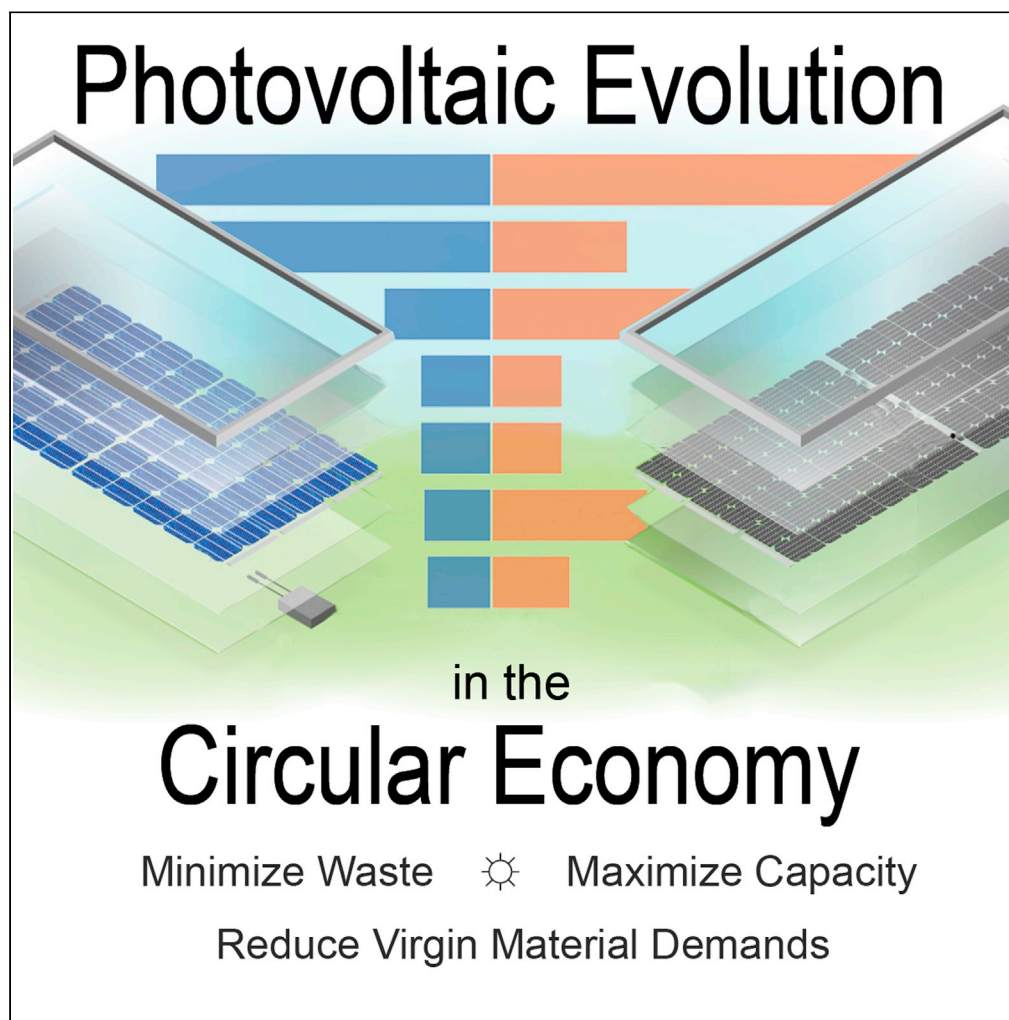


Article

PV in the circular economy, a dynamic framework analyzing technology evolution and reliability impacts



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Highlights

PV ICE is an open-source tool that evaluates circular paths for photovoltaics

Features material flow tracking for waste, virgin needs, and installed capacity

Dynamic baselines of historic and projected c-Si PV data are provided

Sensitivity analysis shows increasing PV lifetime reduces material requirements

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Article

PV in the circular economy, a dynamic framework analyzing technology evolution and reliability impacts

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SUMMARY

Rapid, terawatt-scale deployment of photovoltaic (PV) modules is required to decarbonize the energy sector. Despite efficiency and manufacturing improvements, material demand will increase, eventually resulting in waste as deployed modules reach end of life. Circular choices for decommissioned modules could reduce waste and offset virgin materials. We present PV ICE, an open-source python framework using modern reliability data, which tracks module material flows throughout PV life cycles. We provide dynamic baselines capturing PV module and material evolution. PV ICE includes multimodal end of life, circular pathways, and manufacturing losses. We present a validation of the framework and a sensitivity analysis. Results show that manufacturing efficiencies strongly affect material demand, representing >20% of the 9 million tons of waste cumulatively expected by 2050. Reliability and circular pathways represent the best opportunities to reduce waste by 56% while maintaining installed capacity. Shorter-lived modules generate 81% more waste and reduce 2050 capacity by 6%.

INTRODUCTION

The “energy transition” refers to the transformation of the global energy sector from fossil-based to renewable energy by 2050. In the United States, solar energy capacity additions in the 2040s are expected to exceed 30 GW per year (Murphy et al., 2021), and globally, additions could exceed 400 GW per year (Gervais et al., 2021). Multiple studies have explored possible material shortages and potential waste volumes from this energy transition (Weckend et al., 2016; Bloomberg.Com, 2020; [Episode #54] - Resource Limitations; Gervais et al., 2021; IEA, 2021). Renewable technologies must be deployed fast enough to decarbonize the economy and minimize the effects of catastrophic climate change (which will require exponential growth), while minimizing cumulative life cycle waste and environmental impacts (from raw-material sourcing, manufacturing, and poor dispositioning at end of life).

Integrating solar photovoltaics (PV) and other renewable energy sources into the circular economy (CE) is important for sustainable, rapid growth. Although definitions of CE vary, the implementation is materials recirculation reaching economy scale, leveraging actions including reduce, reuse, repair, remanufacture, and recycle (Kirchherr et al., 2017; van Loon et al., 2021). This integration requires proactive planning for circular disposition options and supply chains. The current state of the art in CE tools involves metricizing or quantifying circularity into a single factor by assessing mass flows, typically for a single product (Saidani et al., 2019; Smith and Jones). However, implementing circularity requires a whole-system view that considers all life cycle stages, including virgin material extraction, manufacturing, use phase, and end of life (EoL). Mass-flow tracking requires knowledge of deployment date, embodied material, and lifetime.

Several studies have focused on the EoL of PV and have estimated the forthcoming mass of PV waste (Sander et al., 2007; Paiano, 2015; Weckend et al., 2016; Domínguez and Geyer, 2017, 2019; Peeters et al., 2017; Kim and Park, 2018; Santos and Alonso-García, 2018; Mahmoudi et al., 2019; CSA Group, 2020). Existing methods for estimating the mass and composition of the PV waste stream provide high-level guidance that society will need to manage a large flow of PV waste in the next 20–30 years. CE pathways for PV could eventually offset some raw material needs; however, EoL material flows are currently small, widely dispersed—both geographically and in time—and mismatched with the short-term virgin material

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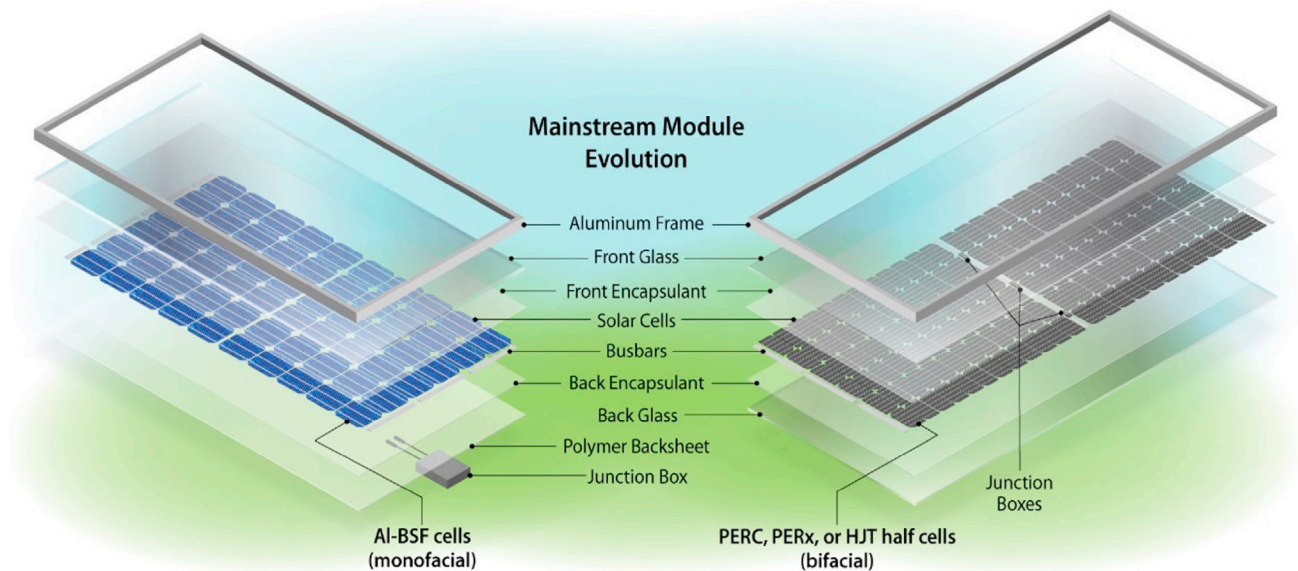


Figure 1. PV module technology has evolved rapidly. This image shows what an "average" module looked like 15 years ago (left) versus current technology (right). Power production per meter square has also improved due to efficiency improvements and other levers such as bifaciality (Fischer et al., 2020).

demands required to decarbonize the grid (Weckend et al., 2016; Santos and Alonso-García, 2018). These factors, as well as economics, have delayed the adoption of circular strategies for PV technologies. However, a better understanding of material needs for PV deployment, PV life cycle, and EoL material streams can help to proactively plan for circular disposition and develop a sustainable, reliable supply chain (Sandor et al., 2018; IEA, 2021).

Most existing studies do not capture the rapid, nonlinear evolution of PV technologies or the improved material efficiency and circular disposition options throughout the PV life cycle. Instead, they focus primarily on EoL waste projections for a single, static module. Mass balance calculations require a conversion from PV capacity (expressed in watt-peak or W_p) to total mass, which is usually done using a static "mass-power factor" (kg/W_p) for an average module (although some projections use an empirical fit to generate a dynamic mass power factor based on historical module improvements) (Weckend et al., 2016). The waste stream material composition is then described by a static, average component material fraction, which fails to capture PV material technology evolutions, as represented in Figure 1. Another drawback of current waste projections is that they fail to capture the multimodal processes and decisions that dictate when PV systems reach EoL, including variable degradation rates (Jordan et al., 2016), failures (Jordan et al., 2017), and economic decisions (Weaver, 2019; Author Anonymous, 2020a; Repower PV Systems), as well as ongoing improvements in durability of PV technology. Instead, these projections use fixed module lifetimes (Paiano, 2015; Domínguez and Geyer, 2017, 2019) or failure probability functions (Weckend et al., 2016). Finally, these PV waste studies only model EoL material streams, neglecting earlier supply chain and PV life cycle stages, such as manufacturing (CSA Group, 2020). This is problematic for closing circular loops, and it ignores important environmental justice considerations, such as localized mining, refining, and manufacturing pollution (Yue et al., 2014; Mulvaney, 2019; Author Anonymous, 2019b).

Sustainably increasing the deployment of renewables for decarbonization requires a set of analysis tools that can quantitatively evaluate circularity and sustainability based on mass, energy, carbon emissions and intensities, and other life cycle impacts. Circularity and environmental impacts are measured on both a mass and lifetime basis (Figge et al., 2018; Smith and Jones; Author Anonymous); thus, both mass and lifetime evolutions must be tracked. In addition, research has shown that development of sector-specific CE tools and metrics can increase circular practices (Saidani et al., 2019).

In this paper, we propose a set of baselines and a new tool to assist in the proactive planning of a CE for PV. The following section documents the rapid evolution of PV technology in terms of technology and materials, providing updated, dynamic module and material property baselines. Then, we propose a methodology for performing a dynamic mass-flow-based analysis of renewable energy waste streams, focused on PV. This methodology incorporates the changing PV technology baseline, includes manufacturing waste streams, leverages the effects of lifetime and reliability to provide an encompassing definition of EoL, and implements various circular pathways. A comparison to prior literature is made, followed by a sensitivity analysis, to understand the relative impact of improvements in manufacturing, module technology, reliability, lifetime, and EoL disposition on virgin material demands, life cycle waste, and installed capacity. This approach also allows for further calculations based on mass, such as energy, environmental impacts, and economics. This framework is presented as an open-source, Python-based tool, with data and algorithms publicly available.

PV technology evolution

PV technology, including cell, module, packaging material, and system design, has evolved dramatically since 1995, with efficiency increasing from 12.5% in 1995 to 20.0% in 2020. We have developed a new, time-resolved material baseline that captures this evolution, based on an analysis of the literature and industry data that captures the properties and materials of an average module deployed in any given year. We created these open-source baselines with the goal of improving total mass-flow predictions and specific material flows from the dynamic composition of the EoL PV waste stream. We split PV technology evolution data into module properties and material properties, with an annual material mass per module area baseline to relate module and material data. A sampling of how we derived these baselines from available data is presented alongside other waste prediction values from the literature to demonstrate improvements in capturing PV technology evolution. Full documentation and calculations of all baselines are available on GitHub (Ovatt et al., 2021a).

Baselines start from available bill of materials information (e.g., module efficiency, wafer thickness). We then use market share weighting of these granular technology data to create an average deployed technology module for each year from 1995 through 2050. Technology evolutions appear first in manufacturing survey data, followed by shipment data and deployment data 3–18 months later (Sun, 2020). The global PV market further blurs the exact timeline of PV evolution, as trends can be different in different regions (e.g., the coming mandate for lead-free solder in the EU). This study will primarily focus on US PV deployment; however, where national-level data were not available, global data were used. After 2020–2021, all data are projections/predictions. Most baseline values are held constant after 2030, representing a conservative estimate of technology improvements (Fischer et al., 2020).

We first present the United States' annual PV capacity deployment, where the baseline is market share weighted for crystalline silicon (excluding thin-film technologies). This work does not consider material flows for thin-film modules, as those are mostly Cadmium Telluride (CdTe) and have well-established circular waste management practices (Sharma et al., 2019). The silicon module market share is then presented as monocrystalline (mono-Si) versus multicrystalline (mc-Si) modules. Next, we examine the changes in module efficiency and material composition. These values are compared with prior waste projection literature values using a mass-power factor. Finally, we examine the evolution of PV reliability and lifetime in the context of prior waste projection modeling.

PV installations in the United States

PV installations in the United States have grown by three orders of magnitude between 1995 and 2020. However, there is no single, consistent source of installation data, and there are large disagreements between the datasets, especially pre-2010. Figure 2 compiles six available datasets for PV installations between 1995 and 2020 and provides a baseline that combines the available data. This baseline (in black) uses a single literature source per year, rather than an average, thereby relying on consistent underlying assumptions. Pre-2010, the International Energy Agency (IEA) Photovoltaic Power Systems Program (PVPS) 2010 National Survey Report (Bolcar and Ardani, 2010) installation data were used, and for 2010 through the present, Wood Mackenzie Power & Renewables data were used (Author Anonymous, 2020b). These annual installation data were then annually market share weighted for crystalline Silicon (c-Si) technology. This baseline currently excludes CdTe, despite its significant presence in US utility-scale PV, because CdTe already has high collection and recycling rates.

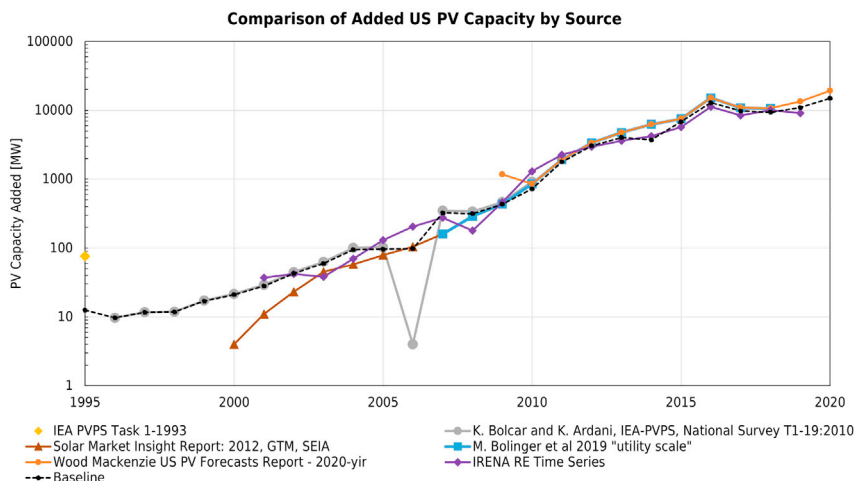


Figure 2. Megawatts of PV added in the United States per year, according to different sources of PV installation data. Please note that the scale is logarithmic, and the source data include all PV technologies. Sources: Morse, 1995; Bolcar and Ardani, 2010; Kann et al., 2013; Bolinger et al., 2019; Author Anonymous, 2020b; IRENA RE Time Series. The black dashed line shows the silicon market share weighted installations.

Monocrystalline and multicrystalline silicon technology market share

Crystalline silicon solar cells can be made from mc-Si or mono-Si wafers. The reported market share of mono-Si is shown in Figure 3 (mc-Si market share is the complement of these numbers). Mc-Si was the dominant technology until about 2015, when mono-Si wafer prices dropped dramatically (Feldman et al., 2021). The transition from mc-Si to mono-Si modules is one example of the rapid and unanticipated shifts in the PV market and is a critical consideration for mass-flow analysis. Technology aspects such as cell type, size, and thickness influence the mass of silicon per module area, cell efficiency, and yields in the wafer manufacturing process. These attributes change with time and market sector and differ among reporting sources.

PV deployments are often divided into three main sectors—utility-scale, commercial, and residential. Technology evolves at different rates in each of these sectors. Lawrence Berkeley National Laboratory (LBNL) reports show that historically, mono-Si dominated the residential sector, whereas mc-Si was deployed at utility-scale (Barbose and Darghouth, 2019; Bolinger et al., 2019). The market share reports represented in Figure 3 vary by only a few percentage points in years with overlapping data, except for the LBNL nonutility-scale (Barbose and Darghouth, 2019) market share, which deviates starting in 2015. The LBNL report shows mono-Si dominating nonutility-scale markets. As of 2020, mono-Si captured a majority market share across sectors (Mints, 2021; Author Anonymous, 2021). A proposed baseline that blends these data to attempt to capture multiple sectors is also provided in the figure in black. For this baseline, we averaged overlapping data from the literature sources. Where data were missing, such as between 1980 and 1998, linear interpolation was used. After averaging, the mono-Si and mc-Si data were renormalized to ensure the market shares added up to 100%, because the baseline for installations does not include CdTe.

Average module efficiency

Figure 4 shows the increase in average module efficiencies from 1975 through 2020, gathered from multiple sources (Maycock, 2003; Nemet, 2006; Fischer, 2019; Fischer et al., 2020). In 1975, the average module was 6.32% efficient (Nemet, 2006), and by 2020, efficiency had reached 20.0% (Author Anonymous, 2021). The module efficiency baseline is provided in black; this baseline includes a linearly interpolated efficiency for years without available data from the literature. Expected future module efficiencies from 2020 to 2050 are calculated from an exponential decay function for a 2050 average c-Si module efficiency of 25% (Oberbeck et al., 2020).

The annual average module efficiency represents the improvements in the power-to-area ratio, which is relevant for mass-flow calculations that require a mass-to-power conversion. The efficiency is an imperfect metric, because energy yields have also improved due to factors other than efficiency (e.g., bifacial

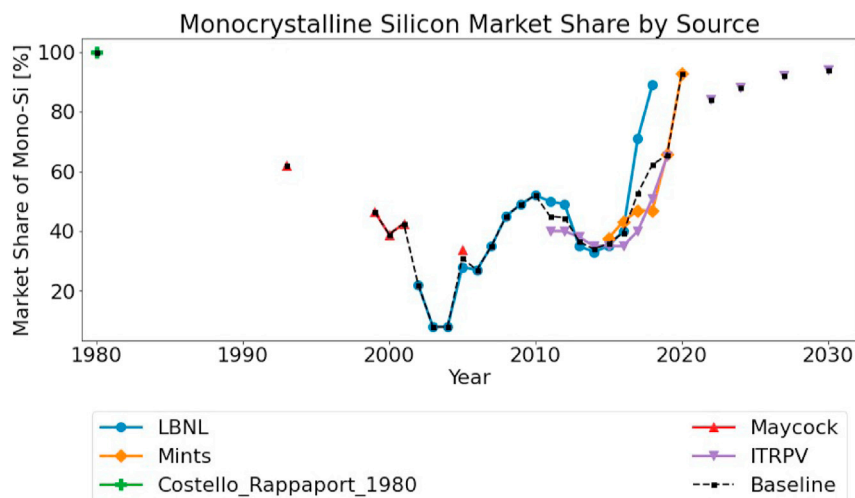


Figure 3. The market share of mono-Si technologies, from Costello and Rappaport, 1980; Maycock and Box, 1993; Maycock, 2003, 2005; Barbose and Darghouth, 2019; Mints, 2019; Fischer et al., 2020. Market shares of mc-Si (not shown) are the complement of these values. The dashed black line is the average of the sources.

modules, as explored in Ovaitt et al. [2021c]). However, efficiency is a well-documented module property that captures performance improvement trends. Prior waste projection literature values for average module output power, mass, and efficiency are shown in Table 1 for comparison. These assume significantly lower module efficiency values than the historical values from the International Technology Roadmap for Photovoltaics (ITRPV) or the baseline in Figure 4.

Material composition

The material composition of modules has changed as module technologies have evolved. C-Si modules are still primarily composed of glass, silicon, aluminum, etc., but the mass fractions and quality of these materials have changed—attributes that are critical for estimating raw material requirements and evaluating EoL management options. Table 2 provides a summary of module material composition fractions used in the waste projection literature. These static averages are derived either from representative module datasheets (Weckend et al., 2016; Santos and Alonso-García, 2018; CSA Group, 2020) or from life cycle analysis (LCA) databases (Dominguez and Geyer, 2017, 2019; Kim and Park, 2018; Mahmoudi et al., 2019). Uniquely, Peeters et al.'s (Peeters et al., 2017) study of PV waste originating in Flanders explicitly captures the material evolution of deployed PV module technologies to more accurately estimate the rapidly changing material composition of PV waste with time.

Static values do not reflect the historical changes or projected compositions of PV modules. For instance, this approach fails to capture the increasing glass fraction, as glass-glass modules have become more prevalent in recent years (Author Anonymous, 2021). Furthermore, the material efficiency improvements and technology shifts in silicon, silver, copper, and aluminum (thinner wafers, reduced silver intensity, and thinner module frames) are not captured with a static module composition. International Renewable Energy Agency (IRENA) 2016 End-of-Life Management report (Weckend et al., 2016) attempts to capture material efficiency improvements by modifying the mass-to-power factor (see Mass-Power Factor section); however, this approach misses underlying technology developments that allow materials to be substituted or relative compositions to be changed (e.g., busbars to multiwires, lead-free solders). An ideal alternative to deriving material composition data from the literature is to use PV manufacturer datasheets (Peeters et al., 2017)—however, complete material data are not often included, and scalability of this method is daunting. Another option is to derive material compositions from LCA datasets, which can be precise data collected from a manufacturing production line (Jungbluth, 2005). However, the LCA data used by several studies in Tables 1 and 2 were collected in 2000 in Switzerland, making it hard to generalize to other countries in 1995–2050. Heidari and Ancil (Heidari and Ancil, 2021) created a dynamic “bottom-up” material composition from silicon technology designs; however, the analysis only covers a decade, and detailed baselines are not provided.

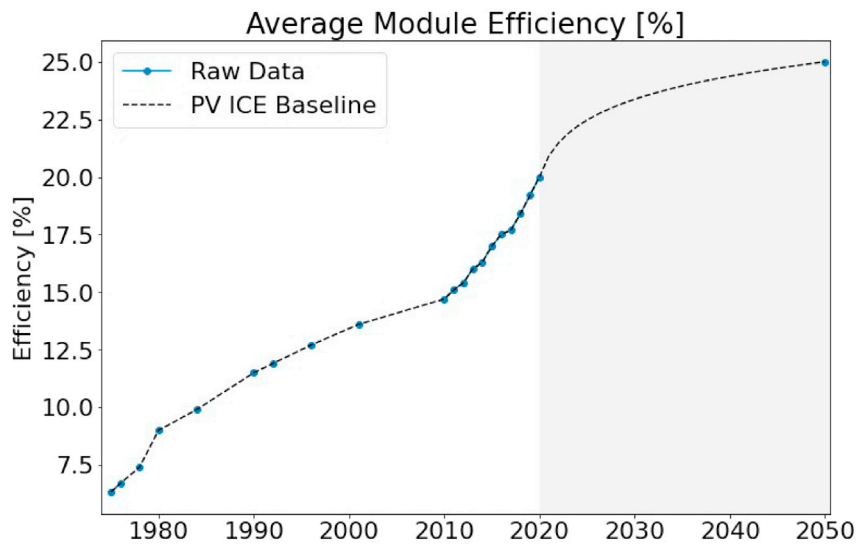


Figure 4. Average module efficiency over time, from Nemet, 2006; Fischer, 2019; Fischer et al., 2020; Oberbeck et al., 2020; Wilson et al., 2020; Author Anonymous, 2021 and a proposed interpolated baseline in black.

A dynamic composition baseline accounts for historical changes and future projections. The PV ICE composition baseline is shown in Figure 5. This is a calculated material composition breakdown of glass, aluminum, silicon, silver, copper, encapsulants, and backsheets in the average c-Si module for each year through 2030. Mass fractions (Figure 5) are calculated from each component's mass per module area baseline. Each component material baseline incorporates market share weighting of module technologies (e.g., glass-glass versus glass-backsheet) and material efficiency improvements (e.g., thinner silicon wafers). Estimations of future material efficiency improvements or trends for the next 10 years are typically derived from ITRPV projections (Fischer et al., 2020; Author Anonymous, 2021) and are held constant through 2050.

Comparing Figure 5 and Table 2, we see that the historical glass fraction includes the entire range of prior literature values, from ~61% in 1995 to above ~80% in 2030, due to increasing adoption of bifacial modules. The silicon mass fraction is a function of wafer thinning and cell size, which has increased in recent years. As part of the calculation, the multi-Si versus mono-Si market share data from Figure 3 were used in conjunction with each respective technology's cell size (which have increased differently with time). The baseline's copper fraction is lower than the values found in Table 2 because it only captures encapsulated copper (i.e., not the junction box or wiring).

Utilizing a dynamic material composition is critical for waste forecasting and CE decision-making. Currently, the literature assumes that PV recycling will become financially viable via high-quality material recovery, including recovery of silicon, silver, and copper (Ardente et al., 2019). However, as the material efficiency of silver use in modules decreases, this may become an increasingly untenable proposition. Leveraging historical data to provide foresight into this potentially valuable EoL material stream is critical for circular EoL decisions.

Mass-power factor

Most PV waste projection literature relies on a mass-power factor, which relates module mass and power/efficiency. Mass-power factors are used to convert from deployment data, which are often expressed in units of W_p or W_{AC} (watt-AC) to total module mass, and are then paired with representative modules' datasheets or LCA database records to quantify material composition (Weckend et al., 2016; Domínguez and Geyer, 2019). Figure 6 shows mass-power factors from the literature along with a proposed dynamic mass-power factor. Most of the literature values are static and are shown as horizontal lines. In Weckend et al. (2016), a dynamic mass power factor was introduced based on a fit. Mass-power factors fitted to an exponentially improving function compound uncertainties in the raw data, whereas static mass-power factors fail to capture technology improvements. Our proposed factor, shown in black, was calculated from the presented baselines for module

Table 1. Mass, power, and module efficiency used in the literature

	Average module power [W]	Average module Mass [kg]	Average module efficiency [%]
Sander et al., 2007 (Sander et al., 2007)	215	22.3, 22 ^a	–
Paiano, 2015 (Paiano, 2015)	215	22	11%–19%
IRENA 2016 (Weckend et al., 2016)	270	18.6	–
Domínguez and Geyer, 2017 (Domínguez and Geyer, 2017)	226.3	23	14.3%
Kim and Park, 2018 (Kim and Park, 2018)	250	18.6	–
Mahmoudi et al., 2019 (Mahmoudi et al., 2019)	226.3	23	14.3%
Domínguez and Geyer, 2019 (Domínguez and Geyer, 2019)	224	23	–
ITRPV 2019 (Fischer, 2019) ^b	302.5	–	18.4%
ITRPV 2020 (Fischer et al., 2020) ^b	326	–	19.2%

^aIndicates value was calculated from available data in the study.

^bIncluded as an impartial reference; ITRPV does not attempt to project PV waste.

efficiency (Figure 4) and material composition (Figure 5). The baseline mass-power factor is consistently lower than that used in Weckend et al. (2016), potentially due to the exclusion of thin-film technologies.

The dynamic baseline methods and material data enable a more accurate analysis of deployment and eventual waste forecasts by accounting for manufacturing, module, and material improvements or “eco-efficiency.” By utilizing outdated mass-power factors, waste projections are likely to overestimate the quantity of PV waste, which could be exacerbated by the increasingly aggressive deployment forecasts for decarbonization. Overestimating waste projections could undermine attempts to implement circular pathways—for example, by building up recycling facilities too soon.

PV reliability and lifetime

With improvements in accelerated testing and field experience, PV module lifetimes have steadily improved. Initial lifetimes and warranties were only 10–15 years (Christensen, 1985) but are now more than 25–30 years (Wiser et al., 2020). PV system reliability is dependent on a myriad of factors (Jordan et al., 2020), making it challenging to model PV system and component lifetimes. In the literature, several factors have been leveraged to model system and component lifetimes.

Economic project lifetime/warranty period. This is the PV system’s expected lifetime as dictated by contract terms (e.g., 25 years) (Wiser et al., 2020). PV warranty lengths have increased steadily, currently averaging 30 years [44]. Using this fixed lifetime assumption in a model involves a simple time shifting from deployment, which is mathematically simple and provides a rough estimate of mass flow over time.

Underperformance (degradation). During their lifetime, modules are expected to produce power per their warranty terms, including a maximum degradation of power production each year. System owners and financial models generally expect 90% of modules to continue generating power at an expected percentage of the initial rating at the end of the economic project lifetime (usually above 80% of original nameplate capacity) (Wiser et al., 2020; Curtis et al., 2021b). This method is similar to the economic/warranty method discussed earlier and is suitable for rough estimates.

Failure (unexpected EoL). Module failure can be defined as “sudden terminations of production or precipitous reduction in performance below a specified threshold” (Wilson et al., 2020). Failure is a random occurrence where the module produces less than the expected amount of power at any time during the warranty or finance period, as defined by the warranty terms or pro forma. Modules may also fail if they are no longer safe due to damage or aging (e.g., if they lose electrical insulation due to cracked back-sheets). Premature failures are often due to manufacturing defects, low-quality components, installation errors, or catastrophic weather events. A higher number of failures presents in the first 4 years of

Table 2. Static material composition values for the primary constituent materials in PV modules used in previous studies

Source	Years Applicable	Module composition [%]						
		Glass	Aluminum	Silicon	Copper	Silver	Plastics	Steel
Sander et al., 2007 (Sander et al., 2007)	2003	64.4	20.3	4.1	0.37	0.14	~10.4	–
	2007	74.16	10.3	3.48	0.57	0.005	~11.3	–
Paiano et al., 2015 (Paiano, 2015)	1987–2050	74.16	10.3	3.35	0.57	0.005	11.31	–
IRENA 2016 (Weckend et al., 2016)	2010	76	8	5	1	0.1	10	–
	2030	80	7	3	1	–	~8	–
CSA Group, 2020 (CSA Group, 2020)	2020–2050	76	8	3	1	<1	10	–
Santos et al., 2018 (Santos and Alonso-García, 2018)	1990–2050	76	8	5	1	0.1	10	–
Mahmoudi et al., 2019 (Mahmoudi et al., 2019), Domínguez and Geyer, 2017 (Domínguez and Geyer, 2017), Domínguez and Geyer, 2019 (Domínguez and Geyer, 2019), Kim and Park, 2018 (Kim and Park, 2018)	1990–2080	65.4	16.5	0.791	0.731	0.0577	6.5	9.51

This table of values is compared to the dynamic composition in Figure 5.

deployment, a phenomenon known as “infant mortality.” Failure probability also increases as modules near their designed EoL. Failure is often modeled through probability distribution functions (pdfs), such as the Weibull function. Using a pdf better represents different lifetimes expected at various sites and can account for premature module failures.

The most commonly used lifetime definition, “regular loss,” which is defined in (Weckend et al., 2016), uses a Weibull pdf to approximate failures in systems expected to produce for 30 years. This Weibull pdf uses a shape parameter (5.3759), derived from Kuitche (2010), that implies a 64% loss of the fleet at the end of the 30-year warranty period. The financial terms for PV systems often dictate that only 10% of modules can “fail” at the end of the system lifetime. Modern warranties would not allow for such a high loss; thus, use of “regular-loss” parameters leads to an overestimate of system and module loss. Neither fixed module lifetime nor Weibull-controlled longevity can capture the multimodal processes and decisions that dictate when PV systems reach EoL, including variable degradation rates (Jordan et al., 2016), failures (Jordan et al., 2017), and economic decisions (Weaver, 2019; Author Anonymous, 2020a; Repower PV Systems). Using multiple pdfs can describe module or system failures, such as “infant mortality,” more accurately by using pdfs based on module quality or reliability data (Hieslmair, 2021).

To address this challenge, we propose a set of baselines, a dynamic average economic project lifetime, a dynamic average PV module degradation rate, and a dynamic Weibull pdf. The historical average economic project lifetime is drawn from Wiser et al. (2020). The PV module degradation rates for each decade since 1995 are derived from Jordan et al. (2016). Finally, the Weibull pdf is controlled by T50 and T90 values, which are used to calculate alpha and beta shape parameters. T50 is the time (in years) at which 50% of the modules have failed, and T90 is the time (in years) at which 90% of the modules have failed. For the proposed baselines, T50 and T90 values are calculated from the economic project lifetime such that only 10% of modules have failed at the economic project lifetime. This dynamic, multifaceted PV module lifetime definition enables improved time resolution of PV EoL. Furthermore, with a historical-data-based understanding of PV module lifetime, quality, and reliability, implementation of higher-priority circular pathways, such as reuse, repair, and remanufacturing, becomes more feasible. For example, repowering practices could lead to the development of a secondary use market for modules that have reached economic EoL but not degradation EoL and have not suffered failure (Weaver, 2019). In addition, known failure modes (e.g., AAA backsheets) could be tracked and sent for repair (Voronko et al., 2021).

Methodology

Here, we implement the granular, historical-data-backed, dynamic baselines presented in the previous section in conjunction with a dynamic mass-flow analysis framework. This combination allows exploration of time-resolved changing mass flows of PV deployment, EoL, and several circular pathways.

Table 3. Weibull shape parameters from the literature and the proposed new range of values

Source	Scenario name	Lifetime (years)	Weibull alpha	Weibull beta
Baseline		10–35	4.414 to 12.596	17.38 to 41.18
Kumar and Sarkar, 2013 (Kumar and Sarkar, 2013)	Set 1	–	14.41	245,155.565
	Set 2	–	9.982	243,309.680
Paiano et al., 2015 (Paiano, 2015), Domínguez and Geyer, 2017 (Domínguez and Geyer, 2017)	–	25	–	–
IRENA 2016 (Weckend et al., 2016)	Regular loss	40	5.3759	30
	Early loss	40	2.4928	30
Kim and Park, 2018 (Kim and Park, 2018)	Regular Loss-1	30	5.3759	–
	Regular Loss-2	25	5.3759	–
	Early Loss-1	30	3.5	–
	Early Loss 2	25	3.5	–
Santos et al., 2018 (Santos and Alonso-García, 2018)	Regular loss	20, 30	5.3759	–
	Early loss	20, 30	2.4928	–
Domínguez and Geyer, 2019 (Domínguez and Geyer, 2019)	Regular loss	30	5.3759	–
CSA Group, 2020 (CSA Group, 2020)	Regular loss	30	5.3759	–
	Early loss	30	2.4928	–

We first provide an overarching description of the framework and then provide definitions and values for pre-use-phase flows, followed by use phase and EoL explanations. Finally, we define circular pathways and provide baseline values.

PV ICE framework

The dynamic mass-flow analysis framework used in the PV ICE tool is presented in Figure 7. This mass-flow approach is similar to those proposed by the Ellen MacArthur Foundation (Smith and Jones) and others, but it retains the final metrics in terms of mass flow rather than providing a single CE metric. The purpose of PV ICE is to enable circularity and mass-flow analyses in a flexible platform, incorporating granular, evolving material baselines that can be expanded to consider dimensions of energy, environmental impacts, and economics. These analyses can inform decision-makers and guide investment (public and private) toward the implementation of CE for PV (Saidani et al., 2019). Therefore, our goal is to provide stakeholders and decision makers with a data-backed, mass-flow-based tool evaluating CE-focused decisions for PV in the energy transition.

The system boundaries of PV ICE start at “Virgin Extraction & Refinement” of raw materials. PV ICE uses a single efficiency factor per material to capture process efficiencies for producing the raw material (i.e., extracting and refining the material). Subsequent stages are “PV Manufacturing,” where the processed materials are made into cells and then modules; “Use Phase,” where the module is installed and degrades over time; and “End of Life,” where the module has either failed or degraded beyond use and needs to be repositioned. Arrows represent the physical mass flows, including materials embedded in the PV modules during use. The double black arrows show the linear flow of modules and their constituent materials from extraction to EoL. The single blue arrows show circular pathways. Process efficiencies are shown as circles and affect total virgin material demands and waste generated in a process step (e.g., kerf loss of silicon). Circularity decision points are indicated with hexagons and are influenced by stakeholders or policy decisions and regulations. These decision points dictate the fraction of modules or materials that follow a specific pathway (e.g., the fraction of modules recycled at EoL). The left side of the diagram, with the unshaded background, represents material properties and decisions, and the gray shading represents module properties and decisions. The delineation of module and material properties is shown in Table 4. All materials are tracked on a mass per module area, allowing conversion between module and material. This modeling approach can capture the differences between mass flows of different PV module technologies (e.g., c-Si versus CdTe) or even simulate other renewable energy generating sources.

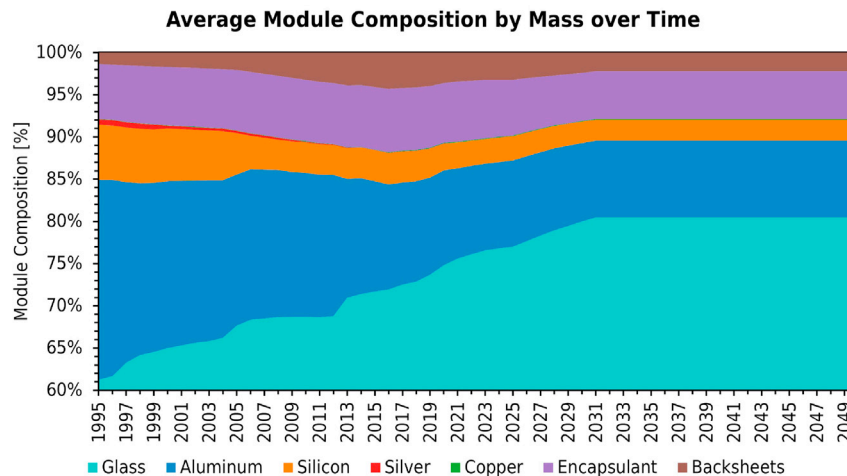


Figure 5. Annual module composition by mass percentage, as calculated from the material baselines presented here. 2030 values are assumed to be constant through 2050.

Using this framework, the PV ICE tool tracks the virgin material demands, landfilled manufacturing scrap, installed capacity (nameplate and effective), and landfilled EoL waste generated by a modeled scenario, both annually and cumulatively.

PV ICE is unique in that it does not use a fraction of module mass to derive material mass or the mass-power factor. PV ICE uses an annual average module efficiency and annual capacity deployments (currently sourced from [Murphy et al. \[2021\]](#), but broadly compatible) to calculate the module area installed each year. Then, component material masses are calculated on a per-module area basis. The “average module” for each year is defined as a module with the weighted average energy yield and material composition of modules deployed in that year. This average module and material composition is unique for each year due to PV technology evolutions, and it enables PV ICE to capture efficiency and reliability improvements, design changes in newer modules, and known material risks from specific years (e.g., AAA backsheets between 2010 and 2015 [[Oreski, 2019](#); [Owen-Bellini, 2019](#); [Kempe et al., 2021](#)]). We performed a sensitivity analysis (described in the [sensitivity analysis](#) section) to account for errors in the values we obtained or assumed. The complete descriptions of the baseline average PV technology module and material composition are described in the [PV technology evolution](#) section and are further detailed in the online documentation of the PV ICE tool ([Ovatt et al., 2021a](#)). The data can also be explored at https://openei.org/wiki/PV_ICE. Currently, the PV ICE baselines are for an average crystalline silicon (c-Si) PV module; this is because c-Si is the most widely deployed PV technology and currently lacks established CE pathways.

The following subsections expand on the uniqueness of PV ICE approach, giving further details on how each PV life cycle stage is approached in this framework.

Virgin extraction, refinement, and manufacturing

PV ICE adds to previous work on PV waste modeling by accounting for efficiencies associated with mining, refining, and manufacturing of both modules and materials ([CSA Group, 2020](#)). Neglecting these earlier supply chain and life cycle stages is problematic; it glosses over opportunities for closing manufacturing circular loops and ignores environmental justice considerations such as localized mining, refining, and manufacturing pollution—notoriously the most impactful life cycle stage of a PV module ([Yue et al., 2014](#); [Mulvaney, 2019](#); [Author Anonymous, 2019b](#)). These two omissions handicap the ability of many existing studies to examine the impacts of circular choices holistically.

To this end, we calculated virgin material efficiency for each material by multiplying mining yields (the fraction of product material in the total mass extracted) and refining yields (the product material versus the product content of slag). As an example, for silicon, the conversion of silica-quartz to metallurgical grade silicon is 80%–90%, and the refinement of metallurgical into electronic grade silicon via the Siemens process is 20%–30% ([CIFTJA, 2008](#)). These yields were multiplied together to create an upper and lower

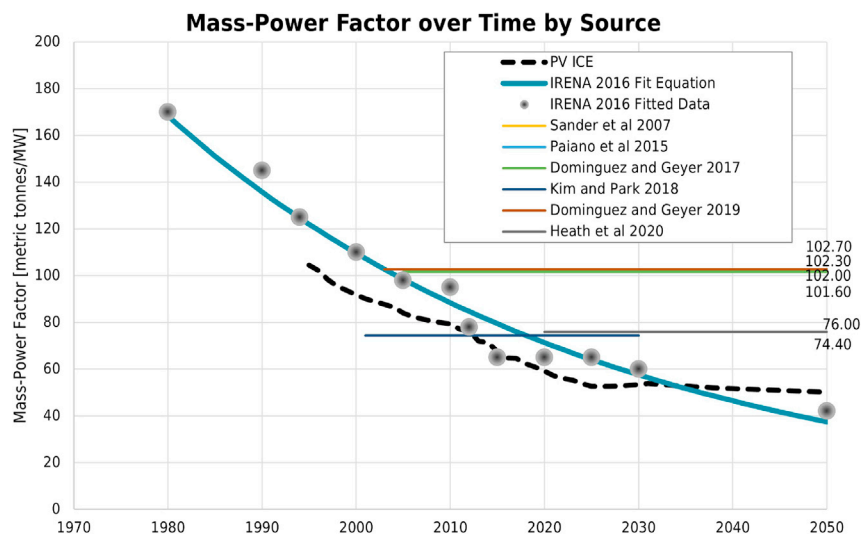


Figure 6. Comparison of mass-power factors used in waste projection literature and a dynamic mass-power factor calculated from the module and material baselines presented here. The static mass-power factors are shown as a flat line for all the years considered in the study. The proposed baseline (black) only considers c-Si technology (excluding thin films) and incorporates granular module and material technology evolutions, whereas IRENA 2016 (Weckend et al., 2016) attempts to capture technology improvement trends using a best-fit curve.

efficiency, which were then used to interpolate a linear improvement from 1995 to 2020. We recognize that this is an oversimplification of complex industrial processes; however, it should provide an order of magnitude for the value of material circularity in offsetting virgin extraction. Figure 8 displays the time-varying values used in PV ICE for glass, silicon, aluminum, copper, and silver for (1) the virgin material extraction efficiency and (2) the efficiency of the material used in PV manufacturing.

Module manufacturing efficiency describes preconsumer module waste, i.e., modules that do not pass final inspection. For modules, we assumed a 98% manufacturing yield (Willeke, 2002). The PV ICE framework implies a 100% collection efficiency of manufacturing scrap modules. There are analogous recycling pathways considered at the manufacturing and EoL stages, described later.

Use phase and EoL mechanisms

During the use phase of the PV module life cycle, modules are in the field producing power. For any region, cumulative installed capacity, historical annual installations, and forecasted annual additions are available from many different sources. However, most capacity deployment models rely on simplified module and system degradation assumptions, neglecting the effects of rated degradation, failures, and EoL module/system losses on deployed generating capacity. PV ICE uses a new method to calculate installed capacity and define lifetime. Each annually installed cohort of modules is tracked annually for degradation (% power loss/year). Degradation rates were obtained from Jordan et al. (Jordan et al., 2016). The installed capacity in a given year then represents the new installs of that year plus all the previous generations installed, minus losses from degradation and from modules that have reached EoL.

Three mechanisms for reaching EoL are considered: economic module lifetime, degradation beyond 80% of initial capacity, and failures. Module lifetimes are established based on economic project life and warranty lengths (Wilson et al., 2020). Failures for each cohort of PV modules were determined by Weibull shape parameters, using T50 and T90 values such that only 10% of the original installed capacity has “failed” at the end of the modules’ economic project lifetime. Thus, T50 and T90 improve with time, along with economic project life and warranty.

Circular pathways

All modules and system components need to be decommissioned and managed at EoL. The first step for any circular pathway is collection. If modules are not collected at EoL, PV ICE considers them landfilled. If

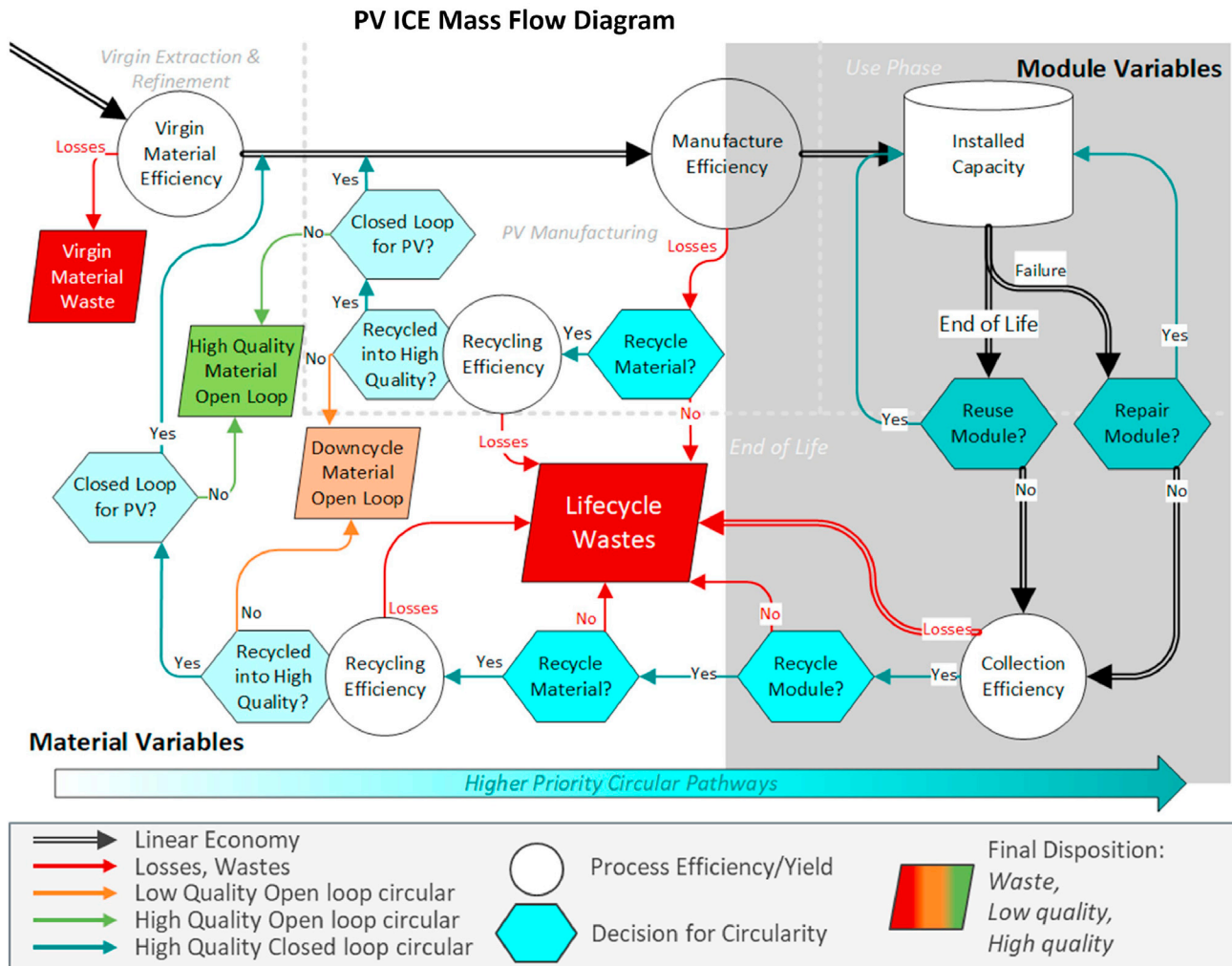


Figure 7. Mass-flow diagram showing PV life cycle stages, processes, and decisions as represented in the PV ICE tool. Arrows represent the mass flow, circles represent process efficiencies, hexagons denote decision points, and rhombuses are final dispositions. The background colors show whether the variable is controlled by the material or module baselines. Dotted lines provide a visualization of the different life cycle stages.

collected, they can undergo reuse, repair, or recycling. Reuse is the PV module’s potential to be kept in or returned to the field despite power degradation past the nominal threshold. This represents the real-world use case of PV systems being sold as part of the “merchant tail” to continue operation after a Power Purchase Agreement (PPA) ends, as well as sales of individual modules on the secondary market. Repair is the potential for a failed module to undergo a repair (e.g., replacing a junction box, taping a backsheet) and be returned to the use phase. The module continues generating power at the cohort-determined degradation rates. Few modules currently undergo repair in the field, and there is little data on the results; we currently do not differentiate between different repair types. Definitions for each of the three “Rs” found in the PV ICE framework are given in Table 5.

PV ICE models the effects of circular disposition pathways, including reuse, repair, EoL collection efficiency, and fraction of EoL modules sent to recycling. However, most silicon PV modules in the United States are landfilled at EoL rather than following a circular disposition path. The EU and some US states currently have policies requiring PV module recycling (Curtis et al., 2021a, 2021c; PV Waste & Legislation). Therefore, baseline values for EoL pathways are set to approximate current values: repair and reuse rates are 0%, 15% of EoL modules are collected for disposition, and 40% of collected modules are sent to recycling. Table 6 shows the values of the baselines for each material in each circular loop throughout the life cycle. Where possible, time-dependent values were obtained for each material (e.g., improvements in sawing

Table 4. Module and material properties, as used in the PV ICE tool

Module-level properties	Material-level parameters
<ul style="list-style-type: none"> PV capacity additions (new installations in DC power) Module lifetime & reliability (project lifetime, T50 & T90, power degradation) Module manufacturing efficiency/yield Module efficiency Fraction of modules entering EoL and CE pathways (reuse, repair, collection, landfilling, recycling) 	<ul style="list-style-type: none"> Virgin material efficiency (extraction, refinement) Material manufacturing efficiency (screen printing, trimming, others) Manufacturing scrap recycling (yield and quality) EoL process recycling fractions and efficiencies (collection, landfilling, recycling, yield and quality)

silicon ingots into wafers). Where time-dependent values were unavailable, a literature source was used for 1995 through 2050, and failing a literature source, reasonable assumptions were made.

The following material properties determine the mass flow through the recycling loop steps, both in manufacturing and EoL stages:

1. Collection efficiency: at EoL, this value determines the fraction of modules collected for disposition. Modules not collected are landfilled and cannot undergo circular paths. The materials and modules lost in manufacturing are assumed to be 100% collected.
2. Module recycling fraction: this value refers to scrap modules from manufacturing and collected EoL modules that are disposed to undergo recycling. Anything not dispositioned for recycling is assumed to be landfilled.
3. Material recycling fraction: this variable dictates whether a specific material in an EoL module is a recycling target (assuming that the module is being recycled). For example, a module might be recycled for glass 100% of the time, but only 20% of the time for silver and 0% for encapsulants. Similarly, in manufacturing, silicon and silver scrap might be targeted for recycling, whereas plastic trimmings might not. The inverse of this value is landfilled.
4. Recycling efficiency: if a material undergoes recycling (manufacturing or EoL), this variable dictates the recycling process's yield. This recycling yield or process efficiency can be different between manufacturing scrap and EoL waste, as postconsumer waste is potentially more contaminated. The inverse of this value is landfilled.
5. High-quality recycled material fraction: this value dictates the amount of recycled material that emerges from the recycling process at high quality (e.g., metals). The inverse of this value is assumed to be other-quality material that is still usable in other industries or "downcycle material" (e.g., glass as fillers in concrete or fiberglass).
6. High-quality recycled material reused for PV manufacturing fraction: this variable closes the loop on recycling, offsetting virgin material demand (Figure 7). The inverse of this fraction is assumed to be high-quality open-loop recycled material.

The variables in these recycling loops are related such that values of earlier variables influence the impact of improvement in later variables. For example, radically improving a material's recycling yield will not matter if the specific material is not a recycling target. Values used in PV ICE for the aforementioned efficiencies and fractions can be found in Table 6. The circular options are all decision points that are affected by economics and regulatory requirements. PV ICE can take the outputs of various decision models and quantify the effects of different waste-management intervention scenarios, such as those from Walzberg et al. (Walzberg et al., 2020; Walzberg et al., 2021), as explored in Hegedus et al. (Hegedus et al., 2021).

RESULTS

Comparison of life cycle mass flows: PV ICE and Weibull-only methodologies

PV ICE can use any capacity deployment model or historical data as a basis for the mass-flow calculations. In this study, PV ICE was used with the US PV growth projections from the *Electrification Futures Study* (Murphy et al.,

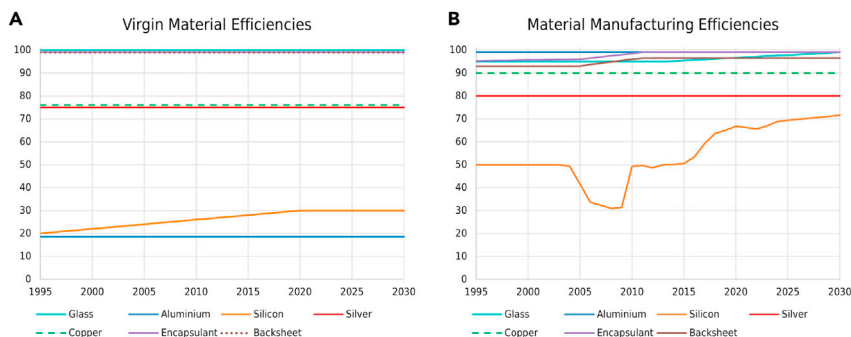


Figure 8. Virgin material efficiencies and material manufacturing efficiencies

Material properties of (A) virgin material extraction efficiency and (B) material use efficiency during PV manufacturing. 2030 values are held constant through 2050 for a conservative estimate.

2021). Figure 9 shows the annual combined distributed and utility-scale PV installations predicted for a reference scenario (ref)—which considers the lowest electrification rate in the United States and a modest adoption of cost-competitive electric end-use technologies—and for a high electrification scenario (h.e.)—which reflects transformational electrification in multiple demand sectors. The projections begin in 2018 and predict installations through 2050 (this is why we only include waste flows up to 2050 in this study). Figure 9 displays the cumulative capacity (shaded area) resulting from the annual installations (bars). The annual deployment data jumps are due to the Regional Energy Deployment System (ReEDS) modeling process, which uses a “system-wide, least-cost” analysis method and reports annual values biannually (Brown et al., 2020). These irregular installation rates are comparable with those found in other modeling projections. We acknowledge the improbability of such widely varying annual deployments but have chosen to leverage the *Electrification Futures Study* because it provides open-source data for reproducibility (Murphy et al., 2021).

By leveraging these installation projections and the module and material baselines discussed in this paper, we used PV ICE to predict annual and cumulative material demands, manufacturing scrap, EoL materials, and installed capacity and materials. Installation predictions from the *Electrification Futures Study* were scaled by the average market share of silicon technologies (85%), rather than assuming all PV installations were silicon based, as PV ICE baselines currently only include c-Si technologies. In addition, the PV ICE tool was configured to test several different lifetime and failure assumptions, including the literature “regular-loss” and “early loss” reliability approaches (Weckend et al., 2016), in order to evaluate the increased installation projections from *Electrification Futures*. To reproduce regular loss and early loss,

- Lifetime values (beta values) were set to 30 years and project lifetime was set to 40 years, with the Weibull alpha parameter set to 2.49 (early loss) and 5.3759 (regular loss).
- Virgin material efficiencies and manufacturing efficiencies for modules and materials were set to 100% (i.e., no losses).
- All circular pathways (reuse, repair, recycle) were set to 0%.
- Installed capacity was allowed to vary, i.e., a targeted capacity was not actively maintained by “back-filling” failed/EoL modules.

In comparison, PV ICE baselines include the following assumptions/specifications:

- Economic project lifetime dynamically increases from 10 years in 1995 to 35 years in 2020 and is conservatively held constant through 2050. T50 and T90 values begin at 16 and 21 years in 1995, respectively, and increase to 40 and 44 years by 2020 (see [PV reliability and lifetime](#) and [Use phase and EoL mechanisms](#) sections).
- Virgin material efficiency and manufacturing efficiency were set to their literature-determined baseline values, as shown in [Figure 8](#) and [Table 6](#).
- Circular pathways were set to literature-determined baseline values, as shown in [Table 6](#).

Table 5. Circular “R” options, as captured and defined by the PV ICE tool.

Circular option	Definition
Recycle at manufacturing stage	Pre-consumer, industrial scrap recycling. Material enters this recycling loop due to manufacturing inefficiencies.
Repair	A module has failed, and an onsite fix to the module defect or problem is possible. If the module is not repaired, it is assumed to be at EoL. If the module is repaired, it continues generating power at the cohort-determined degradation rates.
Merchant tail	System owners agree to produce power for a set period of time through a PPA or other contractual mechanism. After the PPA expires, the owner can choose to keep the system operating beyond the module warranty or project finance period if it is still economically viable. System owners continue selling power from the system or sell the system.
Reuse	The module is at EoL (through degradation or end of the project) and is demounted and removed from the field. Offsite, the module is assessed/tested/recertified and found to be in acceptable working condition to be sold on a secondary market (perhaps as a spare for a similar system) and is subsequently installed at a new site.
Recycle at EoL	When a module is at EoL and is not reused, repaired, refurbished, or sent directly to a landfill, it can be recycled into its constituent materials. High-quality recycled materials can replace virgin materials in the manufacturing of new modules or other products (e.g., flat glass to container glass). Low-quality recycled materials can be downcycled into other products with less stringent material quality requirements.

- Installed capacity was allowed to vary, i.e., a targeted capacity was not actively maintained by “back-filling” failed/EoL modules.

In PV ICE, EoL is determined by three modes: economic project lifetime, degradation beyond 80% nameplate, and Weibull-based failures. The Weibull parameters used in the PV ICE tool are calculated based on the expected number of functioning modules at the end of the project lifetime. In contrast, the regular-loss and early loss reliability approaches (Weckend et al., 2016; CSA Group, 2020) utilize the same Weibull function for both failure and wear-out; and both trash 64% of the cohort by their 30th year in the field. Comparisons of these methods and prior literature values are shown in Figures 10–12 and Table 7. Figure 10 shows the annual virgin material demands (a), EoL material generated (b), and manufacturing scrap (c) for the two *Electrification Futures* deployment scenarios (ref and h.e.) and the PV ICE and IRENA loss models. Each yearly graph is paired with a cumulative bar chart for each scenario showing the breakdown by material composition from 2020 to 2050, and all masses are expressed in million tons.

Figure 10A shows that the virgin material demands are similar (as expected) for both models, with PV ICE requiring slightly more due to accounting for manufacturing inefficiencies. The comparison in Figure 10B demonstrates that the regular-loss and early loss reliability approaches estimate shorter PV module lifetimes, resulting in five times the cumulative EoL material by 2050 in the early loss approach compared with PV ICE. Furthermore, although early loss and regular-loss reliability approaches predict large quantities of EoL material prior to 2050, PV ICE predicts that the majority of EoL materials will leave the field after 2050. In addition, previously published studies do not account for manufacturing scrap material. In contrast, PV ICE estimates a cumulative 2–3.6 million metric tons of manufacturing waste by 2050, as shown in Figure 10C. The PV ICE baselines also account for recycling of manufacturing scrap. The updated reliability and lifetime data used for the PV ICE reliability approach indicate that most of the EoL PV material mass will come later than previously predicted. For near-term deployment, the largest opportunity for off-setting material extraction and closing loops can be derived from manufacturing scrap. As seen in Figure 10C, the temporal alignment of manufacturing scrap with PV manufacturing demand appears superior to EoL material. Furthermore, manufacturing scrap typically has a high potential for recycling due to presumed lower contamination and more reliable sourcing (time and geography).

A comparison of installed capacity in the United States in 2030 and 2050 between PV ICE and regular-loss and early loss reliability approaches is shown in Figure 11. For PV ICE, installed capacity is equal to cumulative installations at their degraded power production, minus retired modules due to failures or EoL. It is

Table 6. Material circular flow values for manufacturing and EoL.

	Glass	Silicon	Aluminum	Copper	Silver
Virgin mining and refining efficiency	99.9%	20%–30% (CIFTJA, 2008)	18.6% (Ayres, 1997)	76% (Ayres et al., 2003)	75% (Butterman and Hilliard, 2005; Lanzano et al., 2006; Goonan, 2014)
Manufacturing					
Fraction of Manufacturing Scrap Modules Collected for Recycling: 100%					
Efficiency of material use in PV manufacturing (MFG)	95%	30%–71% (Willeke, 2002; Fischer et al., 2011, 2020; Berger et al., 2012; Froitzheim et al., 2013; Forstner et al., 2014; Metz et al., 2015; Cellere et al., 2016, 2017; Pujari et al., 2018; Fischer, 2019)	99%	90%	80% (Alexander et al., 2019)
Fraction of MFG scrap recycled	80%	100%	100%	98% (Hernandez et al., 2017)	95%
Yield of MFG scrap recycling	50%	20%	60% (Plunkert, 2006)	98% (Hernandez et al., 2017)	97% (Hilliard, 2000)
Fraction of recycled material scrap that is high quality	20%	0%	100%	100%	100%
Fraction of high-quality recycled material scrap reused for manufacturing	10%	100%	100%	27%–31% (Author Anonymous, 2017, 2019a)	15%–23% (Alexander et al., 2019; Author Anonymous, 2020c)
EoL					
Fraction of Modules Repaired: 0%					
Fraction of Modules Merchant Tail: 0%					
Fraction of Modules Reused: 0%					
Fraction of Modules Collected for EoL Disposition: 15%					
Fraction of Modules sent for Recycling: 40%					
Fraction of material recycled	90%	20%	100%	0% (Ardente et al., 2019)	0% (Helweg, 2015; Ardente et al., 2019)
Yield of EoL scrap recycling	40%	80%	42% (Plunkert, 2006)	95% (Hernandez et al., 2017)	97% (Hilliard, 2000)
Fraction of recycled material that is high quality	15%	0%	100%	100%	80% (Author Anonymous, 2020c)
Fraction of high-quality recycled material that is reused for manufacturing	8%	0%	100%	27%–31% (Author Anonymous, 2017, 2019a)	15%–23% (Alexander et al., 2019; Author Anonymous, 2020c)

Where sources are not noted, reasonable estimates were made. Ranges represent the upper and lower bounds of a property that varies with time (1995–2030). 2030 values are held constant through 2050 for a conservative estimate.

unclear if literature values (Weckend et al., 2016; CSA Group, 2020) account for module decommissioning in their cumulative installed PV capacity. Figure 11 compares the resulting expected capacity for single Weibull regular-loss and early loss models with a 30-year lifetime to the PV ICE baseline case. Separate Weibulls are used, and EoL is defined at T90 rather than a fixed 30 years. PV ICE differentiates between expected EoL wear-out and premature failure using different Weibull functions for each. Figure 11 shows that the PV ICE reliability approach predicts 19% more capacity than early loss and 6% more capacity compared with regular-loss IRENA models by 2050 for the h.e. scenario (Kuitche, 2010; Weckend et al., 2016).

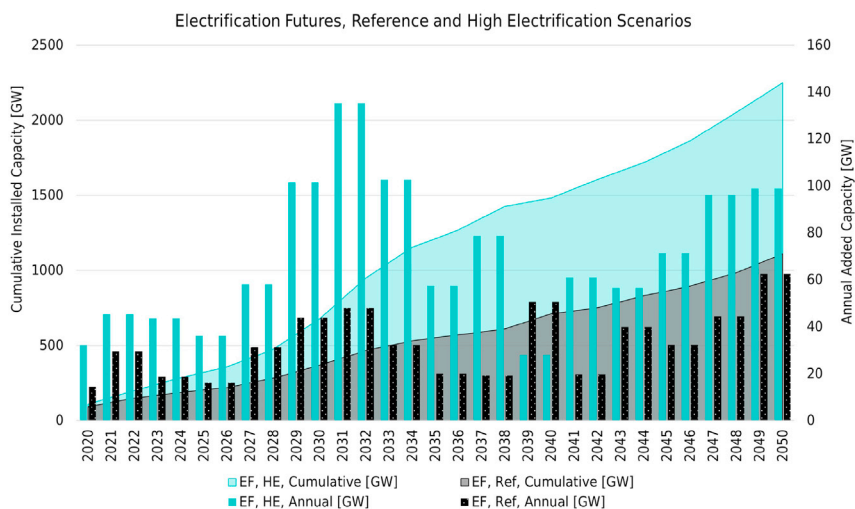


Figure 9. Distributed and utility-scale PV annual installations and cumulative installed capacity in the United States through 2050 for the reference and high electrification scenarios as predicted by Murphy et al. (2021). The annual installations (bars) are modified by the market share of silicon technology and the DC/AC ratios, then used as input to the PV ICE tool. The shaded area shows the cumulative capacity resulting from these annual installations. The annual deployment data jumps are due to the ReEDS modeling process, and these jumps are found in other modeling projections.

PV ICE results can also be compared with literature results on an installed material basis (i.e., mass in the field), as seen in Table 7. This comparison validates the granular material-by-material baselines against the static module-mass composition. The Canadian Standards Association (CSA) Group (CSA Group, 2020) estimated that 437 GW will be installed in North America in 2030, falling between the two scenarios drawn from Murphy et al. (2021). The total module mass of CSA Group’s estimate is 27,200,000 metric tons of installed PV mass, compared with the 20,400,000–37,300,000 metric tons predicted by PV ICE. These estimates are highly comparable. PV ICE mass may be slightly lower on a per-GW basis due to differing predictions of future technology improvements, the underlying granular material mass approach in PV ICE, and the exclusion of thin-film technologies. The CSA prediction includes all types of PV module technologies; in contrast, the material baselines developed for the PV ICE tool only include mono-Si and mc-Si (on the basis that CdTe waste is already being addressed successfully by First Solar and that other technologies have a negligible market share). This comparison demonstrates good agreement in module composition assumptions, validating the granular PV ICE approach.

Finally, Figure 12 presents a comparison of cumulative EoL material in the PV ICE scenarios and the literature. The three different reliability approaches used in Figures 10 and 11—“regular loss,” “early loss,” and “PV ICE loss”—are also used in this comparison. Manufacturing scrap is excluded from Weckend et al. (2016) by default and from CSA Group (2020) explicitly on the basis that this mass would enter the waste stream in areas other than North America. Although PV ICE calculates manufacturing scrap each year, these values have been excluded to enable a direct comparison to the published literature. PV ICE predicts similar EoL waste to IRENA’s regular loss until 2030, when the improving module lifetimes reduce the waste stream (shifting it after 2050), despite the higher installations considered in this projection. The improved PV lifetimes and reliability projections captured in PV ICE reveal a larger installed PV capacity and a longer delay before these PV modules reach EoL, granting time to plan and implement circular pathways. The impact of implementing various circular pathways is discussed in the following section.

Sensitivity analysis

We conducted a sensitivity analysis of all module and material parameters in the PV ICE framework to identify the impact of manufacturing and module efficiencies on virgin material demands, cumulative waste, and remaining installed capacity and to demonstrate the capabilities of PV ICE. This analysis also identifies parameters with sensitivity to errors in module and material baseline data or assumptions. Our sensitivity analysis was accomplished by increasing and decreasing each parameter by 10 percentage points

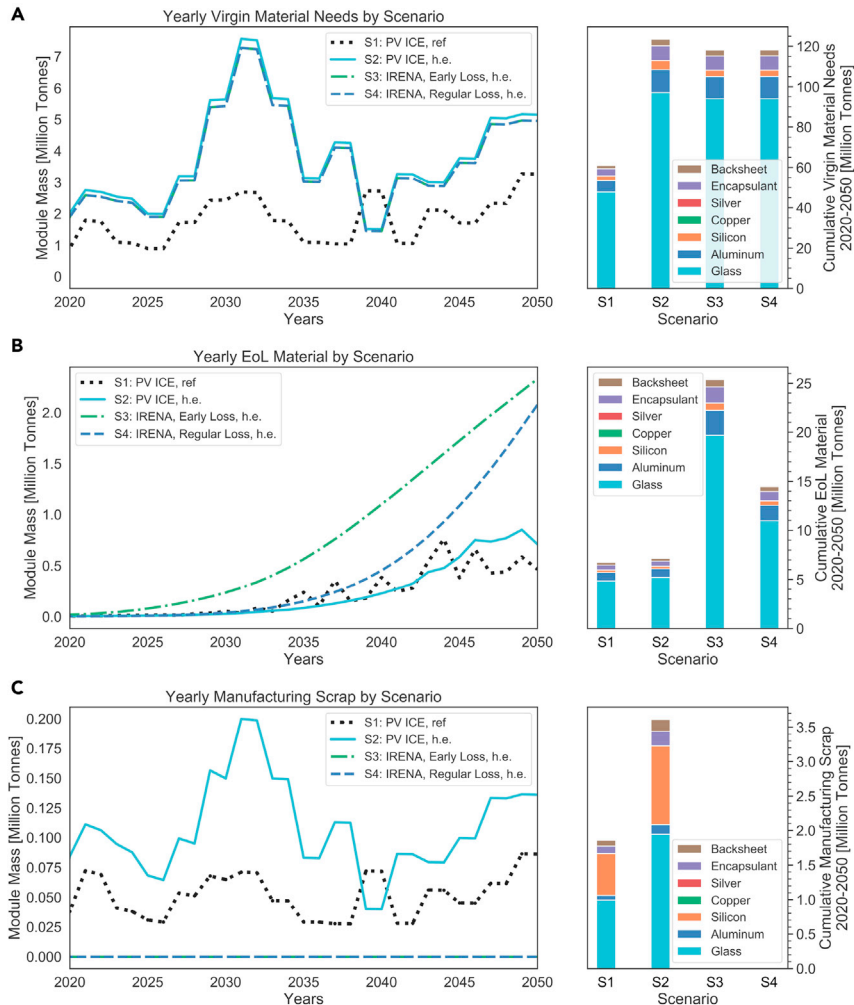


Figure 10. Yearly and cumulative material needs and lifecycle wastes by scenario

A series of three paired graphs, showing (A) the annual and cumulative virgin material needs, (B) the annual and cumulative EoL materials, and (C) the annual and cumulative manufacturing scrap, compared across four scenarios. The scenarios compared are the PV ICE reliability approach and baselines using the Electrification Futures ref and h.e. electrification installation projections and the IRENA early loss and regular-loss reliability approaches using the Electrification Futures h.e. installation projection. The comparison demonstrates that PV ICE’s lifetime methods predict less EoL waste while forecasting a larger quantity of manufacturing scrap.

(absolute, unless otherwise noted). First, each parameter was varied individually; if increasing or decreasing the baseline value would have resulted in >100% or <0%, then 100% or 0% was used. Several of the manufacturing efficiency parameters (e.g., module manufacturing yield) were already >95% and therefore were increased by <10% absolute in our analysis. Next, sets of parameters representing circular loops were varied together to reduce compounding the effect of dependent variables (e.g., if module collection is small, then module recycling yield can only have a small system effect). We recorded the percent change in raw material demands, life cycle waste, and installed capacity in 2050 as our primary indicators, given that these are three of the most critical aspects of implementing a CE for PV and are interdependent. For this analysis, only the glass material baseline was considered, but the effects should be similar for other materials. The most impactful parameters (>1% change) and their effects on material demands and life cycle waste are shown in Figures 13 and 14, respectively. In these figures, a decrease (larger bars to the left) in material demands and life cycle waste is beneficial.

The material demands are only sensitive to a few of the PV ICE parameters (Figure 13). Additional installed capacity and mass of material per module area display a 1:1 relationship, as expected; 10% more module

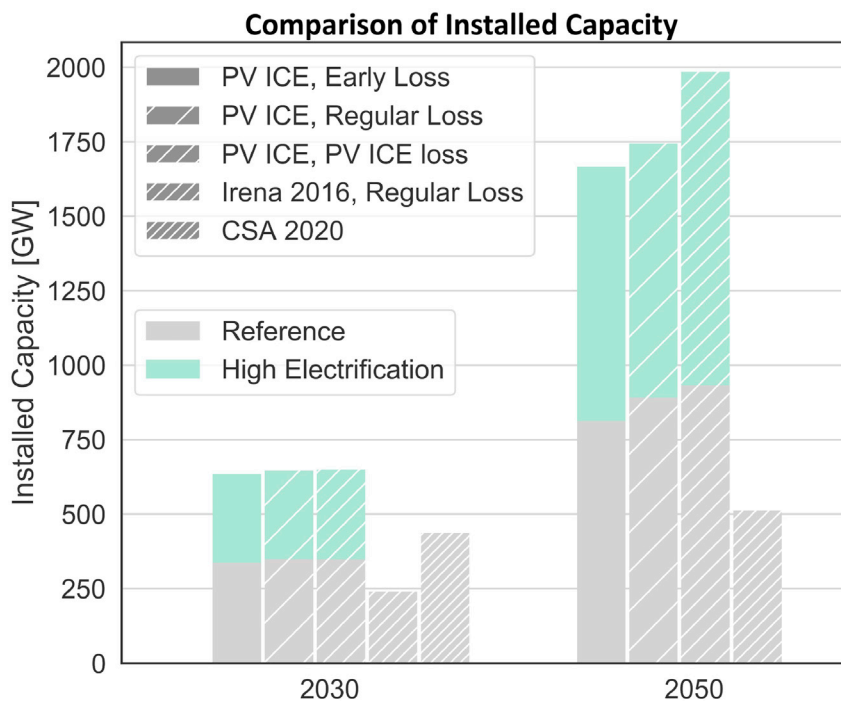


Figure 11. Comparison of predicted installed capacity in 2030 and 2050 across the three PV IC simulations and against literature values (Weckend et al., 2016; CSA Group, 2020). The solid bars represent the reference scenario, whereas the hashed bars represent the high electrification scenario. This comparison demonstrates that PV ICE’s lifetime and reliability data predict significantly more active capacity in the field in 2050 than prior methodologies. This increase in active capacity is also present to a lesser extent in 2030.

installations will require 10% more material. Similarly, increased module efficiency (i.e., more power generation per area) reduces the number of modules required to achieve a certain nameplate value and thus also displays a nearly 1:1 relationship. The other two parameters that impact the material demands concern mass flows during PV manufacturing. Module manufacturing efficiency, or the yield of modules during manufacturing, is typically above 95% (and therefore cannot be increased by a total of 10 percentage points). The <5% potential for improvement only decreases material demands by ~1%. However, if module manufacturing yields were to fall, it would result in a >10% increase in material demand. Similarly, material use efficiency in PV manufacturing decreases material demands slightly but would have a >10% impact if the process were to become more wasteful. These results suggest that maintaining or improving module efficiency and manufacturing yields have the most impact on reducing material demands overall. Market forces already incentivize improvements in these areas.

Figure 14 shows the impacts of our modeling parameters on total life cycle waste, and many of these effects are nonlinear. New installed capacity, mass per module area, and module efficiency all have a ~1:1 impact on life cycle waste, the same as for material demands. Improvements to the manufacturing scrap recycling loop and EoL recycling loop have a less than 1:1 effect on life cycle waste; a 10% increase or decrease in these parameters results in a less than 10% effect. Three parameters/sets of parameters have an outsized impact: module manufacturing efficiency (or yield), module lifetime and reliability, and a combination of EoL circularity and module lifetime and reliability. A 10% change in module manufacturing efficiency/yield can cause a 15% decrease or 86% increase in waste. Module manufacturing is already very efficient; therefore, only a small improvement (decrease in waste) can be achieved. However, a full 10% decrease in yield is possible and results in the waste of modules worth of materials. These results compliment the effects of module manufacturing efficiency on virgin material demand (Figure 13) and emphasize the importance of manufacturing yields and material efficiency.

Increasing module lifetime through improved reliability has the biggest effect on life cycle waste. A 10% improvement in module lifetime and reliability results in a 53% decrease in life cycle waste. Alone, EoL

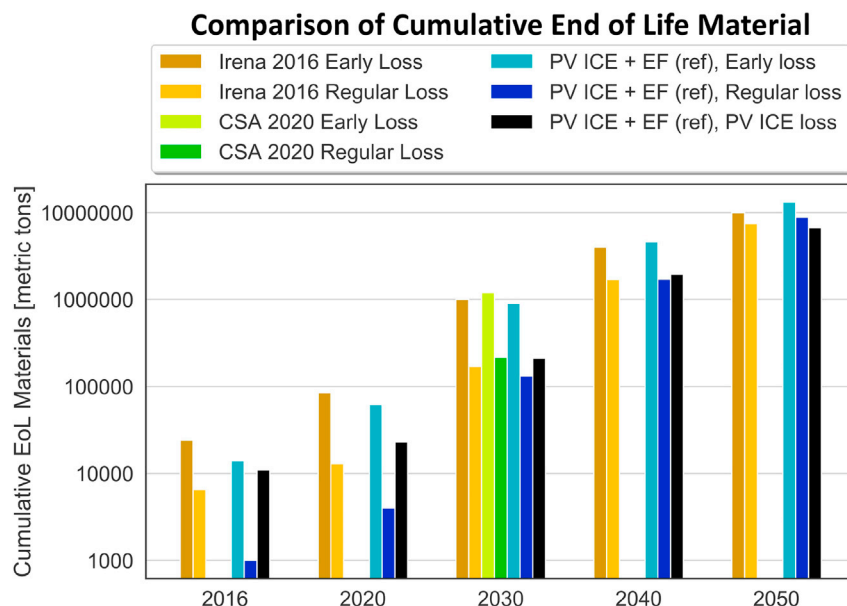


Figure 12. Comparison of cumulative EoL material, each decade through 2050, for the scenarios modeled in PV ICE. Note the logarithmic scale on the y axis. Literature results have been included here as a comparison, demonstrating that prior EoL material predictions have more material reaching EoL earlier than PV ICE.

circular pathways, which include repair, reuse, and recycling, result in a 7% decrease in life cycle waste, comprised of a 3% contribution from repair and a 2% contribution from reuse and the rest from recycling. However, when improvements in EoL circularity are combined with improved module lifetime and reliability (i.e., improvements in all CE-related parameters), the largest reduction of 55% life cycle waste is achieved. These results are consistent with other waste projections that explore module lifetime (Kim and Park, 2018) and with circularity indicators (Figge et al., 2018).

The cumulative installed capacity in 2050 is also sensitive to reliability and module lifetime—shorter lifetimes lead to fewer active field modules. As expected, installed capacity in 2050 is sensitive to additional annual installations on a 1:1 basis. Increasing reliability by 10 percentage points increases the installed capacity in 2050 by 4%, whereas decreasing reliability by 10% results in a 6% lower capacity in 2050. Furthermore, when we controlled for meeting a target capacity in the field (as opposed to controlling annual installations), we obtained a 4% decrease in virgin material demands and 90% decrease in life cycle wastes from improving reliability by 10% and a 7% increase in virgin needs and a 54% increase in life cycle wastes from decreasing reliability by 10%. Increased lifetimes and reliability yield the benefits of increased installed capacity and power generation while reducing material demands and life cycle waste.

CONCLUSIONS

This paper presents the open-source, Python-based, dynamic mass-flow PV ICE framework and proposes evolving module technology and material composition baselines to explore PV in the circular economy. PV ICE accounts for mining and manufacturing waste in addition to EoL waste and incorporates circular pathways beyond recycling (including reuse, repair, and open-loop recycling). It leverages a combination of project lifetimes, degradation rates, and Weibull functions to characterize module lifetime and reliability. The impacts of circular choices are explored by tracking virgin material demands, life cycle waste, and installed capacity.

We compare the PV ICE tool with existing waste projection methods, leveraging the *Electrification Futures* deployment scenarios through 2050 (Murphy et al., 2021). PV ICE predicts 2–3.5 times lower cumulative EoL waste by 2050 than the established early loss and regular-loss reliability approaches, indicating that the improved lifetime and reliability of modern modules (Jordan et al., 2016; Wiser et al., 2020) shifts most EoL PV to post-2050. In the coming decades, manufacturing scrap associated with TW-scale PV deployment presents a significant opportunity for circular pathways, economic savings, and waste minimization.

Table 7. Comparison of 2030 installed PV mass in metric tonnes, with material breakdown, between CSA Group’s (CSA Group, 2020) 2030 material demands projection and PV ICE’s baseline projections and approach, demonstrating reasonable agreement

Material	Metric tonnes installed in the field in 2030		
	CSA Group (437 GW) (CSA Group, 2020)	PV ICE	
		Ref. Scenario (348 GW)	High electrification (650 GW)
Module	27,200,000	20,400,000	37,300,000
Glass	20,600,000	15,600,000	28,800,000
Polymers			
Encapsulants	2,800,000	1,320,000	2,360,000
Backsheets		639,000	1,120,000
Aluminum	2,100,000	2,120,000	3,770,000
Copper ^a	239,000	14,000	25,000
Silicon	1,270,000	661,000	1,160,000
Silver	11,000	6,000	10,000
Other	170,000	–	–

PV ICE baselines currently do not include polymers or “other.”

^aOther material compositions include copper external to the module, such as junction box and cabling; currently, the baseline used in PV ICE only includes the busbar and cell stringing internal to the module.

We also conducted a sensitivity analysis of the parameters in the PV ICE framework. We found that module manufacturing yields had the most potential to reduce virgin material demands. In contrast, module life-time and reliability had the most significant impact on life cycle waste. Moreover, increasing module life-time and reliability increased the installed capacity in 2050 while reducing material demands and waste.

The proposed framework can evaluate tradeoffs and opportunities in circular decision pathways for energy materials in a circular economy. Future work will expand component baselines and implement new parameters and metrics, including energy flows, environmental impacts, economic values, and geospatial resolution. Understanding mass circularity and installed capacity effects is necessary but insufficient to provide a holistic analysis for sustainable deployment. Therefore, further research is needed to understand the full energetic, economic, and human impact of terawatt-scale solar PV deployment.

Limitations of study

There are two main sources of potential error in these analyses: historical data and projections. The historical data for module and materials were gathered from numerous publicly available sources (found in the [References for PV ICE Baselines](#)), and sources not used directly in creation of the PV ICE baselines were consulted for accuracy. However, the varying data sources derive their numbers from different points in

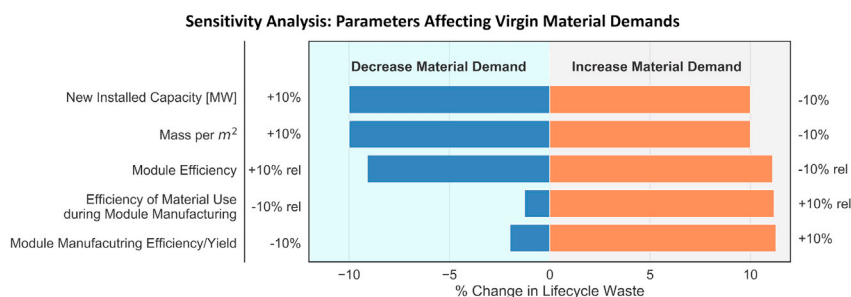


Figure 13. The percent improvement—i.e., decrease in virgin material needs—of the most impactful parameters affecting virgin material demand in the PV ICE tool. A decrease in material demands (larger bars to the left) is considered beneficial. The 10% columns indicate in what direction and magnitude the parameter, listed on the left, was varied (with the caveat of maintaining 0% and 100% boundaries).

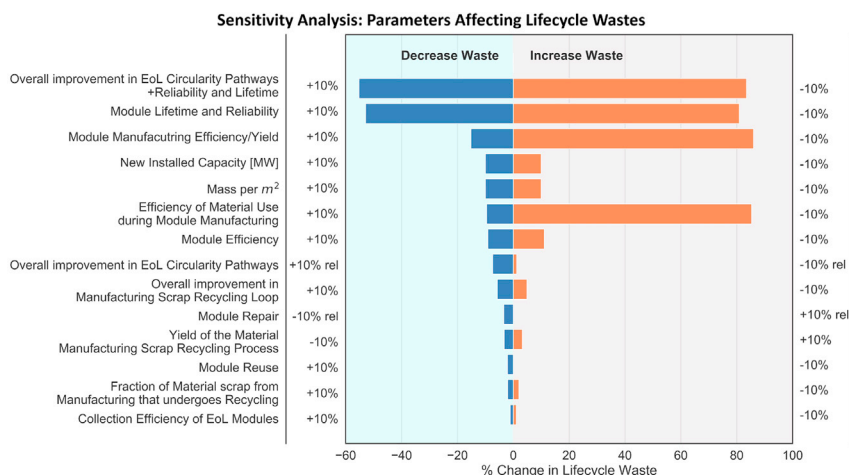


Figure 14. The percent improvement (i.e., decrease) in life cycle waste from varying the most impactful parameters affecting waste in the PV ICE tool. A decrease (larger bars to the left) in life cycle waste is considered beneficial. The 10% columns indicate in what direction and magnitude the parameter, listed at the left, was varied.

the PV supply chain (e.g., manufacturing surveys versus utility data), which results in differing values (e.g., market share of c-Si technology). Forecasting the future inevitably entails uncertainty. Where possible, future predictions were drawn from broadly accepted literature values (such as the ITRPVs). To address inaccuracies in both historical data and uncertainties in future projections, we used a combination of multiple scenarios (high and low deployment futures) and a sensitivity analysis. Furthermore, all assumptions made in creation of the average module and materials are documented in Jupyter Journals on Github (Ovatt et al., 2021a).

The baselines used in this paper only incorporate c-Si materials, excluding the junction box, balance of system components, processing materials (e.g., solvents, packaging), and other PV technologies.

STAR★METHOD

Detailed methods are provided in the online version of this paper and include the following:

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AUTHOR CONTRIBUTIONS

Validation, Formal Analysis, Investigation, Writing (Original Draft), Writing (Review & Editing), H.M., and S.O.; Data Curation, Resources, H.M.; Conceptualization, Methodology, Software, S.O.; Supervision, Funding Acquisition, Writing (Review & Editing), T.B. and S.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. While citing references scientifically relevant for this work, we also actively worked to promote gender balance in our reference list.

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STAR★METHOD

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
PV in the circular economy software, version 2.1	This paper	https://doi.org/10.5281/zenodo.5659151 (Ovaitt et al, 2021b)
Other		
Resource website for the PV ICE publication	This paper	https://github.com/NREL/PV_ICE , 10.5281/zenodo.4324010 (Ovaitt et al., 2021a)
Visualization of PV ICE data	This paper	https://openei.org/wiki/PV_ICE (Hegedus et al., 2021)
References lists	This paper, Zotero	https://www.zotero.org/groups/2476193/circulareconomyforpv

RESOURCE AVAILABILITY

Lead contact

Additional request for information should be directed to the lead contact Silvana Ovaitt (Silvana.Ayala@nrel.gov)

Material availability

Not Applicable.

Data and code availability

- The PV in Circular Economy (PV ICE) module and material baselines are publicly available at https://github.com/NREL/PV_ICE (Ovaitt et al., 2021a).
- PV ICE is available as an open-source installable Python package. The baselines and code used in this correspond to version 2.1, <https://doi.org/10.5281/zenodo.5659151> (Ovaitt et al, 2021b).
- For any additional questions or information please contact the lead contact, Silvana Ovaitt (Silvana.Ayala@nrel.gov)

QUANTIFICATION AND STATISTICAL ANALYSIS

Sensitivity analysis for the data and procedure included in the paper.

ADDITIONAL RESOURCES

This study's data inputs and results can be explored on https://openei.org/wiki/PV_ICE (Hegedus et al., 2021).

METHOD DETAILS

- Requests for further information about the tool can be directed to Silvana Ovaitt (Silvana.Ayala@nrel.gov).
- Requests for further information about the baseline data can be directed to Heather Mirletz (heather.mirletz@nrel.gov).