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Are Technological Developments Improving the Environmental Sustainability of Photovoltaic Electricity?

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Innovation in photovoltaics (PV) is mostly driven by the cost per kilowatt ratio, making it easy to overlook environmental impacts of technological enhancements during early research and development stages. As PV technology developers introduce novel materials and manufacturing methods, the well-studied environmental profile of conventional silicon-based PV may change considerably. Herein, existing trends and hotspots across different types of emerging PV technologies are investigated through a systematic review and meta-analysis of life-cycle assessments (LCAs). To incorporate as many data points as possible, a comprehensive harmonization procedure is applied, producing over 600 impact data points for organic, perovskite (PK), dye-sensitized, tandem, silicon, and other thin-film cells. How the panel and balance of system components affect environmental footprints in comparable installations is also investigated and discussed. Despite the large uncertainties and variabilities in the underlying LCA data and models, the harmonized results show clear positive trends across the sector. Seven potential hotspots are identified for specific PV technologies and impact categories. The analysis offers a high-level guidance for technology developers to avoid introducing undesired environmental trade-offs as they advance to make PV more competitive in the energy markets.

1. Introduction

Since the introduction of the first solar cell in the early 1950s, the market share of photovoltaic (PV) electricity has expanded exponentially, and it is now the fastest growing source of renewable energy.[1] PV was quickly embraced as a clean, albeit expensive, source of energy, yet today it can compete with conventional fossil fuel-based sources purely on economic grounds.[2] In an effort to drive this advantage even further, many technological enhancements are being pursued to either reduce manufacturing costs or increase the PV cells' conversion efficiencies.[3] However, as the focus narrows on cost and conversion efficiency, awareness has risen to place equal importance on the potential environmental trade-offs that technological innovations in PV may introduce.

Improving efficiency and lowering costs of PV cells present technology developers with many technical barriers. Developers have often addressed these barriers by incorporating new materials and modifying cell architectures, spawning numerous alternative cell designs. Technological enhancements aim to increase the light-absorption capacity of the cells, increase conductivity, or replace existing materials of the cell for cheaper ones that fulfill the same function. For example, several thin-film technologies completely replaced silicon—a nontoxic and highly abundant material—while aiming for cost reductions. Changes in manufacturing methods may also alter the environmental profile of the PV industry, as they can require more complex equipment and energy-demanding processes. The technological enhancement and diversification is going at a fast pace, making it difficult for relevant stakeholders to keep track of and manage the long-term environmental impacts of successful PV innovations that may disseminate very quickly.

The earlier the stage of development of the technology, the harder it is to produce a realistic assessment of the environmental impacts once it is implemented at commercial scale.[4]

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But an early assessment is all the more important, given the fact that design changes are easier to make during earlier R&D stages.[5] Stamford and Azapagic made a first step in this direction by assessing the environmental impacts of recent technological improvements of silicon-based PV.[6] However, this was still a retrospective assessment of technological improvements that had already penetrated the market. It was also limited to the currently dominating silicon-based PV systems and did not investigate the technologies that are competing to replace them. Chatzisideris and Laurent[7] investigated more recent technologies, yet their analysis was based on the limited quantitative data prior to 2015 and numerous studies have been published since then.

In this study, we adopt a more prospective and comprehensive approach by assessing the emerging PV technologies that may dominate in the next 10 or more years. Our aim is to discern whether the PV industry is moving forward in terms of environmental sustainability as it develops toward lower costs and/or higher efficiencies. For this, we conduct a systematic review and harmonization of life-cycle assessment (LCA) studies of current state-of-the-art and emerging PV. We then apply a novel method to conduct a statistical meta-analysis on the harmonized data. We address five specific questions: 1) what—if any—are the observable trends in the environmental impacts of each type of PV technology; 2) what the variability of impact scores is within and across different PV technologies; 3) what the effects are, if any, of technological advances on environmental performance; 4) how the environmental impacts compare across technology types and across different stages of technological maturity; and 5) which potential hotspots can be anticipated by comparing the relative contributions to impacts from different elements of the PV technologies. Our analysis is meant to ultimately provide valuable guidance for PV technology developers, policy-makers, and other stakeholders so that they can factor in environmental sustainability considerations during the early R&D stages.

2. Experimental Section

2.1. Classification of PV Technologies

For our analysis, we classified the emerging PV technologies as shown in **Table 1**, adapting definitions from Green et al.[8] and NREL.[9] Some of these technologies were already introduced in the market, such as thin-film cadmium telluride (CdTe). Others have been limited to niche applications, implemented only as pilots, or are still in the development phase. The table also shows the advantages and disadvantages that have been reported in various literature sources[10,11] for each technology in terms of efficiency, cost, and environmental aspects.

2.2. Assessment Framework and Meta-Analysis Approach

LCA is a commonly used framework to assess sustainability aspects of emerging technologies, as it provides a holistic accounting of environmental impacts throughout a product's entire life cycle.[13] This holistic approach ensures that environmental trade-offs are identified and quantified, and that new technologies do not result in environmental burdens larger than those of the incumbent technology.[14] We conducted a systematic review and meta-analysis of LCA studies of state-of-the-art and emerging PV by following the guiding principles for meta-analyses contained in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.[15] First, we identified potentially relevant publications since 2010 using the Web of Science tool[16] and the Google Scholar search tool. Then we screened and filtered the results according to the criteria described in Section 2.3. In a final step, we harmonized the quantitative LCA results from the eligible studies, adapting and significantly extending the harmonization

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Table 1. Classification and characteristics of PV technologies and cell types assessed.

PV technology	Cell types	Advantages	Shortcomings
Silicon	Single-Si; multi-Si	Nontoxic; high efficiencies; long-term stability; abundant materials	Energy intensive; high cost
Thin-film silicon	Amorphous silicon (a-Si); micro-Si (μ-Si)	Low cost; less materials; nontoxic	Low efficiency
Thin-film chalcogenide	Cadmium telluride (CdTe); CIGS, CZTS	Less materials; low cost; high efficiencies	Critical materials; toxicity of Cd
Dye-sensitized solar cell (DSSC)	Ruthenium complex sensitizers; organic dyes	Low cost; flexible; non-toxic; ease of fabrication; ability to operate in diffuse light[12]	Temperature sensitivity of liquid electrolyte; low efficiency[12]
OPV	Polymer; single-wall carbon nanotube (SWCNT)	Low cost; flexible; light-weight; nontoxic; ease of fabrication; can be tailored for application	Stability (short lifetime); low efficiency
PK	Lead halide, tin halide	Low cost; flexible; light-weight; ease of fabrication; high efficiencies	Stability (short lifetime); toxicity of lead
III–V	Gallium arsenide (GaAs)	High efficiency	High cost; material scarcity; toxicity of As
Quantum dot	Cadmium selenide (CdSe)	High efficiency (potential)	Toxicity of Cd; high cost
Tandem/hybrid	Silicon HJ; III-V/Si; PK/Si; TF/TF; TF/PK	High efficiency	Expensive; material scarcity; toxicity of As

approach proposed by the NREL Life Cycle Assessment Harmonization Project (Section 2.4).[17,18]

2.3. Identification, Screening, and Selection of Studies

To identify LCA studies of PV, we searched three different sources. First, we searched the Web of Knowledge database using the following search strings:

> *(TS = ((LCA OR (life cycle assessment OR (life-cycle assessment OR (life-cycle analysis OR life cycle analysis)))) AND (solar OR (photovoltaic* OR PV)))) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article) Timespan: 2010-2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, ESCI.*
>
> *(TI = ((LCA OR (life cycle assessment OR life-cycle assessment)) AND (photovoltaics OR (solar AND cells)))) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article) Timespan: 2010–2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, ESCI.*

A second source was the Google Scholar search tool, where we searched for similar search strings and compared the first 1000 hits to the results obtained in the Web of Knowledge. A third source was the cross-references in the reviewed articles that were not identified in the previous steps. We then screened these results to exclude those which 1) repeated results from previous works; 2) focused on a specific geographical implementation; 3) did not use a PV cell or panel (m^2) or generation of electricity with a PV system (kWh) as the basis for the assessment (functional unit) (see Section 2.4.1); 4) did not use own data and/or calculations for the technological system; and 5) assessed PV cells integrated on other devices.

From the screened studies, we selected for inclusion only those studies, in which the data provided allowed for the harmonization steps described in Section 2.4. The full list of included and excluded studies is provided in Table S1, Supporting Information.

2.4. Harmonization

2.4.1. Functional Unit

We chose the generation of 1 kWh of electricity as a comparative basis (i.e., functional unit in LCA[19]) for the meta-analysis. This functional unit is used frequently in LCA studies of PV electricity generation,[20] and accounts for technological advantages or disadvantages from the cell technology that translate to the ancillary PV infrastructure. For example, cells with higher efficiencies require less area to produce 1 kWh. Therefore, they also require smaller infrastructures and correspondingly less materials for the installation. However, many relevant studies reported impacts for a unit area of cell, typically 1 m^2. To harmonize these units, we calculated the equivalent area required to produce 1 kWh, as shown in Equation (1).[21]

$$A = \frac{\varepsilon}{n \cdot r \cdot \mathrm{PR} \cdot \mathrm{LT}} \tag{1}$$

where ε is the electricity output of the PV system (1 kWh), A is the total solar panel area (m^2), η is the solar panel efficiency (%), r is the annual average solar radiation on panels (measured in kWh $year^{-1}$ m^{-2}), PR is the performance ratio (i.e., a coefficient that adjusts for conversion losses), and LT is the lifetime of the PV system.

Most LCA studies for PV converge on values of PR = 0.75 and solar radiation = 1700 kWh m^{-2}, representative of Southern Europe and close to the world average, respectively. The panel efficiencies η vary depending on each cell technology. Additional efficiency losses occur when the cells are incorporated into the panels due to the small separations between the cells. Therefore, whenever cell efficiencies were reported instead of panel efficiencies, we subtracted 2% to account for these area losses, following the approach of Louwen et al.[22]

Some studies reported electricity output in kilowatt-hour, but for different operating conditions than the typical ones assumed for Equation (1). Adjustments to the impact scores were made according to the proportional difference in the parameters radiation and performance ratio. O'Donoghue et al.[23] refer to this kind of adjustment as "proportional adjustment," where the adjusting factor is the ratio of the parameter value in the study to the intended harmonized parameter value. This adjustment is possible because usually more than 99% of the total impacts of renewable electricity generation is embedded in the infrastructure, which is represented by the area parameter in Equation (1). Following the method of Asdrubali et al.[24] for harmonization in renewables, we combined the three-parameter adjustments into a single formula to calculate the harmonized impact scores (Equation (2)).

$$D_{i\text{harm}} = D_{i\text{pub}} \cdot \frac{r_{\text{pub}} \cdot \text{PR}_{\text{pub}} \cdot \text{LT}_{\text{pub}}}{r_{\text{harm}} \cdot \text{PR}_{\text{harm}} \cdot \text{LT}_{\text{harm}}} \tag{2}$$

where $D_{i\text{harm}}$ is the harmonized impact score, $D_{i\text{pub}}$ is the reported impact score, r_{pub} is the solar radiation assumed in the study, PR_{pub} is the performance ratio assumed in the study, LT_{pub} is the lifetime of the PV system in the study, r_{harm} is the average solar radiation in Southern Europe (1700 kWh m^{-2}), PR_{harm} is the average performance ratio of 75%, and LT_{harm} is the average lifetime. We set 30 years of lifetime for the harmonized value of all PV systems except for perovskites (PKs) and organic PV, which have many technical barriers to long-term stability. Meng et al.[25] and Cai et al.[26] assess that PKs may need lifetimes of 15 years to achieve lower costs per kilowatt-hour than traditional energy sources. However, it is not yet clear what the maximum achievable lifetime of PKs is. Therefore, we adopt 15 years as a conservative lifetime under the assumption that once the technology becomes cost-competitive, the efforts to extend the related lifetime may even slow down further.

2.4.2. System Boundaries

We also harmonized system boundaries by ensuring that the same life-cycle stages and comparable unit processes were considered across all technologies. For this, we divided the life-cycle inventories of each technology into five broad life-cycle phases: 1) material extraction and assembly of PV cell, 2) material extraction and assembly of panel components, 3) material extraction and assembly of balance-of-system (BOS) components; 4) electricity generation, and 5) end-of-life (EOL) including decommissioning, recycling, and/or final disposal. Within these system boundaries, the least common denominator was established as all life-cycle stages up to electricity generation. When necessary, unit processes were excluded and impact scores were recalculated by subtracting the corresponding contributions. We calculated panel (2) and BOS (3) components separately and added them proportionally in relation to the required area of the installation. The amount of installation required is calculated in ecoinvent,[27] as shown in Equation (3).

$$Q_{\text{inst}} = \frac{1\,\text{kWh}}{\text{LT} \cdot \text{capacity} \cdot \text{yield}} \tag{3}$$

Based on the ecoinvent data for a single-Si slanted-roof installation, $Q_{\text{inst}} = 1.158\text{E}{-5}$ installations are required for the generation of 1 kWh. The yield is proportional to the efficiency of the solar module; therefore, we adjusted Q_{inst} in each case by a factor calculated as in Equation (4) and added the corresponding impacts for the adjusted area of installation as follows

$$\frac{\eta_{\text{si}}}{\eta_{\text{em}}} \tag{4}$$

where η_{si} is the efficiency of the single-Si solar module from ecoinvent, i.e., 13.6%, and η_{em} is the efficiency of the assessed PV technology in each case.

An exception to this proportional adjustment was the inverter, which scales with power and not with panel area or efficiency. Therefore, the quantity of inverter required for generating 1 kWh was kept constant across all systems. This quantity was calculated, as shown in Equation (5).

$$Q_{\text{i}} = \frac{1\,\text{kWh}}{P \cdot S \cdot 365 \cdot \text{LT}} = 2.2\text{E} - 5\,\text{units} \tag{5}$$

where Q_{i} is the amount of inverter units required to generate 1 kWh, P is the power rating of the modeled inverter (2.5 kW unit^{-1}), S is the equivalent amount of sunlight hours for the Southern European location (5 h day^{-1}), 365 is the number of days in a year, and LT is the average lifetime of an inverter (10 years). Individual life-cycle inventories for BOS and panel components were updated to reflect the changes proposed by the International Energy Agency (IEA) PVPS 2015 report.[28]

2.4.3. Impact Assessment Methods

To assess impacts in LCA, characterization factors must be used which translate environmental emissions into different types of impacts.[29] Different methods have been proposed to estimate these, and they can use different indicators and units for such. For example, the CML method[14] expresses toxicity impacts in units of kilogram 1–4 dichlorobenzene equivalents, whereas the USEtox method[30] uses comparative toxicity units (CTUs). Therefore, we converted all results to the units used by the reference impact assessment methods recommended by the European Commission in the International Reference Life Cycle Data System (ILCD).[31] For some impact categories, conversions are relatively straightforward and can be achieved by a constant factor with acceptable accuracy. In other cases, such as toxicity and resource depletion, the modeling behind each indicator is considerably different across characterization methods. This results in conversion factors that could vary across several orders of magnitude for different product systems, making harmonization of impact indicators impracticable. However, we are mainly focused on the change of environmental profile of the emerging PV technology relative to the dominating crystalline silicon systems in 2010. Therefore, we consider it appropriate to approximate these conversion factors according to Equation (6).

$$\text{Ie}_{\text{ILCD}} = \frac{\text{Ir}_{\text{ILCD}}}{\text{Ir}_x} \cdot \text{Ie}_x \tag{6}$$

In Equation (6), Ie_{ILCD} is the impact score of the emerging technology in harmonized ILCD units; Ie_x is the impact score of the emerging technology in the units of the original methodology used by the study; Ir_x is the impact score of a reference single-Si PV system (as modeled in ecoinvent v3.4)[27] in the units of the impact assessment methodology used by the study; and Ir_{ILCD} is the impact score of the reference single-Si PV system in ILCD units. The result gives a consistent idea of how much better or worse each system is compared with the reference crystalline silicon system. The resulting conversion factors for each impact category are provided in Table S2, Supporting Information.

A flowchart describing the full identification, screening, selection, and harmonization process is shown in Figure S1, Supporting Information.

2.5. Statistical Analysis

To discern trends in time, we used linear regression models and Pearson correlation coefficients for impact scores as a function of time (i.e., year in which technology developers first describe the PV cell design in literature). Louwen et al.[32] investigated exponential learning curves to assess the greenhouse gas emissions of silicon-based PV over a period of 40 years. However, there is still scant supporting evidence for the existence of such curves for the data at hand in this study. Furthermore, our interest is not to predict but rather to observe whether the trends exist and if so, whether they are positive or negative.

To investigate the effects of technological development on the environmental performance of PV systems, we used a random effects model.[33,34] Random effects models commonly applied in meta-analyses require the definition of an experimental group (i.e., the population of individuals exposed to a certain treatment) and a control group (i.e., the population of individuals not exposed to the treatment). Effects are, then, estimated comparing the outcome of the treatment across studies using effect size metrics, such as odds ratios, correlation coefficients, and standardized mean differences (SMDs).[33,34] We framed our case such that the commercially established single and multicrystalline PV systems served as a *pseudo*-control group, using the harmonized data compiled from the meta-analysis by Hsu et al. of the National Renewable Energy Laboratory and the Brookhaven National Laboratory.[18] The data in these studies refer to commercial PV systems assessed in 2000–2008. We defined as *pseudo*-experimental groups the emerging PV technologies assessed in 2010–2019 (see Table S1, Supporting Information). We considered the diverse technological enhancements as the treatments performed on the experimental groups. The effects of the technological enhancements were interpreted as the changes in the SMDs[35] in impact scores. The SMD is equivalent to the difference in the mean score between the emerging PV technology and the reference PV system, divided by the standard deviation of the scores. To get a sufficiently large population (N) for each group, we grouped results by PV technology type, rather than by study. This is admittedly a departure from convention in meta-analysis, but is—to an extent—reasonable insofar as the harmonization is comprehensive enough.

3. Results and Discussion

3.1. LCA Studies and Data Points Identified and Selected

A total of 1024 potential LCA studies were identified in the Web of Knowledge database and Google Scholar. The screening process resulted in 85 studies, of which 40 resulted eligible for the quantitative synthesis. These 40 studies produced 682 data points (LCA impact scores), distributed as shown in **Figure 1**.

The studies were produced by 28 lead authors and published in 18 different peer-reviewed journals. As shown in **Figure 2**, the majority of the studies were related to PKs and thin films. The eligible contributions in 2018 doubled those from the next most productive year (2011).

3.2. Trends per Technology Type

Figure 3 shows the impact scores for each of the ILCD impact categories classified by PV technology type and maturity, as a function of the year in which the cell design was introduced. A first important insight can be obtained from looking at the Y scales, which provide both maximum and minimum values

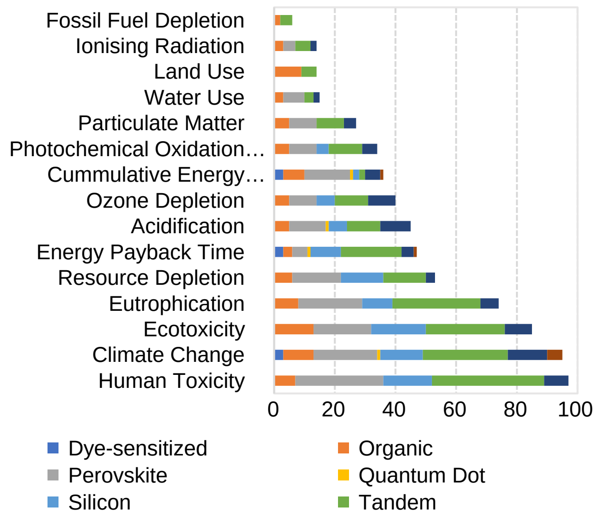

Figure 1. Number of impact indicators considered for different PV technologies, 2010–2019.

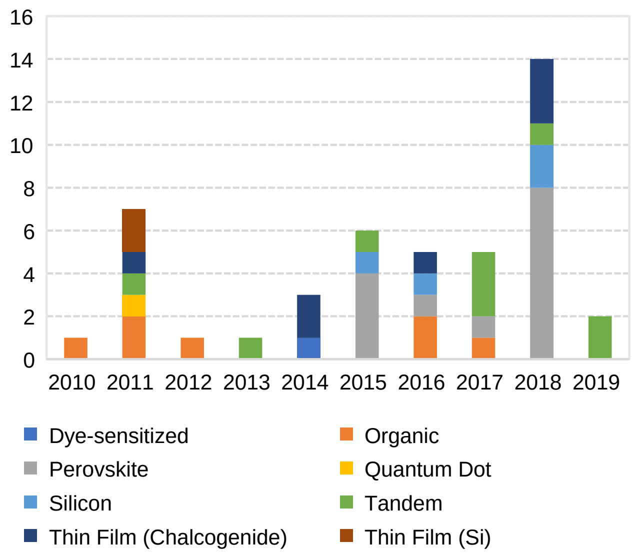

Figure 2. Number of LCA studies selected for different PV technologies, 2010–2019.

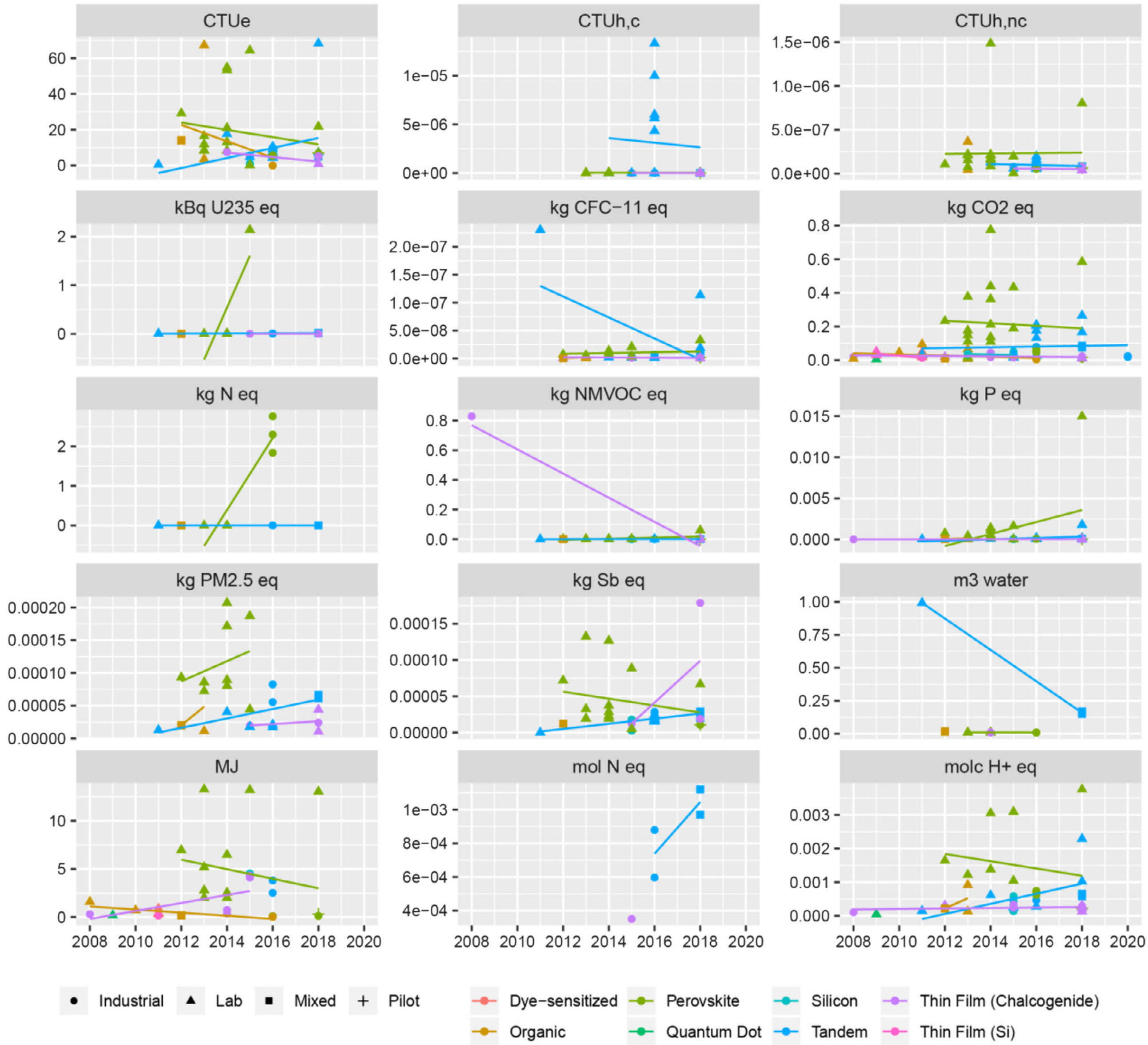

Figure 3. Harmonized LCA impact scores of PV technologies as a function of time. CTUe, freshwater ecotoxicity; CTUh,c, human toxicity—cancer effects; CTUh,nc, human toxicity—noncancer effects; kg CFC-11 eq, ozone depletion; kg CO_2 eq, climate change; kg N eq, marine eutrophication; kg NMVOC eq, photochemical oxidation; kg P eq, freshwater eutrophication; kg PM2.5 eq, particulate matter; kg Sb eq, mineral resource depletion; kg U235 eq, ionising radiation; m3 water, water use; MJ, cumulative energy demand; mol H+ eq, acidification; and mol N eq, terrestrial eutrophication.

as well as an idea of the variability of the scores reported. Most impact scores are within an order of magnitude despite differences in modeling and cell designs. It can be observed that there is no clear trend in time, and the steeper slopes are only present for technology and impact-type combinations with few data points. Of the impact cell–type subgroups with more than ten data points, only four trends with strong correlations ($r = >0.5$ or $r = <-0.5$) were detected. Tandem cells showed a strong positive correlation (increasing impact) with respect to resource depletion and photochemical oxidation and a strong negative correlation with respect to ozone depletion. The former may be explained by the increased use of transparent conductive oxides in tandem cell manufacturing. Full results of the regression modeling are provided in Table S3, Supporting Information.

For climate change impacts, the scores appear to be stabilizing toward <0.03 kg CO_2 eq. Here, thin-film silicon and chalcogenides appear to perform remarkably well, most likely due to a good balance between conversion efficiency, low material requirements, and replacement of energy-intensive silicon. A predominance of green data points (PKs) can be observed on top, suggesting an overall larger footprint for this technology type. In contrast, the state-of-the-art versions of silicon-based technologies are among the most competitive from an environmental perspective.

3.3. Variability of Impact Scores

When compared with a single-Si rooftop PV system as a reference (as modeled in ecoinvent v3.4[27]), the relative impacts of all technologies aggregated fell within a factor of 2 (where single Si = 1; see **Figure 4**). The only exception to this was the category of marine eutrophication. This holds for the 75% confidence interval in 13 out of 14 ILCD impact categories when outliers were removed (outlier values are considered as any values over 1.5 times the interquartile range over the 75th percentile or any values under 1.5 times the interquartile range under the 25th percentile). None of the medians exceed that of the reference system, and ten categories fall under 1.5 for a 75% confidence interval. Considering that most of the emerging PV systems were assessed based on the lab-scale designs that do not represent optimized industrial-scale processes, the landscape looks positive as long as upscaling to the industrial scale is reflected in further material and energy optimization.

A closer look at the distribution of scores per technology type is shown in **Figure 5**, for the impact categories with most data points. PKs show the largest variability. An interesting thing to note is the apparently lognormal shape of the distributions. In the case of freshwater eutrophication, the normal-shaped curved is on a logarithmic *x*-axis, which also suggests a lognormal distribution for this category. Lognormal distributions are often found in the probabilistic impact scores of individual systems, but we had no reason to assume the same type of distribution for meta-analyses across different systems. We used the geometric means and standard deviations to describe the populations, which are better suited for skewed distributions (**Table 2**).[36]

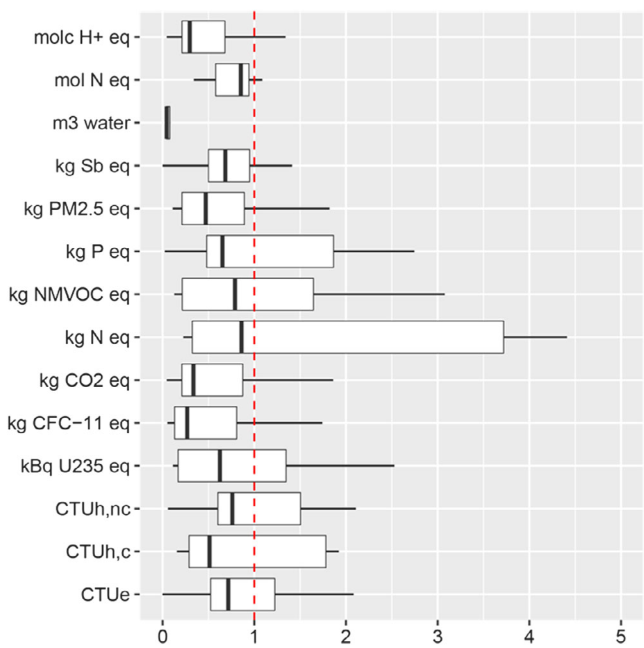

Figure 4. Relative LCA impact scores compared with a reference single-Si PV rooftop system as modeled in ecoinvent v3.4[27] (single-Si impact score = 1, indicated by the red dotted line).

3.4. Effects of Technological Enhancement on Environmental Impacts

Technological innovations appear to have had positive results on climate change impact scores, as can be seen from the random effects model results shown in **Figure 6**. The heterogeneity is, however, still quite large and the low *p*-value suggests that there may be underlying factors. This may be attributed to the differences in materials, manufacturing processes, or efficiencies of each technology type, but it could also be attributed to modeling differences that were not sufficiently corrected via the harmonization procedure.

We further subgrouped the data by cell-conversion efficiency and disaggregated by subtechnology types (see Figure S2, Supporting Information). The results suggest that an increased cell-conversion efficiency does not necessarily determine a statistically significant reduction in climate change impacts measured using SMD. However, the subgrouping did not reduce the inherent heterogeneity of the data. The results may suggest that either additional underlying factors (e.g., material choice, manufacturing processes, and cost) are better suited than efficiency to represent the relationship between technological enhancements and climate change impacts or that the strive for reduced efficiency is not reflected in improved environmental performance of the PV sector. If the latter is the case, PV technologies can still bring about environmental benefits by replacing other types of energy sources (e.g., fossil fuel based), which are not considered in this study.

3.5. Contribution and Hotspots Analysis

3.5.1. Light-Absorbing Layers and Cells

The focus of most LCA studies of emerging PV technologies is on innovations in the light-absorbing layers, whether in terms of their materials or configurations. Each type of absorbing layer places some additional requirements on the ancillary components of the cell (e.g., organic photovoltaic [OPV] requires encapsulation and PKs are deposited on a transparent conductive oxide). **Figure 7** shows the average contributions of the modules to each impact category for each PV technology. It can be seen that for PKs and tandem technologies, the main contributions come from the cell, rather than from the panel and BOS components.

3.5.2. From Cells to Panels

Based on the 2015 inventory data from IEA PVPS,[28] panel contributions for a single-Si roof-mounted PV system can range between 4% to water depletion, 11% to climate change, and 28% to mineral resource depletion. Within the panel, aluminum and solar glass typically account for over 50% of the contributions in most impact categories, although small amounts of copper weigh heavily on the toxicity categories. Therefore, cells that may require less or no glass and aluminum highly benefit from these avoided emissions in certain installations. Examples of these are roll-to-roll manufactured OPV, PKs, dye-sensitized cells, and thin-film chalcogenides. This is an important outcome because it implies that technologically enhanced PV cells have a good opportunity to offset environmental trade-offs if the new

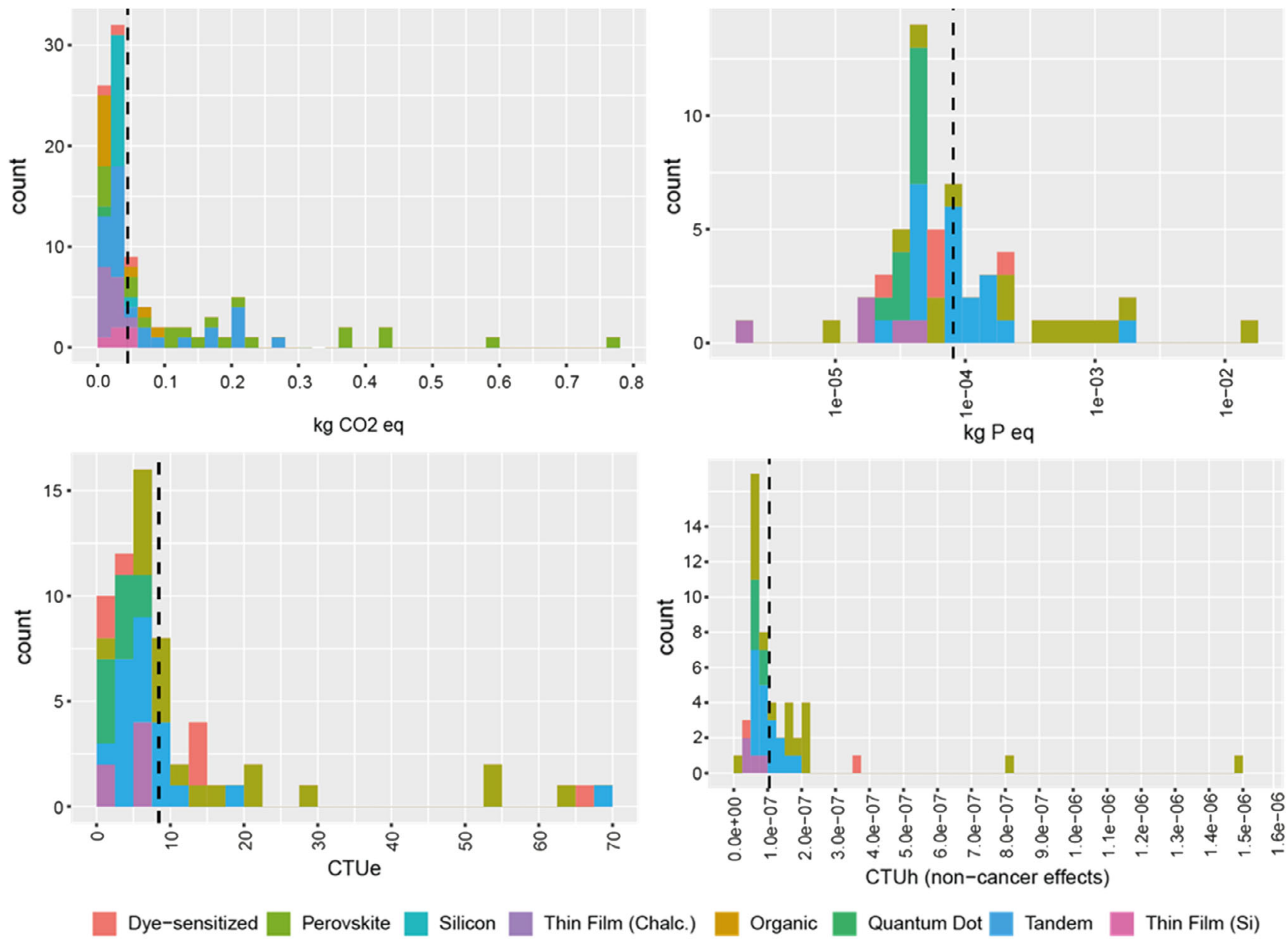

Figure 5. Histogram of harmonized impact scores categorized by PV technology type. The black dotted line indicates the score for the reference single-Si rooftop PV system.[27]

Table 2. Statistics for impact scores, all PV technologies.

Impact category	Units	Geometric mean	Geometric standard deviation	Min	Max	*n*
Freshwater ecotoxicity	CTUe	4.91E+00	6.472367	1.73E−03	6.83E+01	62
Human toxicity, cancer effects	CTUh,c	2.09E−08	15.339903	1.97E−09	1.33E−05	39
Human toxicity, noncancer effects	CTUh,nc	9.66E−08	2.283539	6.15E−09	1.49E−06	48
Ionising radiation	kBq U235 eq	6.33E−03	7.209188	9.34E−04	2.14E+00	14
Ozone depletion	kg CFC-11 eq	2.88E−09	4.331922	4.18E−10	2.30E−07	40
Climate change	kg CO_2 eq	4.20E−02	3.085995	4.34E−03	7.74E−01	95
Marine eutrophication	kg N eq	6.70E−04	89.11475	2.48E−05	2.76E+00	14
Photochemical oxidation	kg NMVOC eq	3.16E−04	7.437551	4.24E−05	8.28E−01	34
Freshwater eutrophication	kg P eq	8.21E−05	4.315235	1.93E−06	1.50E−02	55
Particulate matter	kg PM2.5 eq	4.30E−05	2.413509	1.04E−05	2.07E−04	27
Resource depletion	kg Sb eq	1.63E−05	3.9506	1.89E−08	1.79E−04	46
Water depletion	m3 water	2.03E−02	4.287818	8.68E−03	9.92E−01	15
Terrestrial eutrophication	mol N eq	7.25E−04	1.597175	3.51E−04	1.12E−03	5
Acidification	mol H+ eq	4.10E−04	2.667304	4.65E−05	3.76E−03	45

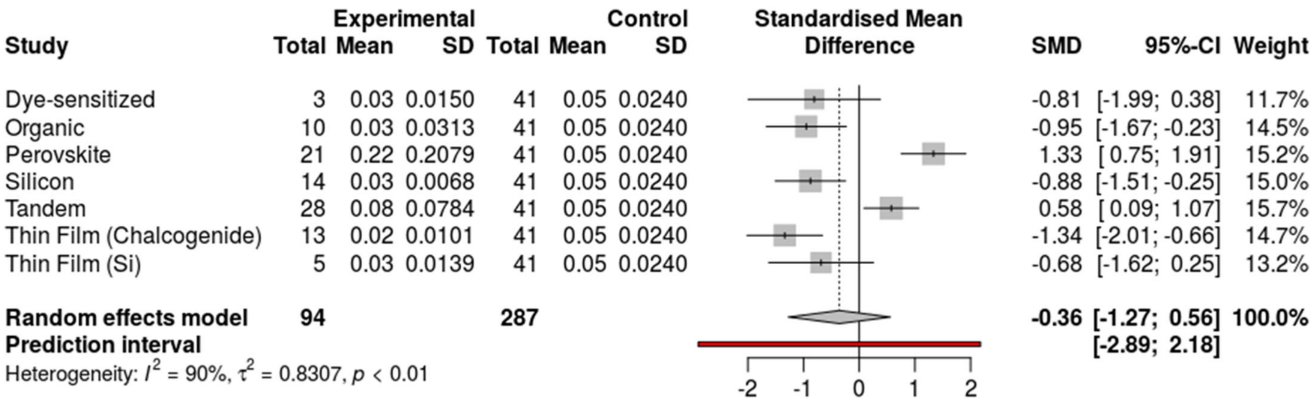

Figure 6. Random effects model results for climate change impact.

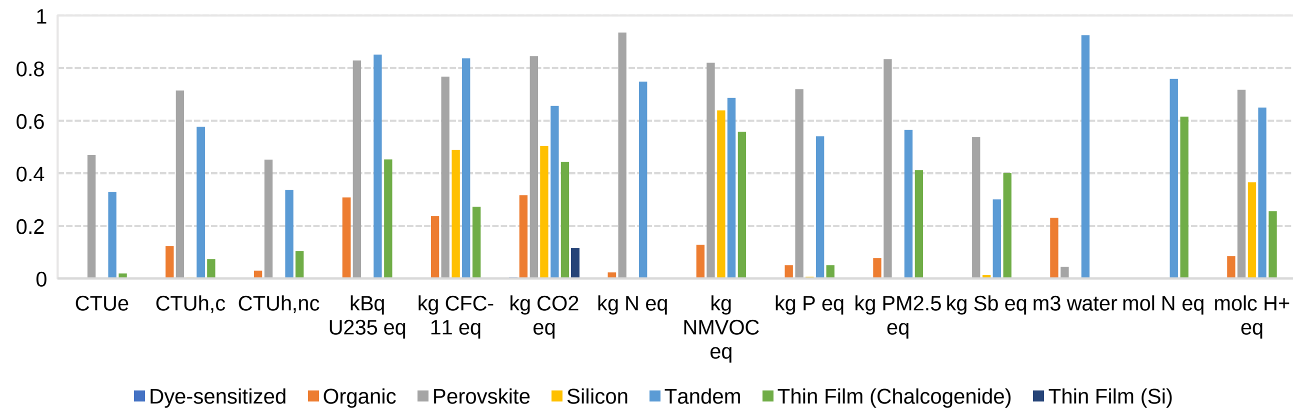

Figure 7. Average relative contributions of PV cells as compared with the corresponding PV system.

cell design favors less material-intensive panels. The need for less panel materials can result from lighter cells, allowing lamination or lighter paneling, and/or from higher cell efficiencies requiring less panel area per kilowatt-hour.

3.5.3. From Panels to PV Installations

The BOS is also a main contributor and is in a large part independent of cell design. Particularly the inverter, which is required equally for all systems independent of cell efficiency, contributes on average 11% to impact categories, with 32% to mineral resource depletion and 29% to human toxicity, non-cancer effects for a reference single-Si roof-mounted system. The remainder of the installation is composed of mounting systems and cabling which contribute on average 33% to all impact categories, with 71% contribution to freshwater ecotoxicity, 37% to human toxicity and cancer effects, and 18% to climate change. Here, the key contributions come from aluminum and copper, where aluminum from the mounting system represents 87% of the climate change contribution and copper from the electric installation 97% of the contribution to freshwater ecotoxicity.

3.5.4. Hotspots in the Emerging PV Landscape

Figure 8 shows a radar plot with relative impacts of the different types of PV cells, where 100% corresponds to the impact score

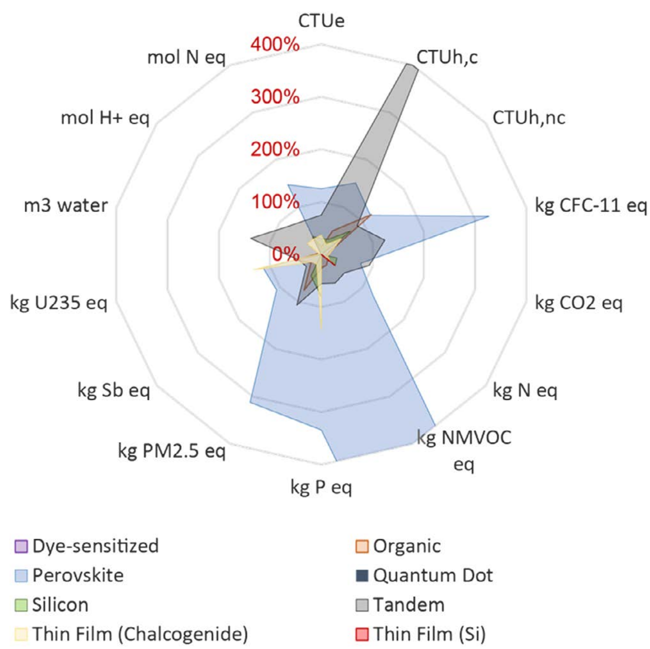

Figure 8. Relative ILCD impact scores for different PV technologies, compared with a reference single-Si roof-mounted PV system as modeled in ecoinvent v3.4 (=100%). The plot is truncated at 400% for visualization purposes.

Table 3. Key potential environmental hotspots in emerging PV technologies, compared with a reference single-Si roof-mounted PV system.

PV technology	Impact category	Comparative hotspots
PKs	Photochemical oxidation	Isopropanol emitted in blocking layer
		Fluorine-doped tin oxide (FTO) glass
		Gold layer
	Freshwater eutrophication	FTO glass
		Isopropanol emitted in blocking layer
		Gold layer
		Waste streams
	Particulate matter	FTO glass
		PK layer
		Gold layer
	Ozone depletion	FTO glass
		Gold layer
		PK layer
	Marine eutrophication	Dimethylformamide (DMF) in solution-deposited PK
		FTO glass
	Human toxicity, cancer effects	Methylammonium iodide (MAI)
		Tin
Tandem	Human toxicity, cancer effects	DMF and isopropanol solvents in PK/Si

for a reference single-Si roof-mounted system as modeled in ecoinvent v3.4.[27] For each type of PV cell, we have used the geometric mean impact score, following the indications of Section 3.3. PKs dominate the plot and exceed the reference single-Si system by factors of 2 and more in four impact categories. These potentially important hotspots are shown in **Table 3**, along with their possible sources.

It is important to highlight that the results discussed earlier represent the impacts of the PV technologies in comparable applications, i.e., roof-mounted installations. However, several of these technologies are finding alternative applications and may end up creating their specific market niches. Some of these technologies can be embedded into other systems (e.g., building integrated or flexible cells integrated on consumer products). From an LCA perspective, this means that the assessed functional unit would change, and this can considerably change the calculation of the life-cycle impact scores of the technologies.

4. Conclusions

A comprehensive harmonization effort combined with diverse statistical analyses allowed us to answer important questions about the direction the PV sector is taking in terms of sustainability. This was possible despite the large underlying uncertainties in predicting the future evolution of immature technologies, and the wide array of modeling choices across LCA studies, which can greatly magnify the variabilities in the harmonized results. From an overall environmental perspective, thin-film silicon and dye-sensitized cells presented a considerable lead, followed by thin-film chalcogenide, organic, and silicon. As many of the assessments are still based on early design concepts, the results we presented should not be used as arguments to hinder further research on specific technologies. Rather, they may be used constructively to highlight research pathways that can result in more environmentally competitive designs. Emerging concepts that are lagging in this respect can address their shortcomings by aiming to reach higher efficiencies, longer lifetimes, substituting novel materials, and/or reducing the energy intensive of their manufacturing processes.

This meta-analysis investigated environmental life-cycle impacts based on the LCA method. LCA aggregates environmental emissions and impacts in large production and consumption systems that occur in many different places and times. This temporal and spatial integration is helpful to compare product systems based on their total life-cycle emissions, but LCA results do not necessarily reflect actual risk at a specific location or time. Risk assessment can provide an idea of actual risk by combining release, environmental fate, and exposure to emissions and comparing them to thresholds on which adverse effects occur.[37] Both frameworks are complementary and necessary.[13,38] We believe future studies incorporating risk assessment results into a meta-analyses framework like the one developed in this study can provide a comprehensive and valuable tool for guiding research and policy in the PV sector.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

environmental impacts, life-cycle assessments, photovoltaics, solar, sustainability

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[1] IEA, *Renewables 2018 - Market Analysis and Forecast from 2018 to 2023*, IEA, Paris **2018**.
[2] Lazard, *Levelized Cost of Energy Analysis-Version 12.0 2018*, Lazard **2018**.
[3] ITRPV, S. P. Group, ITRPV, *Int. Technology Roadmap for Photovoltaic*, VDMA, Frankfurt am Main **2019**.
[4] S. Cucurachi, C. Van Der Giesen, J. Guinée, *Procedia CIRP* **2018**, *69*, 463.
[5] D. Collingridge, *The Social Control of Technology*, Frances Pinter, New York **1980**.
[6] L. Stamford, A. Azapagic, *Energy Technol.* **2018**, *6*, 1148.
[7] M. D. Chatzisideris, A. Laurent, *Sol. Energy Mater. Sol. Cells* **2016**, *156*, 2.
[8] M. A. Green, Y. Hishikawa, E. D. Dunlop, D. H. Levi, J. Hohl-Ebinger, M. Yoshita, A. W. Y. Ho-Baillie, *Prog. Photovoltaics Res. Appl.* **2019**, *27*, 3.
[9] NREL, Best Research-Cell Efficiency Chart | Photovoltaic Research | NREL, https://www.nrel.gov/pv/cell-efficiency.html (accessed: June 2019).
[10] S. Rao, A. Morankar, H. Verma, P. Goswami, *J. Appl. Chem.* **2016**, *2016*, 1.
[11] A. Zakutayev, *Curr. Opin. Green Sustainable Chem.* **2017**, *4*, 8.
[12] K. K. S. Lau, M. Soroush, in *Dye-Sensitized Solar Cells* (Eds: M. Soroush, K. Lau), Elsevier, London **2019**, pp. 1–49.
[13] J. B. Guinée, R. Heijungs, M. G. Vijver, W. J. G. M. Peijnenburg, *Nat. Nanotechnol.* **2017**, *12*, 727.
[14] J. B. Guinée, *Handbook on Life Cycle Assessment: Operational Guide to the ISO Standards*, Kluwer Academic Publishers, Dordrecht **2002**.
[15] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, T. P. Group, *PLoS Med.* **2009**, *6*, e1000097.
[16] Clarivate, Web of Science, www.webofscience.com (accessed: May 2019).
[17] G. A. Heath, M. K. Mann, *J. Ind. Ecol.* **2012**, *16*, S1.
[18] D. D. Hsu, P. O'Donoughue, V. Fthenakis, G. A. Heath, H. C. Kim, P. Sawyer, J.-K. Choi, D. E. Turney, *J. Ind. Ecol.* **2012**, *16*, S122.
[19] G. Rebitzer, T. Ekvall, R. Frischknecht, D. Hunkeler, G. Norris, T. Rydberg, W. P. Schmidt, S. Suh, B. P. Weidema, D. W. Pennington, *Environ. Int.* **2004**, *30*, 701.
[20] R. Frischknecht, G. Heath, M. Raugei, P. Sinha, M. de Wild-Scholten, V. Fthenakis, H. C. Kim, E. Alsema, M. Held, *Methodology Guidelines on Life Cycle Assessment of Photovoltaic Electricity*, 3rd ed., *IEA PVPS Task 12, International Energy Agency Photovoltaic Power Systems Programme* **2016**.
[21] M. Monteiro Lunardi, S. Moore, J. P. Alvarez-Gaitan, C. Yan, X. Hao, R. Corkish, *Energy* **2018**, *145*, 700.
[22] A. Louwen, W. G. J. H. M. Van Sark, R. E. I. Schropp, W. C. Turkenburg, A. P. C. Faaij, *Prog. Photovoltaics Res. Appl.* **2015**, *23*, 1406.
[23] P. R. O'Donoughue, G. A. Heath, S. L. Dolan, M. Vorum, *J. Ind. Ecol.* **2014**, *18*, 125.
[24] F. Asdrubali, G. Baldinelli, F. D'Alessandro, F. Scrucca, *Renewable Sustainable Energy Rev.* **2015**, *42*, 1113.
[25] L. Meng, J. You, Y. Yang, *Nat. Commun.* **2018**, *9*, 5265.
[26] M. Cai, Y. Wu, H. Chen, X. Yang, Y. Qiang, L. Han, *Adv. Sci.* **2017**, *4*, 1600269.
[27] G. Wernet, C. Bauer, B. Steubing, J. Reinhard, E. Moreno-Ruiz, B. Weidema, *Int. J. Life Cycle Assess.* **2016**, *21*, 1218.
[28] R. Frischknecht, R. Itten, P. Sinha, M. de Wild-Scholten, J. Zhang, V. Fthenakis, C. H. Kim, M. Raugei, M. Stucki, *Life Cycle Inventories and Life Cycle Assessments of Photovoltaic Systems*, International Energy Agency (IEA) PVPS Task 12 **2015**.
[29] D. W. Pennington, J. Potting, G. Finnveden, E. Lindeijer, O. Jolliet, T. Rydberg, G. Rebitzer, *Environ. Int.* **2004**, *30*, 721.
[30] P. Fantke, M. Bijster, C. Guignard, M. Hauschild, M. Huijbregts, O. Jolliet, A. Kounina, V. Magaud, M. Margni, T. McKone, R. K. Rosenbaum, USEtox® 2.0, Documentation Version 1, USEtox International Center, Lyngby, Denmark **2017**.
[31] European Commission Joint Research Center - Institute for Environmental Sustainability, *ILCD Handbook: Recommendations for Life Cycle Impact Assessment in the European Context*, European Union, Luxemburg **2011**.
[32] A. Louwen, W. G. J. H. M. van Sark, A. P. C. Faaij, R. E. I. Schropp, *Nat. Commun.* **2016**, *7*, 13728.
[33] M. Harrer, P. Cuijpers, T. A. Furukawa, D. D. Ebert, *Doing Meta-Analysis in R: A Hands-on Guide*, PROTECT Lab **2019**.
[34] J. C. Valentine, T. D. Pigott, T. Lau, in *International Encyclopedia of the Social and Behavioral Sciences* (Ed: J. D. Wright), Elsevier, Amsterdam/New York **2015**, pp. 906–913.
[35] *Cochrane Handbook for Systematic Reviews of Interventions*, 2nd ed. (Eds: J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, V. A. Welch), John Wiley & Sons, Chichester, UK **2019**.
[36] M. N. Martinez, M. J. Bartholomew, *Pharmaceutics* **2017**, *9*, 14.
[37] R. Fairman, C. D. Mead, W. P. Williams, *Environmental Risk Assessment - Approaches, Experiences and Information Sources*, European Environment Agency, Copenhagen **1998**.
[38] C. Franklin, *Nat. Resour. Environ.* **2015**, *29*, 4.