWP_Gco2} = \text{Electricity_kWh} * \text{VALIDATION!\$B\$11}, \tag{3}$$

If Electricity_kWh = L2:

$$\text{Electricity_GWP_Gco2} = L2 * \text{VALIDATION!\$B\$11} \tag{4}$$

$$\text{Thermal_Energy_MJ} = (\text{Active_Time_min}/60) * \text{Active_Power_kW} * (1 - \text{README!\$B\$22}) * 3.6, \tag{5}$$

If:
Active_Time_min = H2
Active_Power_kW = K2
Heat recovery factor = README!\\$B\$22

$$\text{Thermal_Energy_MJ} = (H2/60) * K2 * (1 - \text{README!\$B\$22}) * 3.6, \tag{6}$$

$$\text{Solvent_kg} = \text{Base_Solvent_Input}, \tag{7}$$

If your solvent input is column N2:

$$\text{Solvent_kg} = N2, \tag{8}$$

$$\text{Recovery_Eff_}\% = \text{Recovered_Solvent} / \text{Solvent_kg} * 100, \tag{9}$$

$$\text{Gases_kg} = \text{Base_Gas_Input}, \tag{10}$$

If your gas mass is in column P2:

$$\text{Gases_kg} = P2, \tag{11}$$

$$\text{Substrate_kg} = \text{Area_Pass_m2} * \text{README!\$B\$23}, \tag{12}$$

If Area_Pass_m2 = D2:

$$\text{Substrate_kg} = \text{D2} * \text{README!\$B\$23},$$

(13)

$$\text{Encapsulant_kg} = \text{Area_Pass_m2} * \text{README!\$B\$24},$$

(14)

If Area_Pass_m2 = D2:

$$\text{Encapsulant_kg} = \text{D2} * \text{README!\$B\$24},$$

(15)

$$\text{Waste_kg} = (\text{Solvent_kg} - \text{Solvent_kg} * (\text{Recovery_Eff_}\% / 100)) + (\text{Substrate_kg} * (1 - \text{Yield_}\% / 100)),$$

(16)

Using actual columns:
Solvent_kg = N2
Recovery_Eff_% = O2
Substrate_kg = Q2
Yield_% = G2

$$\text{Waste_kg} = (\text{N2} - \text{N2} * (\text{O2} / 100)) + (\text{Q2} * (1 - \text{G2} / 100)),$$

(17)

$$\text{Time_Check} = \text{IF}(\text{Active_Time_min} = 0, \text{"CHECK ACTIVE TIME"}, ""),$$

(18)

If Active_Time_min = H2:

$$\text{Time_Check} = \text{=IF}(\text{H2}=0, \text{"CHECK ACTIVE TIME"}, ""),$$

(19)

Table A4. BACKGROUND_LINKS - Dataset mapping.

Dataset_Name	Database	Region	Year	Dataset_ID	Transport	Comment
Electricity, medium voltage, EU-27, 2023	ecoinvent	EU-27	2023	elec_mv_eu27_2023	0 km	Used for all electricity entries
Argon, at plant	ecoinvent	GLO	2020	argon_at_plant	500 km truck	Sputtering purge gas
Al ₂ O ₃ ALD precursor, at plant	ecoinvent	GLO	2020	ald_alumina_precursor	300 km truck	Placeholder; adjust to actual

Glass, soda-lime, 3.2 mm, at plant	ecoinvent	RER	2020	glass_32mm	200 km truck	Front/back glass
Encapsulant, POE/EVA, at plant	ecoinvent	GLO	2020	encapsulant_poe_eva	300 km truck	POE/EVA film
Silver paste, at plant	ecoinvent	GLO	2020	silver_paste_lowAg	1000 km truck	Low-Ag paste
Detergent, industrial, at plant	ecoinvent	GLO	2020	detergent_industrial	200 km truck	Substrate cleaning
DI water, at plant	ecoinvent	RER	2020	di_water	Onsite	Closed-loop recirculation

Table A5. ELECTRICITY_SCENARIOS - Regional grid projections.

Scenario	gCO ₂ _per_kWh
EU-27 baseline 2023	270
EU-27 2030 projection	150
EU-27 2050 net-zero projection	50
Custom_User	0

Table A6. DATA_QUALITY - Foreground pedigree and uncertainty.

Process_Step	Tier	Source_Type	Vintage	Uncertainty_Band	Pedigree	Notes
Substrate wash & prep	1	Primary pilot logs	2024–2025	±20%	Good	Measured power and duty cycles
TCO sputter (ITO/AZO)	2	Scaled from tool specs + literature	2020–2025	±30%	Medium	Throughput-sensitive
ALD barrier	2	Literature + vendor models	2020–2024	±35%	Medium	Optional step
ETL coat	2	Pilot measurements + model	2023–2025	±25%	Good	Solvent balance checked
Perovskite coat	2	Pilot measurements + model	2023–2025	±30%	Good	Recovery efficiency critical
Anneal/dry	2	Measured furnace/IR logs	2024–2025	±25%	Good	Heat-recovery assumed 0.2

HTL coat	2	Pilot + model	2023–2025	±25%	Good	Solvent balance checked
Metallization	2	Vendor + line data	2023–2025	±20%	Good	Low-Ag recipe
Encapsulation	1	Plant recipe + datasheets	2024–2025	±15%	High	Glass & POE mass measured
QA	1	Plant logs	2024–2025	±10%	High	Minor energy share

Table A7. EOL_SCENARIOS - Recycling and recovery.

Scenario	Allocation	Si_Recovered	Pb_Recovered	Glass_Recovered	Al_Recovered	Ag_Recovered	Polymer_Recovered	Notes
Baseline (mechanical +thermal)	mass	0	0	0.9	0.85	0	0.95	EU logistics; 200 km avg
Closed-loop enhanced (hydrometallurgical metals)	system_expansion	0	0	0.95	0.9	0.9	0.97	Credits for Ag; foil recovery if present
Landfill (counterfactual)	none	0	0	0	0	0	0	For sensitivity only

Table A8. PROCESS_MAP - Unit operations and routing.

Unit_Operation	Equipment_Class	Tool_ID	Routing	Notes
Substrate wash and prep	wet	SUB-CLN-01	batch	Glass soda-lime 3.2 mm; DI water; detergents
TCO sputter (ITO/AZO)	vacuum	TCO-SPT-01	batch	DC sputter; Ar
ALD barrier (optional)	vacuum	ALD-BAR-01	batch	Al ₂ O ₃ / HfO ₂ ; H ₂ O

ETL slot-die coat	wet	ETL-SD-01	R2R	SnO ₂ dispersion; low-tox solvent
Perovskite slot-die coat	wet	PVK-SD-01	R2R	p-i-n inks; greener solvent mix
Anneal/dry (IR/air)	thermal	ANN-OVN-01	R2R	IR + air knife; heat recovery
HTL slot-die coat	wet	HTL-SD-01	R2R	Polymer HTL ink
Metallization (screen/ink)	ambient	MET-PRT-01	batch	Ag or Cu grid; low Ag route
Encapsulation and lamination	thermal	ENC-LAM-01	batch	Glass-glass; POE/EVA
End-of-line test and QA	ambient	QA-VIS-01	batch	EL test; visual

Table A9. VALIDATION - Energy and solvent balances (calculated).

Check	Value	Status	Comment
Electricity total (kWh)	4.05	INFO	Sum over FOREGROUND_LCI
Thermal energy total (MJ)	4.51	INFO	Sum over FOREGROUND_LCI
Solvent in (kg)	3.88	INFO	Sum over coating steps
Solvent recovered (kg)	22.44	INFO	Recovery_Eff_% applied
Solvent loss (kg)	3.66	INFO	Should be >0 and reasonable
-	-	-	-
EU-27 baseline 2023	-	-	-
Active_CO ₂ _Factor_(g_per_kWh)	270	-	-
Total_Electricity_GWP_(gCO ₂)	6426	-	Electricity × factor
TOTAL GWP from electricity (kg CO ₂)	6.426	INFO	=6426 / 1000
Solvent recovery check (%)	577.7	INFO	=B5 / B4 × 100

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