Guiding safe and sustainable technological innovation under uncertainty: a case study of III-V/silicon photovoltaics

Blanco Rocha, C.F.

Chapter 2

Are technological developments improving the environmental sustainability of photovoltaic electricity?

Abstract

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.

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

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2.1. Introduction

Since the introduction of the first solar cell in the early 1950's, the market share of photovoltaic electricity (PV) 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 to 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 presents 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 fulfil the same function. For example, several thin film technologies completely replaced silicon - a non-toxic 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 are 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] 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 & 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 et al.[7] investigated more recent technologies, yet their analysis was based on 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 towards 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 5 specific questions: (i) what –if any-are the observable trends in the environmental impacts of each type of PV technology; (ii) what the variability of impact scores is within and across different PV technologies; (iii) what the effects are, if any, of technological advances on environmental performance; (iv) how the environmental impacts compare across technology types and across different stages of technological maturity, and (v) 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, policymakers and other stakeholders so that they can factor in environmental sustainability considerations during the early R&D stages.

2.2. Methods

2.2.1. Classification of PV technologies

For our analysis we classified the emerging PV technologies as shown in Table 2-1, 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 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.

2.2.2. Assessment framework and meta-analysis approach

Life cycle assessment (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.[12] 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.[13] 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 PRISMA statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses).[14] First we identified potentially relevant publications since 2010 using the Web of Science® tool[15] and the Google Scholar search tool. Then we screened and filtered the results according to the criteria described in section 2.2.3. In a final step we harmonized the quantitative LCA results from the eligible studies, adapting and significantly extending the harmonization approach proposed by the NREL Life Cycle Assessment Harmonization Project (section 2.2.4).[16,17]

Table 2-1. Classification and characteristics of PV technologies and cell types assessed

PV technology	Cell types	Advantages	Shortcomings	PV technology
Silicon	single-Si; multi-Si	Non-toxic; high efficiencies; long-term stability; abundant materials	Energy intensive; high cost	Silicon
Thin-film silicon	amorphous silicon (a-Si); micro-Si (μ-Si);	Low cost; less materials; non-toxic	Low efficiency	Thin-film silicon
Thin-film chalcogenide	Cadmium telluride (CdTe); CIGS, CZTS,	Less materials; low cost; high efficiencies	Critical materials; toxicity of Cd	Thin-film chalcogenide
Dye-sensitized (DSSC)	Ruthenium complex sensitizers; organic dyes	Low cost; flexible; non-toxic; ease of fabrication; ability to operate in diffuse light[38]	Temperature sensitivity of liquid electrolyte; low efficiency[38]	Dye-sensitized (DSSC)
Organic (OPV)	Polymer; Single-wall carbon nanotube (SWCNT)	Low cost; flexible; lightweight; non-toxic; ease of fabrication; can be tailored for application	Stability (short lifetime); low efficiency	Organic (OPV)
Perovskite (PK)	Lead halide, Tin halide	Low cost; flexible; lightweight; ease of fabrication; high efficiencies	Stability (short lifetime); toxicity of lead	Perovskite (PK)
III-V	Gallium arsenide (GaAs)	High efficiency	High cost; material scarcity; toxicity of As	III-V
Quantum dot	Cadmium selenide (CdSe)	High efficiency (potential)	Toxicity of Cd; high cost	Quantum dot
Tandem/hybrid	Silicon HJ; III-V/Si; PK/Si; TF/TF; TF/PK	High efficiency	Expensive; material scarcity; toxicity of As	Tandem/hybrid

2.2.3. Identification, screening and selection of studies

To identify LCA studies of PVs, 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 with: (i) repeated results from previous work; (ii) focused on a specific geographical implementation; (iii) 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 2.2.4.1); (iv) did not use own data and/or calculations for the technological system; and (v) 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 2.2.4. The full list of included and excluded studies is provided in the Appendix Table A.1-1.

2.2.4. Harmonization

2.2.4.1. Functional unit

We chose the generation of 1 kWh of electricity as a comparative basis (i.e. functional unit in LCA[18]) for the meta-analysis. This functional unit is used frequently in LCA studies of PV electricity generation[19], 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 m2. In order to harmonize these units, we calculated the equivalent area required to produce 1 kWh as indicated in Equation 2-1.[20]

$$A = \varepsilon / (\eta \cdot r \cdot PR \cdot LT) \qquad \text{(Eq. 2-1)}$$

Where $\boldsymbol{\varepsilon}$ is 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 $kWh \cdot year^{-1} \cdot m^{-2}$), 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.[21]

Some studies reported electricity output in kWh, but for different operating conditions than the typical ones assumed for Equation 2-1. Adjustments to the impact scores were made according to the proportional difference in the parameters radiation and performance ratio. O'Donoghue et al.[22] 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 2-1. Following the method of Asdrubali et al.[23] for harmonization in renewables, we combined the three parameter adjustments into a single formula to calculate the harmonized impact scores (Equation 2-2).

$$D_i harm = D_i pub \cdot \frac{r_{pub} \cdot PR_{pub} \cdot LT_{pub}}{r_{harm} \cdot PR_{harm} \cdot LT_{harm}} \qquad \text{(Eq. 2-2)}$$

$D_i harm$ is the harmonized impact score, $D_i pub$ is the reported impact score, r_{pub} is the solar radiation assumed in the study, PR_{pub} is the performance ration assumed in the study, LT_{pub} is the lifetime of 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 a 30 years lifetime for the harmonized value of all PV systems except for perovskites and organic PV, which have many technical barriers to long-term stability. Meng et al.[24] and Cai et al.[25] assess that perovskites may need lifetimes of 15 years to achieve lower costs per kWh than traditional energy sources. However, it is not yet clear what the maximum achievable lifetime of perovskites 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.

2.2.4.2. 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 four 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[26] as indicated in Equation 2-3.

$$Q_{inst} = \frac{1\ kWh}{LT \cdot Capacity \cdot Yield} \qquad \text{(Eq. 2-3)}$$

Based on ecoinvent data for a single-Si slanted-roof installation, Q_{inst} = 1.158E-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 2-4 and added the corresponding impacts for the adjusted area of installation, as follows:

$$\frac{\eta_{si}}{\eta_{em}} \qquad \text{(Eq. 2-4)}$$

In Equation 2-4, 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 area or efficiency. Therefore, the quantity of inverter required for generating 1 kWh was kept constant across all systems. This quantity was calculated as indicated in Equation 2-5.

$$Q_i = \frac{1\,kWh}{P \cdot S \cdot 365 \cdot LT} = 2.2E-5\ units \qquad \text{(Eq. 2-5)}$$

Qi is the amount of inverter units required to generate 1 kWh, *P* is the power rating of the modelled inverter (2.5 kW/unit), *S* is the equivalent amount of sunlight hours for the Southern European location (5 hours/day), 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 PVPS 2015 report.[27]

2.2.4.3. Impact assessment methods

In order to assess impacts in LCA, characterization factors must be used which translate environmental emissions into different types of impacts[28]. Different methods have been proposed to estimate these, and they can use different indicators and units for such. For example, the CML method[13] expresses toxicity impacts in units of kg 1-4 dichlorobenzene equivalents, while the USEtox method[29] 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).[30] 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 modelling 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 relative 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 2-6.

$$Ie_{ILCD} = \frac{Ir_{ILCD}}{Ir_x} \cdot Ie_x \quad \text{(Eq. 2-6)}$$

The result gives a consistent idea of how much better or worse each system is compared to the reference crystalline silicon system. The resulting conversion factors for each impact category are provided in the Appendix Table A.1-2. In Equation 2-6, 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 modelled in ecoinvent v3.4)[26] 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.

A flowchart describing the full identification, screening, selection and harmonization process is provided in Appendix Figure A.1-1.

2.2.5. Statistical analysis

In order 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 firstly describe the PV cell design in literature). Louwen et al.[31] 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 the current 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.[32,33] 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 of 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.[32,33] We framed our case such that the commercially established single and multi-crystalline 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.[17] The data in these studies refers to commercial PV systems assessed in the years 2000 to 2008. We defined as *pseudo*-experimental groups the emerging PV technologies assessed in the years 2010 to 2019 (see Appendix Table A.1-1). We consider 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 standardized mean differences (SMD)[34] in impact scores. The SMD is equivalent to the difference in 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.

2.3. Results and discussion

2.3.1. 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 2-1. The studies were produced by 28 lead authors and published in 18 different peer-reviewed journals. As shown in Figure 2-2, the majority of the studies were related to perovskites and thin films. The eligible contributions in the year 2018 doubled those from the next most productive year (2011).

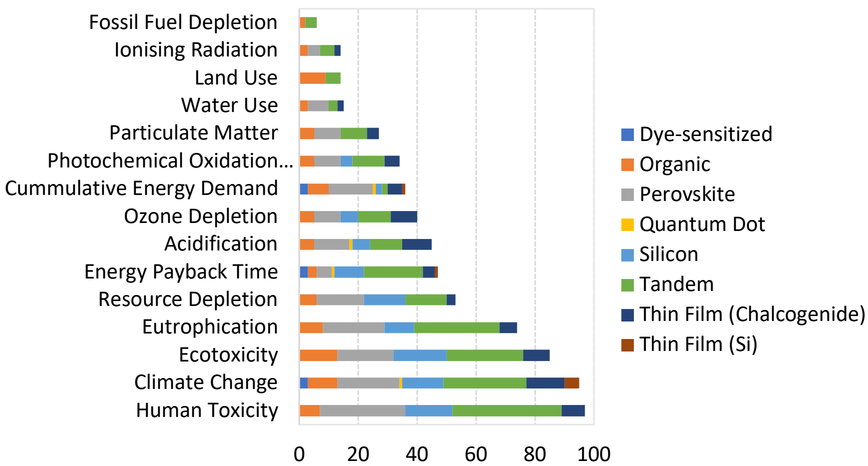

Figure 2-1 Number of impact indicators considered for different PV technologies, 2010-1019.

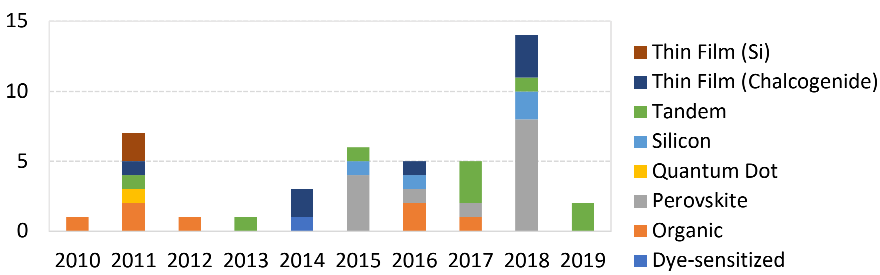

Figure 2-2 Number of LCA studies selected for different PV technologies, 2010-1019.

2.3.2. Trends per technology type

Figure 2-3 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 as well as an idea of the variability of the scores reported. Most impact scores are within an order of magnitude despite differences in modelling 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 10 data points, only four trends with strong correlations 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 calculations are provided in Appendix Table A.1-3.

For climate change impacts, the scores appear to be stabilizing towards <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 (perovskites) can be observed on top, suggesting an overall larger footprint for this technology type. On the other hand, state-of-the-art versions of silicon-based technologies are amongst the most competitive from an environmental perspective.

2.3.3. Variability of impact scores

When compared to a single-Si rooftop PV system as a reference (as modelled in ecoinvent v3.4[26]), the relative impacts of all technologies aggregated fell within a factor of 2 (where single-Si = 1, see Figure 2-4). The only exception to this was the category of marine eutrophication. This holds for the 75th percentile in 13 out of 14 ILCD impact categories when outliers were removed (outlier values are considered 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 10 categories fall under 1.5 for a 75th percentile. Considering most of the emerging PV systems were assessed based on lab-scale designs that are not representing optimized industrial-scale processes, the landscape looks positive as long as upscaling to industrial scale is reflected in further material and energy optimization.

A closer look at the distribution of scores per technology type is presented in Figure 2-5, for the impact categories with most data points. Perovskites 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 summarise the data, which are better suited for skewed distributions (Table 2-2).[35]

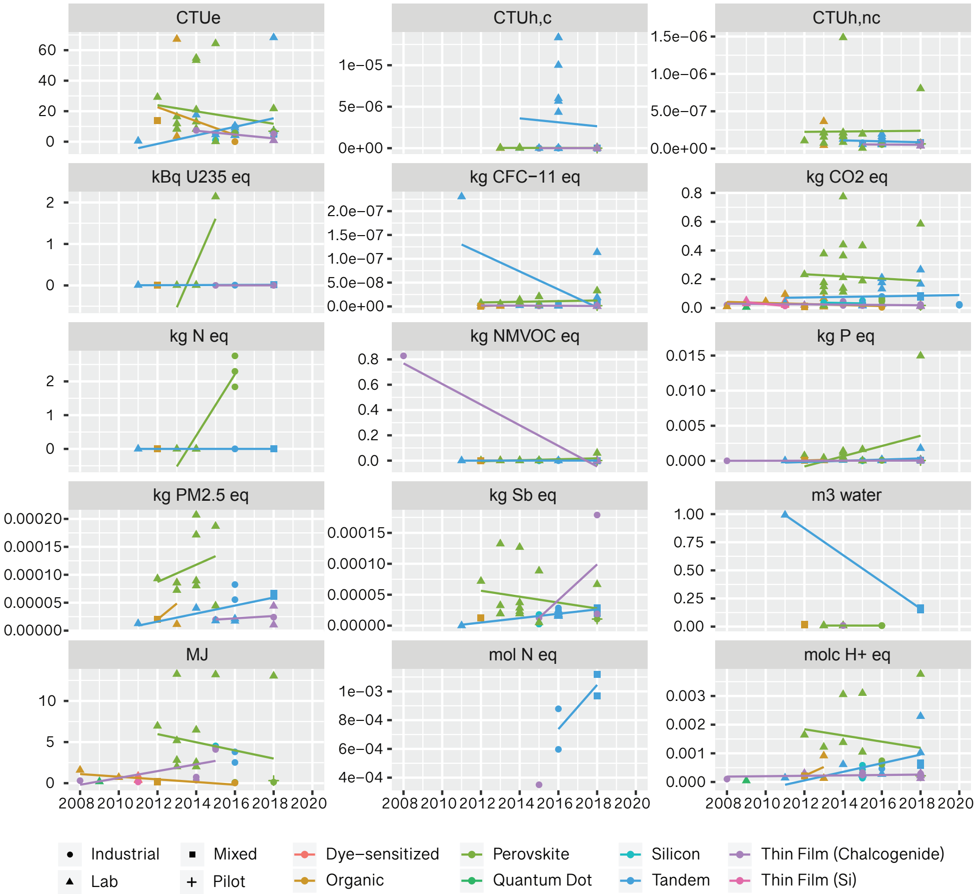

Figure 2-3 Harmonized LCA impact scores of PV technologies as a function of time. CTUe: freshwater ecotoxicity; CTUh,c: human toxicity – cancer effects; CTUh,nc: human toxicity – non-cancer effects; kg CFC-11 eq: ozone depletion; kg CO2 eq: climate change; kg N eq: marine eutrophication; kg NMVOC eq: 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; mol N eq: terrestrial eutrophication.

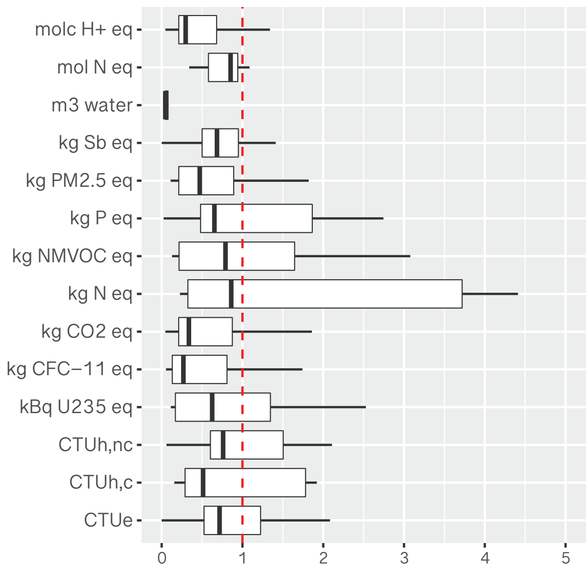

Figure 2-4 Relative LCA impact scores compared to a reference single-Si PV rooftop system as modelled in ecoinvent v3.4[26] *(single-Si impact score = 1, indicated by the red dotted line).*

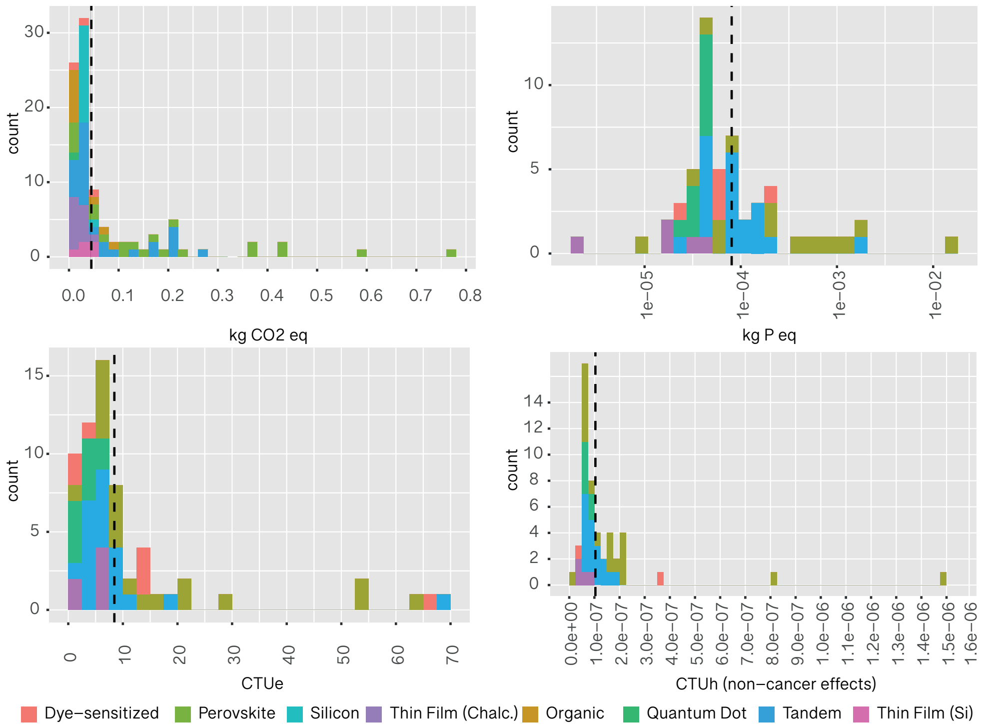

Figure 2-5 Histogram of harmonized impact scores categorized by PV technology type. The black dotted line indicates the score for the reference single-Si rooftop PV system[26].

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

Impact category	Units	Geometric mean	Geometric standard deviation	Min	Max	n
Freshwater ecotoxicity	CTUe	4.91E+00	6.47	1.73E-03	6.83E+01	62
Human toxicity, cancer effects	CTUh,c	2.09E-08	15.33	1.97E-09	1.33E-05	39
Human toxicity, non-cancer effects	CTUh,nc	9.66E-08	2.28	6.15E-09	1.49E-06	48
Ionising radiation	kBq U235 eq	6.33E-03	7.21	9.34E-04	2.14E+00	14
Ozone depletion	kg CFC-11 eq	2.88E-09	4.33	4.18E-10	2.30E-07	40
Climate change	kg CO2 eq	4.20E-02	3.09	4.34E-03	7.74E-01	95
Marine eutrophication	kg N eq	6.70E-04	89.11	2.48E-05	2.76E+00	14
Photochemical oxidation	kg NMVOC eq	3.16E-04	7.44	4.24E-05	8.28E-01	34
Freshwater eutrophication	kg P eq	8.21E-05	4.32	1.93E-06	1.50E-02	55
Particulate matter	kg PM2.5 eq	4.30E-05	2.41	1.04E-05	2.07E-04	27
Resource depletion	kg Sb eq	1.63E-05	29	1.89E-08	1.79E-04	46
Water depletion	m3 water	2.03E-02	4.29	8.68E-03	9.92E-01	15
Terrestrial eutrophication	mol N eq	7.25E-04	1.60	3.51E-04	1.12E-03	5
Acidification	molc H+ eq	4.10E-04	2.67	4.65E-05	3.76E-03	45

2.3.4. 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 plotted in Figure 2-6. The heterogeneity, however, is quite large and we cannot conclude that there is a significant effect overall. Heterogeneity can be attributed to the differences in materials, manufacturing processes or efficiencies of each technology type, but it could also be attributed to modelling differences that were not sufficiently corrected via the harmonization procedure.

We further sub-grouped the data by cell-conversion efficiency and disaggregated by sub-technology types (see Appendix Figure A.1-2). The results did not find a significant reduction in climate change impacts for groups with higher cell-conversion efficiencies

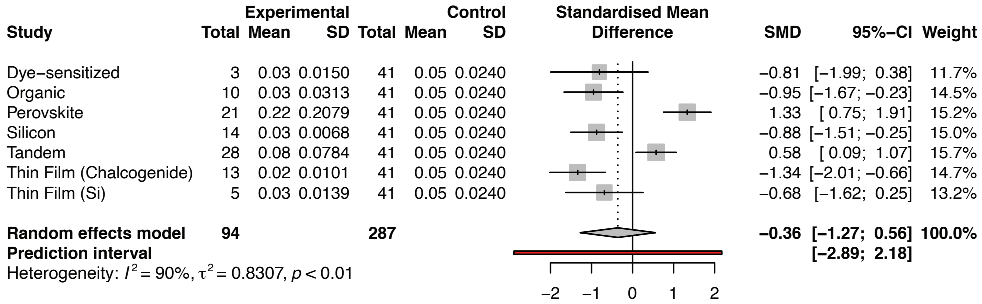

Figure 2-6 Random effects model results for climate change impact.

measured using SMD. The sub-grouping did not reduce the inherent heterogeneity of the data either. The results may suggest that either additional underlying factors (e.g., material choice, manufacturing processes, cost) are better suited than conversion efficiency to represent the relationship between technological enhancements and climate change impacts, or that the strive for reduced efficiency is not necessarily 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 the current study.

2.3.5. Contribution and hotspots analysis

2.3.5.1. 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., OPV requires encapsulation, perovskites are deposited on a transparent conductive oxide, etc.). Figure 2-7 shows the average contributions of the modules to each impact category for each PV technology. It can be seen that for perovskites and tandem technologies, the main contributions come from the cell, rather than from the panel and balance of system components.

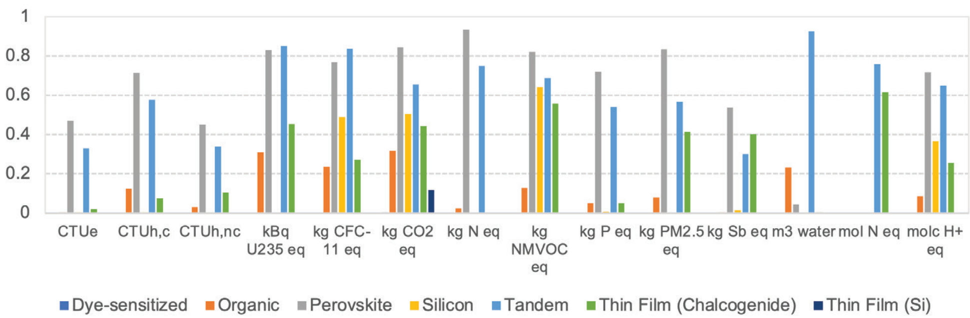

Figure 2-7 Average relative contributions of PV cells as compared to the corresponding PV system.

2.3.5.2. *From cells to panels*

Based on the 2015 inventory data from IEA PVPS[27], 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, aluminium 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 aluminium highly benefit from these avoided emissions in certain installations. Examples of these are roll-to-roll manufactured OPV, perovskites, dye-sensitized cells and thin film chalcogenides. This is an important outcome, since it implies that technologically enhanced PV cells have a good opportunity to offset environmental trade-offs if the new cell design favours less materials-intensive panels. The need for less panel materials can result from lighter cells allowing lamination or lighter panelling, and/or from higher cell efficiencies requiring less panel area per kWh.

2.3.5.3. *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, cancer effects, and 18% to climate change. Here the key contributions come from aluminium and copper, where aluminium from the mounting system represents 87% of the climate change contribution and copper from the electric installation 97% of the contribution to freshwater ecotoxicity.

2.3.5.4. *Hotspots in the emerging PV landscape*

Figure 2-8 presents a radar plot with relative impacts of the different types of PV cells, where 100% corresponds to the impact score for a reference single-Si roof-mounted system as modelled in ecoinvent 3.4[26]. For each type of PV cell, we have used the geometric mean impact score, following the indications of section 2.3.3. Perovskites dominate the plot and exceed the reference single-Si system by factors of 2 and more in 4 impact categories. These potentially important hotspots are summarized in Table 2-3, 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.

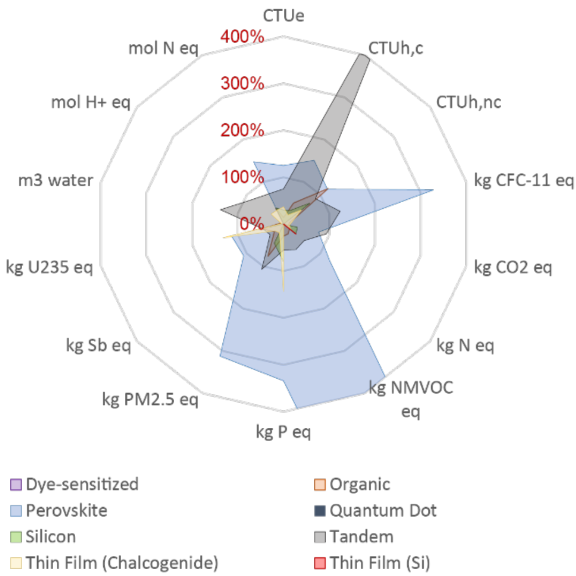

Figure 2-8 Relative ILCD impact scores for different PV technologies, compared to a reference single-Si roof-mounted PV system as modelled in ecoinvent v3.4 (=100%). The plot is truncated at 400% for visualization purposes.

Table 2-3 Key potential environmental hotspots in emerging PV technologies, compared to a reference single-Si roof-mounted PV system.

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

2.4. 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 future evolution of immature technologies, and the wide array of modelling choices across LCA studies which can lead to large variabilities, even in 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.[36] Both frameworks are complementary and necessary.[12,37] We believe future studies incorporating risk assessment results into a meta analyses framework like the one developed in this study could provide a comprehensive and valuable tool for guiding research and policy in the PV sector.

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