Quantifying the cost of leaving the Paris Agreement via the integration of life cycle assessment, energy systems modeling and monetization

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Abstract

Current energy systems models focus on cost minimization with a bound on some greenhouse gas emissions. This limited environmental scope can lead to mixes that are not consistent with our sustainable development. To circumvent this limitation, we here make use of the concept of monetization and life cycle assessment to quantify the indirect costs of electricity generation in the design of energy systems. Applying our approach to the United States, we found that the indirect costs of electricity generation could be reduced by as much as 63% by meeting the Paris Agreement. Consequently, the total opportunity cost (i.e., direct and indirect costs) of withdrawing from the Paris Agreement and continuing with the current mix would be as high as 1103 ± 206 billion USD_{2013} in 2030 (i.e., 6% of the United States gross domestic product in 2017). By optimizing the direct and indirect cost of electricity generation concurrently, we found an optimal ecological solution that attains total economic savings compared to the Paris Agreement mix of as much as 373 ± 164 billion USD_{2013} in 2030. Our work highlights the need to extend the environmental policies that govern energy systems beyond the direct greenhouse emissions to consider other critical environmental criteria.

Keywords

Consequential life cycle assessment; Energy systems modeling; Externalities; Monetization; Paris Agreement; Sustainability

Highlights

- We incorporate life cycle impacts to energy systems models via monetization.
- The cost of leaving the Paris Agreement for the US is 1103 billion USD_{2013} in 2030.

- Further economic savings could be realized by minimizing life cycle impacts.
- Wind onshore is critical for minimizing all environmental impacts concurrently.
- The Paris Agreement could induce burden-shifting between sustainability criteria.

1. Introduction

The Paris Agreement encouraged countries to submit pledges to curb Greenhouse Gas (GHG) emissions in an attempt to mitigate climate change [1]. Unfortunately, the Trump administration recently announced the United States (US) withdrawal from its commitments to the Paris Agreement [2], an action that could potentially trigger an international domino effect [3] highly detrimental to our planet [4].

The power sector, in particular, is key when designing environmental policies due to its high intensity of GHG emissions compared to other economic sectors [5]. The role of the power sector in climate change mitigation will become even more crucial in the future, as the already high electricity demand of sectors, such as the industrial, residential, commercial and transportation, will likely increase further [6]. Therefore, reducing the carbon footprint of the power sector through the adoption of cleaner technologies would have a direct and strong impact on reducing the total carbon footprint of the economy.

The complexity of the power sector is remarkable, given the wide range of engineering and reliability constraints governing its behavior [7]. Consequently, adding environmental constraints on top of the already complex setup of the power sector poses further challenges to policymakers; in this context, it is of utmost importance to find pathways to meet our growing demand for electricity without risking the grid reliability and the Earth's ecological capacity [8].

To simplify the simultaneous assessment of economic and environmental concerns when optimizing energy systems, we here introduce a modeling framework that quantifies their indirect costs (i.e., externalities) by monetizing life cycle impacts and explicitly includes them in their optimal design. By translating environmental impacts into monetary terms, policymakers shall become aware of the indirect costs of polluting our environment and the associated economic implications of environmental policies such as the Paris Agreement. Though we focus on the power sector, our proposed framework could be easily implemented in others to highlight the economic benefits of complying with environmental policies, thereby keeping global momentum towards our sustainable development.

We apply our method to the US in order to quantify the economic opportunity cost of leaving the US Intended Nationally Determined Contribution (INDC) under the Paris Agreement 2 ˚C target

[9]. Given are a set of engineering constraints, electricity demand in 2030, Levelized Cost of Electricity (LCOE) and environmental performance of each electricity technology and state. The goal of the analysis is to find the optimal energy systems design such that the total cost, including externalities quantified using monetization factors, are minimized. Decisions to be made include the selection of the best technologies to be deployed for electricity generation, their location across the US, their capacities and the electricity flows between states to cover the corresponding electricity demand.

We, therefore, present here a methodological framework for energy systems design where life cycle indicators are directly included in the objective function of Energy Systems Models (ESMs) via monetization to design an energy mix that accounts for several sustainability criteria concurrently. We use the developed framework to demonstrate for the first time the real value of the Paris Agreement, often underestimated in many studies. Hence, the main novelties of this work include:

- The incorporation of the life cycle impacts of US electricity technologies in an ESM.
- The monetization of life cycle indicators in an ESM to design an energy mix that minimizes both the indirect costs of life cycle impacts and the direct cost of electricity generation.
- The quantification of the full direct and indirect economic savings that could be potentially attained by implementing the Paris Agreement in the US.

2. Background

This section reviews the main tools available to assess the implications of environmental policies, such as the Paris Agreement, with a special focus on Life Cycle Assessment (LCA), ESMs and monetization methods. We shall make use of them to carry out the analyses described later in the article.

2.1. Life cycle assessment

LCA is a systematic way of assessing the environmental performance of a product or service from cradle to grave that has gained wide acceptance in recent years. The standard LCA, described in the ISO 14040 [10], comprises four steps: (i) goal and scope definition, (ii) life cycle inventory analysis, (iii) life cycle impact assessment and (iv) interpretation. Two types of LCA can be applied to assess the performance of the power sector: attributional and consequential [11]. The attributional LCA quantifies the environmental footprint of a process or a technology at a given point in time [11]. The consequential LCA, in contrast, attempts to quantify the involved dynamics in intermediate processes to produce one functional unit in response to different policies or constraints [12]. For example, given an electricity mix of two technologies (e.g., coal and natural gas), attributional LCA would measure the environmental footprint involved in producing one functional unit (i.e., one kWh) with those mixes; meanwhile, consequential LCA would consider changes in the mixes and their associated impact as a result of a new technical and/or environmental constraint.

In the context of power sector, attributional LCA was mainly used to compare the environmental performance of different electricity technologies across several categories. As an example, motivated by the need to achieve negative emissions beyond 2050 [13], attributional LCA was applied to Bio-energy with Carbon Capture and Storage (BECCS) [14]. It was found that the additional biomass required to offset the efficiency losses due to CCS could increase particulate matter formation, terrestrial acidification, fossil depletion and human toxicity potentials [14]. Furthermore, attributional LCA showed also that replacing coal fuel with bioenergy reduces the damage to human health and ecosystem quality at the expense of higher respiratory effects [15]. The attributional LCA, however, neglects the intrinsic dynamics and interdependencies of intermediate processes, which could potentially underestimate the footprint associated with the functional unit.

2.2. Energy systems modeling

In the past decades, ESMs have emerged as a powerful framework to design energy systems and support policies based on sound quantitative evidence. An ESM is a mathematical model that seeks the optimal values of a set of decision variables, mostly related to technologies selection and their capacities, in terms of a predefined objective, often cost, and subject to a set of constraints describing the energy systems to be designed.

ESMs can be differentiated according to their temporal and spatial resolution. Concerning the temporal resolution, ESMs can be categorized based on their time-step duration. Some ESMs focus on a sub-yearly time-step duration (e.g., weekly, daily or hourly) to address the intermittences associated with some renewable sources [16], as in EnergyPLAN [17] and H_2RES [18]. Other ESMs consider a yearly time-step duration to design long-term storylines while reducing the computational burden [16], like INFORSE [19] and LEAP [20]. Therefore, the nature of the research question at hand dictates the appropriate ESM's time-step duration.

Different spatial resolutions (e.g., global, national or local) can also be considered [16]. Lower spatial resolutions lead to lower computational burdens and data requirements [7]. Unfortunately, the modeling of the intermittences of renewable energy often requires finer spatial resolutions, since generation potentials and cost can vary greatly across regions [7]. Connolly et al. [16] and Pfenninger et al. [7] provide a comprehensive review on the differences between ESMs.

ESMs have often neglected the environmental side of the problem. Only recently, they started to account for environmental impacts, very often computing direct emissions instead of life cycle emissions and focusing only on GHG emissions. This narrow scope may lead to mixes that shift environmental burdens to other categories [8], as evidenced in biomass energy sources that reduce

GHG emissions but consume more water and land, thereby risking species diversity and water scarcity [21]. The recent trend in the literature is, therefore, to incorporate life cycle indicators into ESMs as discussed in the next subsection.

2.3. Consequential life cycle assessment via energy systems models

Life cycle indicators can be incorporated into ESMs to evaluate the life cycle environmental footprint associated with producing a functional unit resulting from different environmental policies. This allows to carry out a consequential LCA where the effect of a policy is systematically analyzed using optimization tools. To this end, an ESM model is developed where LCA principles are explicitly included by making the link between electricity technologies and their associated impacts. This ESM is then solved with constraints reflecting policies whose environmental implications one wishes to understand. The advantage of this approach is that decisions are evaluated considering a wide range of impacts quantified on a life cycle basis, which provides full visibility on the environmental implications of regulations. Indeed, when life cycle emissions are accounted for, the seemingly good environmental performance of some renewable technologies could be questioned [22]. Moreover, when LCA principles are considered hand-in-hand with energy security, mixes that rely on reliable renewables are found optimal [23], yet this could affect finite materials that need to be preserved [24].

The integration of Life Cycle Impact Assessment (LCIA) into ESMs can be handled using multi-objective optimization. Unfortunately, the multi-objective problem becomes more complex as we increase the number of objectives. Hence, to circumvent this issue Rauner and Budzinski aggregated impacts into a single environmental metric that was optimized against the cost [25]. Aggregation often relies on subjective weights on which no general agreement has been reached yet. Furthermore, aggregation provides metrics that cannot be readily used in single-objective ESMs, since the aggregated metric and the LCOE are expressed in different units.

2.4. Monetization

The concept of monetization emerged to translate environmental burdens into a consistent common monetary term. While attempts were made to monetize some environmental criteria, these typically focused on a handful of direct pollutants (e.g., NO_x and $PM_{2.5}$), thereby neglecting other important environmental problems [26].

Life cycle indicators summarize thousands of life cycle inventories into a handful of environmental categories. For instance, life cycle endpoint indicators (i.e., damage to human health, ecosystem diversity and resource availability) were designed following comprehensive ecological methodologies (e.g., the ReCiPe 2008 framework [27]) covering thousands of environmental burdens.

Hence, monetizing life cycle indicators in the context of ESMs, an integration never attempted before, could potentially lead to very insightful results and valuable advice to policymakers.

3. Methodology

3.1. The emissions reduction cooperation model with life cycle impact assessment

To quantify the opportunity cost of leaving the Paris Agreement, we improve an existing ESM known as the Emissions Reduction Cooperation Model (ERCOM) [28] by incorporating life cycle indicators into its formulation. ERCOM employs yearly time-step duration, found suitable for the nature of our research question focused on analyzing long-term storylines without increasing the computational burden [16]. ERCOM minimizes the LCOE while achieving a particular target on emissions. Though such an emission target could be imposed at the state or national level, for simplicity we consider a national target that should be met by coordinating individual efforts at the state level (i.e., assuming full cooperation between states). While a national target is enforced, our model considers state-specific demand and technical constraints (e.g., generation potential and capacity factor), assuming that states are interconnected via transmission lines; this accounts for the variability of the economic and technical competitiveness of renewables across regions [7]. The complete mathematical formulation is described in Appendices A and B, while data and assumptions are summarized in Appendix C.

From here onwards, we refer to the improved ESM, which incorporates life cycle endpoint indicators for each electricity technology and state, as ERCOM-LCIA, where LCIA denotes life cycle impact assessment. We also monetize each endpoint indicator and modify the original objective function to include two cost types concurrently: (i) LCOE (direct costs) and (ii) the cost of the life cycle endpoint indicators (indirect costs, i.e., externalities); the latter corresponds to the summation of the monetized values of the three life cycle endpoint indicators. In essence, the objective function in ERCOM-LCIA weighs the different cost types subject to meeting engineering and reliability constraints. Moreover, we include BECCS in ERCOM-LCIA's set of technologies, which was not considered in the first version we developed and whose LCOE was retrieved from [8]. In essence, we assume that the future LCOE of BECCS will follow the trajectory of biomass power plants published by the US Energy Information Administration (EIA) [29], [30]. Data sources for the life cycle indicators of each technology alongside the employed monetization values are discussed in the next subsection.

The model can be described in compact form as follows:

$$\min_{x,LCAI} \left(\sum_{i} \sum_{j} c_{i,j}^{T} x_{i,j} + \sum_{e} LCAI_e M_e^{2030} \right) \quad (1)$$

s.t.

$$\sum_i \sum_j GWP100_{i,j} x_{i,j} \leq TARG \tag{2}$$

$$LCAI_e = \sum_i \sum_j EB_{i,j,e} x_{i,j} \qquad \forall e \tag{3}$$

$$A_{i,j} x_{i,j} \leq a_{i,j} \qquad \forall i,j \tag{4}$$

$$x, LCAI \in \mathbb{R} \tag{5}$$

where $c_{i,j}^T$ is the LCOE of technology i in state j, $x_{i,j}$ is a variable denoting the amount of electricity generated by technology i in state j, $LCAI_e$ is the total impact of the life cycle endpoint indicator e, M_e^{2030} is the monetary value for the life cycle endpoint indicator e in 2030, $GWP100_{i,j}$ is the 100-year global warming potential for each unit of electricity supplied by technology i in state j, $TARG$ is the emission target in line with the US INDC governed by the Paris Agreement, $EB_{i,j,e}$ is the environmental burden factor connected to the life cycle endpoint indicator e for each unit of electricity generated by technology i in state j, $A_{i,j}$ is the engineering technical matrix of constraints imposed on technology i in state j, $a_{i,j}$ is the associated upper bound vector for every engineering constraint (e.g., grid reliability) imposed on technology i in state j and $\mathbb{R}$ is the set of real numbers to which variables $x_{i,j}$ and $LCAI_e$ belong.

Note that several uncertainties affect the computation of the life cycle indicators of each electricity technology and state. Hence, as discussed in detail next, we here perform a full uncertainty analysis that covers the life cycle indicators as well as the monetization values for human health and ecosystem diversity. Appendix D shows the uncertainty analysis approach. Following Weidema and Wesnaes [31], we assume a lognormal distribution for the life cycle indicators of each electricity technology and state; an assumption that is often used in the literature [32]. The parameters needed to calculate the standard deviation for each life cycle indicator of each electricity technology and state are obtained via the 'Pedigree matrix' [31] as shown in the SimaPro manual [33]. Concerning the monetization values, no probability distribution type is provided in the original reference [34]; consequently, without loss of generality we assume they follow a uniform distribution. The bounds on the uniform distribution for each monetization value are shown in the next subsection as reported by Weidema [34].

3.2. Life cycle assessment

LCA is typically used to thoroughly quantify the environmental performance of products and services by considering their complete life cycle, i.e., from cradle to grave [10]. The LCA application comprises four main stages that are described next in detail in the context of ERCOM-LCIA.

3.2.1. Step 1: Goal and scope

This step defines the goal of the analysis, system boundaries, impact assessment method and functional unit. The goal of the analysis is to assess the LCA of energy systems resulting from different environmental policies. We employ the consequential LCA approach, rather than the attributional one, because we are interested in identifying energy mixes and their associated life cycle impacts when different environmental policies are enforced [12].

The system boundaries include all the services and processes in the life cycle of electricity generation in the US. The ReCiPe 2008 is the impact assessment method of choice [27]; it summarizes the performance of a system using three endpoint indicators: human health, ecosystem diversity and resource availability. The functional unit used is one kWh of electricity to the US energy systems.

3.2.2. Step 2: Inventory assessment

The second step is to quantify the inputs and outputs of mass and energy involved in generating one unit of electricity. Thereafter, all the inputs and outputs are converted into environmental burdens including feedstocks, emissions to air, soil and water as well as wastes. In the context of this paper, these environmental burdens, resulting from the generation of electricity by each technology and state, are quantified by specific mathematical variables defined in ERCOM-LCIA. The life cycle inventory entries for most power technologies were obtained from the ecoinvent database v3.4 [35], while entries for those technologies missing in LCA repositories, namely coal with CCS [36], solar thermal [37], natural gas with CCS [38] and BECCS [14], were obtained from the literature.

3.2.3. Step 3: Impact assessment and translation via monetization

Human health is typically characterized in the LCA modeling framework using the unit of Disability-Adjusted Life Years (DALYs) [39]. DALYs account for the impact of a given process on both life years lost and disabled. It was estimated that the severity that underscores the human health endpoint indicator leads to a monetary value in 1995 of 116,124 ± 18,831 USD_{2013} per DALY [34].

Ecosystems are convoluted and, hence, difficult to model. Typically, ecosystem diversity is measured by the abruption of anthropogenic activities caused by a given process [27]. Such abruption of anthropogenic activities can lead to the loss of species and genes [40]. The ReCiPe framework measures the ecosystem diversity at the species level expressed in species.yr [27]. According to the literature, the monetary value of the ecosystem endpoint indicator in 1995 is 14,939,241 USD_{2013} per species.yr (with an uncertainty range from 3,734,810 to 37,348,102 USD_{2013} per species.yr) [34].

The LCA modeling framework also considers the risk of depleting resources for future generations [27]. In essence, the lack of resource availability leads to demand and market price fluctuations, typically driving the price up and, hence, adversely affecting the maintenance and expansion of our environment. The economic interpretation of the resource availability indicator is the marginal increase in costs due to resource extraction [27]. This indicator is converted from USD_{2000} to USD_{2013} [41] and then used directly in the objective function, Eq. (1).

3.2.4. Step 4: Interpretation of results

To interpret the results, we use adjusted monetization values using benefit transfer (as described in subsection 3.3), which allow quantifying, in economic terms, the externalities associated with each life cycle impact. The concept of monetization avoids the definition of subjective weights, which are replaced by monetization factors quantifying the exact economic value of every life cycle impact. Hence, no subjectivity is introduced in the decision-making process, while simplifying the analysis and allowing for the simultaneous assessment of many LCA metrics.

3.3. Monetization values adjustment via benefit transfer

Monetization values refer to a given year and need to be adjusted for other years in order to account for the expected income growth. For instance, the monetary value for human health indicator was obtained from the budget constraint in 1995 to reflect the maximum amount that could be incurred for an additional life year in line with the annual income [42]. Similarly, the monetary value for the ecosystem diversity reflects the willingness to pay to preserve species diversity in line with the annual income [42]. Monetization values are, therefore, adjusted to account for income growth in the future by using the concept of benefit transfer [43] as follows:

$$M_e^{2030} = M_e^{1995}\left(\frac{GDP^{2030}}{GDP^{1995}}\right)^{\varepsilon_e} \qquad \forall e \in \{HH, ED\} \tag{6}$$

where M_e^{1995} is the monetary value for the life cycle endpoint indicator $e \in \{HH, ED\}$ in 1995, GDP^{2030} is the US Gross Domestic Product (GDP) per capita based on Purchasing Power Parity (PPP) in 2030, GDP^{1995} is the US GDP per capita based on PPP in 1995, ε_e is the income elasticity of willingness-to-pay for each endpoint indicator $e \in \{HH, ED\}$, where HH is the human health endpoint indicator and ED is the ecosystem diversity endpoint indicator.

The income elasticities of willingness-to-pay for human health [44] and ecosystem diversity [45] indicators are 1.10 and 0.38, respectively. These income elasticities show our willingness to spend higher proportions of our income increase to preserve our health compared to ecosystem diversity.

The GDP per capita based on PPP in 1995 was obtained from the World Bank Group database [46], while forecasts were used for the one in 2030 [47].

By adjusting the reported monetization values in subsection 3.2.3 via Eq. (6) to reflect the expected income growth in 2030, we obtain values of 200,018 ± 32,435 USD_{2013} per DALY and 18,026,286 USD_{2013} per species.yr – with an uncertainty range between 4,506,572 and 45,065,715 USD_{2013} per species.yr.

4. Case Study: Quantifying the cost of leaving the Paris Agreement

To demonstrate the value of incorporating all life cycle indicators in the objective function of ESMs via monetization, we evaluate three solutions (Table 1). The 'Business as Usual' (BAU) energy mix represents the default development mix in 2030 if the technological shares in 2012 remained unaltered until then. The 'Paris Agreement' mix represents the least cost solution that meets the US INDC under the Paris Agreement 2 ˚C target in 2030. Lastly, the 'ecological' energy mix minimizes both the direct (LCOE) and indirect (monetized life cycle endpoint indicators) costs concurrently in 2030. For the BAU solution (S1), no optimization is required. The Paris Agreement solution (S2) is obtained with ERCOM-LCIA by omitting Eq. (3) and replacing the objective function, Eq. (1), with Eq. (7) to consider only the LCOE in the objective function while neglecting the indirect costs (i.e., monetized endpoint indicators).

$$\min_{x}\left(\sum_{i}\sum_{j} c_{i,j}^{T} x_{i,j}\right) \tag{7}$$

The ecological solution, in contrast, is given by ERCOM-LCIA when Eq. (2) is omitted, i.e., the model comprises Eq. (1), Eq. (3), Eq. (4) and Eq. (5). Note that the ecological solution might not emerge as optimal in terms of the LCOE only; however, it is the optimal alternative when both cost types are considered concurrently and the externalities are appropriately considered in the objective function (Eq. (1)). Here, all the considered solutions are assessed via long-term consequential LCA. This approach considers a certain degree of substitutability between electricity technologies in 2030 resulting from the need to adapt to different policies, as highlighted in Table 1.

Table 1
Solutions definition, objective functions and constraints.

Solution title	Solution label	Description	Objective function	Constraints
Business as usual	S1	The 2012 energy mix in 2030 (i.e., the share of each technology in 2012 is fixed and the demand is then projected to 2030)	NA	NA

Paris Agreement	S2	The least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement 2 ˚C target	Levelized cost of electricity, Eq. (7)	Eq. (2), Eq. (4) and Eq. (5)
Ecological	S3	The energy mix in 2030 that minimizes the levelized cost of electricity and monetized life cycle endpoint indicators concurrently	Levelized cost of electricity and monetized life cycle endpoint indicators, Eq. (1)	Eq. (3), Eq. (4) and Eq. (5)

Monetizing externalities in the BAU solution (S1) allows quantifying the indirect costs of the damage to human health, ecosystem diversity and resource availability that would be incurred if the US commitment to the Paris Agreement was withdrawn. The Paris Agreement solution (S2), on the other hand, provides the total savings that would be gained by enforcing the Paris Agreement and implementing the corresponding energy mix. Finally, the ecological solution (S3) sheds light on whether more stringent and holistic environmental policies, compared to the Paris Agreement, would lead to additional indirect economic savings. The results of the uncertainty analysis are shown as error bars on each figure, where each error bar represents one standard deviation.

The model contains 13,104 variables and 8,925 constraints. It was implemented in GAMS 25.0.2 and solved with GUROBI 7.5.2 on Intel®Core™ i7-6700 processor operating at 3.40 GHz, taking around 0.18 CPU seconds.

5. Results and discussion

5.1. Implications for the energy mix

We start by comparing the three energy mixes that would emerge in the different solutions (Table 1). The BAU energy mix (S1) is dominated by fossil fuel power plants (38% coal and 31% natural gas) together with nuclear power plants, with a share in the BAU energy mix of around one-fifth (Fig. 1).

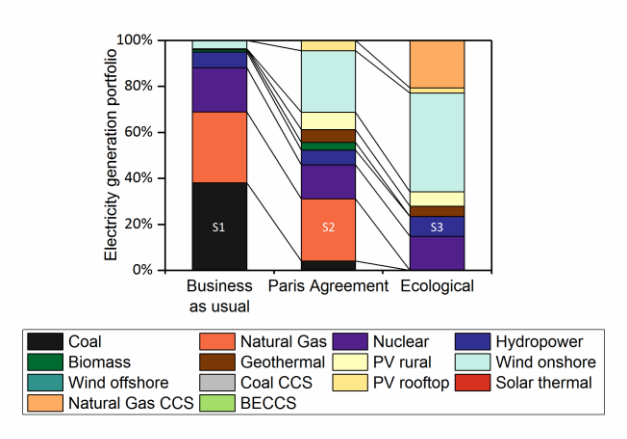


Fig. 1. United States electricity supply portfolio. The business as usual energy mix, solution S1, (column on the left) denotes the 2012 energy mix in the year 2030. The Paris Agreement mix, solution S2, (column on the center) denotes the least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement. The ecological mix, solution S3, (column on the right) denotes the energy mix in 2030 that minimizes both the levelized cost of electricity and monetized life cycle endpoint indicators concurrently. The labeling of solutions is provided in Table 1.

The Paris Agreement solution (S2) pushes the energy mix towards renewables (27% wind onshore and 12% Photovoltaic (PV)). Nevertheless, coal, natural gas and nuclear power plants are still deployed with shares of 4, 27 and 15%, respectively.

Wind onshore plants represent 43% of the ecological energy mix (S3), while nuclear and natural gas with CCS power plants represent 15 and 21%, respectively; the latter technologies are deployed to alleviate the reliability gap created by the intermittent wind onshore plants.

We next study in detail the environmental implications of these mixes considering the associated life cycle endpoint indicators, analyzing each environmental category at a time.

5.2. Damage to human health

The BAU energy mix (S1) shows the highest damage to human health, mainly due to coal power plants, which contribute to 79% of the total damage to human health (Fig. 2). They are followed by natural gas power plants, contributing to 19% of the total impact in this category.

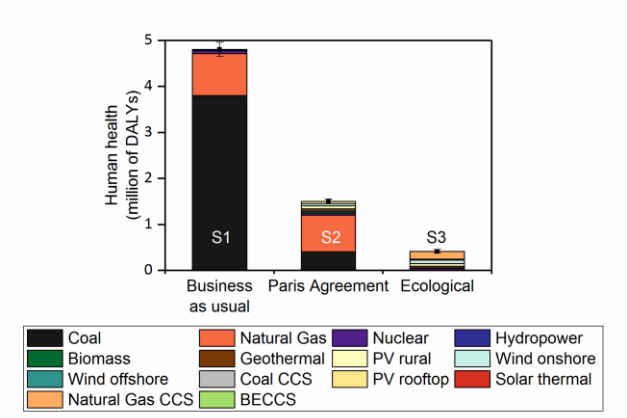


Fig. 2. The human health endpoint indicator of the United States electricity generation portfolio and its technological contribution breakdown. The business as usual energy mix, solution S1, (column on the left) denotes the 2012 energy mix in the year 2030. The Paris Agreement mix, solution S2, (column on the center) denotes the least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement. The ecological mix, solution S3, (column on the right) denotes the energy mix in 2030 that minimizes both the levelized cost of electricity and monetized life cycle endpoint indicators concurrently. Each error bar denotes one standard deviation. The labeling of solutions is provided in Table 1.

The extensive deployment of renewables in the Paris Agreement mix (S2) reduces the damage to human health by two-thirds compared to the BAU energy mix (S1). Nonetheless, the maintained natural gas power plants contribute to 53% of this endpoint value. The remaining coal power plants cause 27% of this damage despite their small share (i.e., 4%) in the Paris Agreement energy mix.

The ecological mix (S3) attains the minimum damage to human health across all the mixes; 91% less than the BAU energy mix (S1) and 73% less than the Paris Agreement mix (S2). This is due to the extensive deployment of wind onshore plants, whose unitary damage in this endpoint indicator is rather low [35]. Considering the indirect costs in the objective functions of ESMs, as in solution S3,

encourages the investment in electricity technologies that have relatively lower damage to human health, such as wind onshore and natural gas with CCS plants, in contrast to other solutions. Although natural gas with CCS power plants represent 21% of the ecological energy mix, they contribute to 40% of the damage to human health. Furthermore, ground-mounted PV in rural areas contribute to 14% of the damage to human health, despite a much smaller share (i.e., 6%) in the ecological energy mix; this is mainly due to the PV cell production phase [48].

5.3. Damage to ecosystem diversity

The BAU energy mix (S1) incurs the highest damage to ecosystem diversity, mainly due to the massive deployment of coal power plants that contribute to 73% of the damage to ecosystem diversity (Fig. 3); this is largely attributed to the coal mining phase [35]. Therefore, coal power plants are the main driver behind the species losses in the BAU energy mix. At a lesser extent, natural gas power plants in the BAU energy mix cause around one-fifth of the damage to ecosystem diversity, largely attributed to the natural gas production phase [35]. Furthermore, biomass power plants exert 5% of the total damage to ecosystem diversity despite their negligible share (i.e., 1%) in the BAU energy mix.

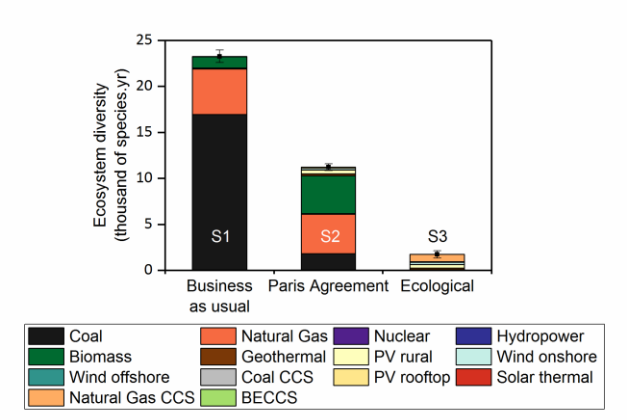


Fig. 3. The ecosystem diversity endpoint indicator of the United States electricity generation portfolio and its technological contribution breakdown. The business as usual energy mix, solution S1, (column on the left) denotes the 2012 energy mix in the year 2030. The Paris Agreement mix, solution S2, (column on the center) denotes the least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement. The ecological mix, solution S3, (column on the right) denotes the energy mix in 2030 that minimizes both the levelized cost of electricity and monetized life cycle endpoint indicators concurrently. Each error bar denotes one standard deviation. The labeling of solutions is provided in Table 1.

The Paris Agreement energy mix (S2) reduces the ecosystem endpoint indicator by 52% compared to the BAU energy mix (S1). Despite the small share of biomass power plants (i.e., 3%) in the Paris Agreement mix, they contribute to 37% of the damage to ecosystem diversity; this is due to the use they make of land types vulnerable to species loss [49]. In the same context, the small share of coal power plants (i.e., 4%) in the Paris Agreement mix still exerts 16% of the damage to ecosystem diversity. Furthermore, natural gas power plants contribute to 38% of the damage to ecosystem diversity in solution S2.

The ecological solution (S3) reduces the damage to ecosystem diversity by 93% compared to the BAU solution (S1) and 85% compared to the Paris Agreement solution (S2); this is mainly due to the extensive deployment of wind onshore power plants with low impact on ecosystem diversity. Some electricity technologies with relatively low cost and GHG emissions emerge as optimal in the Paris Agreement solution, yet they are displaced in the ecological solution due to their noticeable damage to ecosystem diversity. This happens, for instance, with biomass power plants. This insight further underscores the need to incorporate the monetized endpoint indicators in the objective function of ESMs. Natural gas with CCS power plants cause 45% of the damage to ecosystem diversity in solution S3, which is mostly originated in the natural gas production phase [38]. Furthermore, the installation of ground-mounted PV in rural areas affect the species diversity of such lands [48], thereby, contributing to 22% of the damage to ecosystem diversity despite their small share (i.e., 6%) in the ecological mix.

5.4. Damage to resource availability

Fig. 4 shows the performance of each solution in the resource availability endpoint indicator. Similar to the other life cycle endpoint indicators, the BAU energy mix (S1) shows the highest depletion of resources, mainly due to the deployment of coal and natural gas power plants; altogether combined, they cause 99% of the damage to the resource availability endpoint indicator.

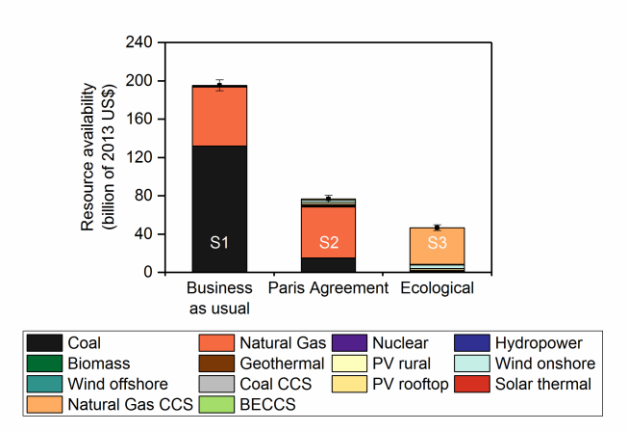


Fig. 4. The resource availability endpoint indicator of the United States electricity generation portfolio and its technological contribution breakdown. The business as usual energy mix, solution S1, (column on the left) denotes the 2012 energy mix in the year 2030. The Paris Agreement mix, solution S2, (column on the center) denotes the least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement. The ecological mix, solution S3, (column on the right) denotes the energy mix in 2030 that minimizes both the levelized cost of electricity and monetized life cycle endpoint indicators concurrently. Each error bar denotes one standard deviation. The labeling of solutions is provided in Table 1.

The extensive deployment of renewable technologies in the Paris Agreement energy mix (S2) reduces the damage to resource availability by 61% compared to the BAU energy mix (S1). Natural gas power plants cause 69% of the damage to resource availability in the Paris Agreement solution.

Despite the small share of coal power plants in the Paris Agreement mix (4%), they contribute to 20% of the damage to resource availability.

The ecological energy mix (S3) reduces the total damage to resource availability by 76% compared to the BAU solution (S1) and 39% compared to the Paris Agreement solution (S2). Monetizing and incorporating endpoint indicators in the objective function of ESMs, therefore, promote the preservation of finite fossil fuels (e.g., coal and natural gas) by deploying wind onshore plants and other renewable technologies. In contrast, the Paris Agreement solution only invests in electricity technologies exhibiting low cost and GHG emissions. Natural gas with CCS power plants are responsible for 82% of the damage to resource availability in the ecological energy mix, which again underscores how sensitive this indicator is to the deployment of fossil fuel power plants.

5.5. Economic implications of leaving the Paris Agreement

Fig. 5 shows the direct cost of each energy mix alongside the monetized life cycle impacts. The BAU energy mix (S1) has the largest monetized life cycle impacts compared to other mixes. For instance, the cost of externalities in the BAU mix is 344% higher than its direct cost (i.e., LCOE). More precisely, the costs incurred due to the damage caused to human health, ecosystem diversity and resource availability indicators represent 50, 22 and 10% of the BAU energy mix total cost, respectively; this highlights the serious pitfalls of neglecting the cost of externalities when designing policies for the power sector.

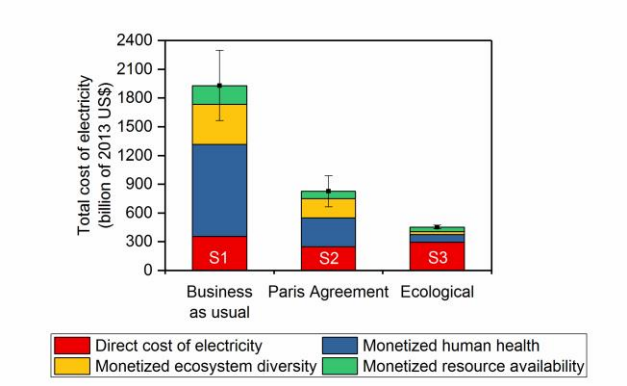


Fig. 5. Total cost of electricity generation in the United States broken by the direct cost of electricity and monetized life cycle endpoint indicators (i.e., indirect costs). The business as usual energy mix, solution S1, (column on the left) denotes the 2012 energy mix in the year 2030. The Paris Agreement mix, solution S2, (column on the center) denotes the least cost energy mix in 2030 that meets the United States commitment to the Paris Agreement. The ecological mix, solution S3, (column on the right) denotes the energy mix in 2030 that minimizes both the levelized cost of electricity and monetized life cycle endpoint indicators concurrently. Each error bar denotes one standard deviation. The labeling of solutions is provided in Table 1.

The Paris Agreement mix (S2) reduces the direct cost of electricity by 30% compared to the BAU energy mix due to the deployment of wind onshore plants with future lower LCOE than fossil fuel plants [29]. Furthermore, the extensive deployment of renewables in the Paris Agreement mix, at the

expense of fossil fuel power plants, reduces the monetized life cycle endpoint indicators by 63% compared to the BAU energy mix. Therefore, the estimated total opportunity cost (i.e., direct and indirect costs) of leaving the Paris Agreement is extremely high to the US, reaching around 1103 ± 206 billion USD_{2013} in 2030. This represents 6% of the US GDP in 2017 and an annual opportunity cost for each citizen in the US of 3387 ± 632 USD_{2013} if the US population in 2017 is considered.

The ecological mix (S3) reduces the direct cost of electricity and monetized endpoint indicators by 17 and 90% compared to the BAU mix (S1), respectively. While the deployment of wind onshore plants reduces both the direct costs and monetized endpoint indicators concurrently, other technologies, such as natural gas with CCS plants, only contribute to the savings in the latter. However, the large share of relatively expensive electricity technologies with low monetized endpoint indicators, such as natural gas with CCS plants, increases the direct cost of electricity in solution S3 by 18% compared to the Paris Agreement mix (S2). All in all, the competitive endpoint indicators of such relatively expensive technologies reduce the cost of externalities in solution S3 by 72% compared to solution S2 and, hence, offset the additional direct cost incurred. Consequently, such large mitigation in externalities makes the total cost (direct and indirect) in solution S3 less than solutions S1 and S2 by 77 and 45%, respectively. More precisely, the ecological solution introduces further economic savings of as much as 1476 ± 367 USD_{2013} compared to the BAU mix and of as much as 373 ± 164 USD_{2013} compared to the Paris Agreement mix. These savings with respect to the BAU and Paris Agreement mixes represent 8 and 2%, respectively, of the US GDP in 2017, translating into annual per capita savings of 4532 ± 1126 USD_{2013} per capita and 1145 ± 503 USD_{2013} per capita, respectively, when the US population in 2017 is considered.

Note that larger monetization values (Appendix E) would further reduce the damage to the life cycle endpoint indicators at the expense of increasing the LCOE of the energy mix (Fig. E.1).

6. Conclusions

Going beyond greenhouse gas emissions is critical to sustain our environment [50]. Consequently, improving the scope of energy systems models is a fundamental step to avoid unsustainable investments in the power sector. Our results demonstrate that the integration of life cycle impacts in energy systems models via monetization clearly shows the monetary value of current environmental policies to policymakers. For instance, the Paris Agreement energy mix shows lower damage to human health, ecosystem diversity and resource availability compared to the business as usual mix based mostly on coal power plants. This translates into economic and environmental savings introduced by the Paris Agreement of as much as 1103 ± 206 billion USD_{2013}; these are attained by primarily

displacing coal power plants in the business as usual mix with renewables, thereby exploiting the economic and environmental advantages of the latter.

We found that minimizing concurrently the levelized cost of electricity and monetized life cycle endpoint indicators can lead to significant savings in externalities. Following our proposed modeling framework, we identified a mix showing a lower total cost (i.e., direct and indirect costs) than both the Paris Agreement and business as usual solutions. The proposed mix, i.e., the ecological solution, increases the direct cost of electricity due to investments in more expensive technologies (e.g., natural gas with carbon capture and storage plants), yet this results in a better overall performance.

Wind onshore, natural gas with carbon capture and storage and nuclear plants seem critical to reducing the monetized life cycle damage to human health, ecosystem diversity and resource availability. Enlarging the scope of the analysis beyond greenhouse gas emissions enhances the assessment of electricity technologies from an environmental viewpoint, i.e., discarding mixes that through the lens of the Paris Agreement would be optimal but perform poorly in other environmental categories. This happens, for instance, when analyzing biomass power plants, which exert a noticeable impact on ecosystem diversity despite their low life cycle greenhouse gas emissions.

Given their competitive environmental and economic performance, wind onshore plants will likely play a key role in minimizing the wide range of environmental indicators concurrently. Nevertheless, they could suffer from intermittency, which could be offset with expensive energy storage facilities [51] that would worsen their economic performance and, hence, their competitiveness to investors [52]. Nevertheless, other solutions, such as smart energy systems, could aid the integration of intermittent renewables to the grid [53], thereby reduce the reliance on dispatchable bioenergy, found to exert noticeable damage to ecosystem diversity. To realize the full economic potential of smart energy systems in integrating intermittent renewables to the grid, however, energy systems models should be expanded beyond just electricity, i.e., taking a cross-sector approach [54].

Across all life cycle endpoint indicators, the proposed ecological mix shows significant environmental savings in contrast to the other mixes, including the Paris Agreement mix. This highlights the need to leave myopic environmental policies focused only on greenhouse gas emissions to incorporate other environmental criteria. Our proposed methodology facilitates such integration via monetization, thereby underpinning the design of comprehensive and more effective environmental policies.

Appendix A: Nomenclature

Indices

e	Life cycle endpoint indicators
i	Electricity technologies
j	States
k	Canadian regions

Sets

BT	Biomass and BECCS plants
CT	Coal and coal with CCS plants
ES	Ecosystem diversity endpoint indicator
HH	Human health endpoint indicator
IR	Intermittent technologies (i.e., PV rooftop and PV rural, wind onshore and offshore, solar thermal and hydropower)
NC_j	Canadian regions next to state j
NGT	Natural gas and natural gas with CCS plants
NU_j	States next to state j

Parameters

BUC	Backup share of dispatchable technologies that must be deployed for every unit of capacity from non-dispatchable technologies
$CAP_{i,j}^{CUR}$	Current installed capacity in 2012 of technology i in state j
$CF_{i,j}$	Capacity factor of technology i in state j
CO^{CAN}	Canadian import price of electricity
$CO_{i,j}^{CAP}$	Capital cost of technology i in state j
$CO_{i,j}^{FIX}$	Fixed portion of the operating cost of technology i in state j

$CO_{i,j}^{VAR}$	Variable portion of the operating cost of technology i in state j
CTB	Maximum share of demand that can be met by electricity imports from Canadian regions
DEM_j	Demand for electricity in state j
$DIST_{j,j'}$	Transmission distance between state j and state j'
$DISTCAN_{j,k}$	Transmission distance between state j and Canadian region k
DSF	Demand satisfaction factor
$EB_{i,j,e}$	Environmental burden factor connected to the life cycle endpoint indicator e for each unit of electricity generated by technology i in state j
$GEN_{i,j}^{POT}$	Electricity generation potential by technology i in state j
GEN_i^{POTGLO}	National electricity generation potential by technology i in state j
$GWP100_{i,j}$	100-year global warming potential of technology i in state j
H	Total number of hours in a given year, 8760 hours
M_e^{2030}	Adjusted monetization value to the year 2030 of life cycle endpoint indicator e
$TARG$	US pledged target in 2030 under the Paris Agreement
TLF	Losses due to electricity transmission, 0.62% for every 100 km

Continuous variables

$CAP_{i,j}^{BU}$	Installed capacity of backup technology i in state j
$CAP_{i,j}^{ST}$	Installed capacity of standard technology i in state j
$COST_j$	Total cost of electricity generation in state j
$COST_j^{CAN}$	Cost of electricity imports from Canadian regions to state j
$COST_j^{CAP}$	Capital cost of electricity generation in state j
$COST_j^{FIX}$	Fixed cost of electricity generation in state j
$COST^{TOT}$	Total cost of electricity

$COST_j^{VAR}$	Variable cost of electricity generation in state j
$GEN_{i,j}^{BU}$	Electricity generation by backup technology i in state j
$GEN_{i,j}^{ST}$	Electricity generation by standard technology i in state j
$LCAI_e$	Total impact of the life cycle endpoint indicator e
$TRD_{j,j'}^{DEST}$	Net electricity imports from state j' to state j
$TRD_{j,j'}^{LOSS}$	Electricity transmission losses due to imports from state j' to state j
$TRD_{j,j'}^{ORIG}$	Electricity exports from state j' to state j
$TRDCAN_{j,k}^{DEST}$	Electricity imports from Canadian region k to state j
$TRDCAN_{j,k}^{LOSS}$	Electricity transmission losses due to imports from Canadian region k to state j
$TRDCAN_{j,k}^{ORIG}$	Electricity exports from Canadian region k to state j

Appendix B: The emissions reduction cooperation model with life cycle impact assessment

This appendix provides a brief description of the mathematical formulations underpinning ERCOM-LCIA. A detailed description of the data used in the original model known as ERCOM can be found in the previous publication [28], while a summary of the data and assumptions used are provided in Appendix C. Our extension to ERCOM [28] involves (i) the incorporation of life cycle endpoint indicators, (ii) the addition of a negative emission technology (i.e., BECCS), (iii) the modification of the objective function to include the monetized life cycle endpoint indicators in the ecological solution (S3) and (iv) the addition of the environmental constraint in line with the Paris Agreement 2 ˚C target in the Paris Agreement solution (S2).

A target on the 100-year global warming potential is set to meet the Paris Agreement 2 ˚C target governed by solution S2 only as follows:

$$\sum_i \sum_j GWP100_{i,j}\left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq TARG \qquad \text{(B.1)}$$

where $GWP100_{i,j}$ represents the 100-year global warming potential for electricity technology i in state j, $GEN_{i,j}^{ST}$ is the electricity generated by standard power technology i in state j, $GEN_{i,j}^{BU}$ is the electricity generated by backup power technology i in state j and $TARG$ is the upper bound on the 100-year global warming potential in line with the US commitment to the Paris Agreement 2 ˚C target in 2030.

The total electricity generation cannot exceed the generation potential for a given power technology and state as follows:

$$GEN_{i,j}^{ST} + GEN_{i,j}^{BU} \leq GEN_{i,j}^{POT} \qquad \forall j, i \neq coal, coal\ CCS, natural\ gas, natural\ gas\ CCS, biomass, BECCS \tag{B.2}$$

where $GEN_{i,j}^{POT}$ represents the electricity generation potential for power technology i in state j. Constraint Eq. (B.2) is valid for technologies that do not share the same fuel resource. On the other hand, technologies that share the same fuel resource (e.g., coal and coal with CCS plants) share also the generation potential of electricity by that fuel resource as shown in constraints Eq. (B.3), Eq. (B.4) and Eq. (B.5) as follows:

$$\sum_{i \in CT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i',j}^{POT} \qquad \forall j, i' = coal \tag{B.3}$$

$$\sum_{i \in NGT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i',j}^{POT} \qquad \forall j, i' = natural\ gas \tag{B.4}$$

$$\sum_{i \in BT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i',j}^{POT} \qquad \forall j, i' = biomass \tag{B.5}$$

where CT denotes the set that contains coal with and without the CCS technology, NGT represents the set that contains natural gas with and without the CCS technology and BT is the set that contains biomass with and without the CCS technology.

Coal, natural gas and biomass could also be traded between states subject to their national availability, i.e., generation potential, as follows:

$$\sum_{j} \sum_{i \in CT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i'}^{POTGLO} \qquad \forall\ i' = coal \tag{B.6}$$

$$\sum_{j} \sum_{i \in NGT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i'}^{POTGLO} \qquad \forall\ i' = natural\ gas \tag{B.7}$$

$$\sum_{j} \sum_{i \in BT} \left(GEN_{i,j}^{ST} + GEN_{i,j}^{BU}\right) \leq GEN_{i'}^{POTGLO} \qquad \forall\ i' = biomass \tag{B.8}$$

where GEN_{i}^{POTGLO} is the national availability of tradable energy resources that include coal, natural gas and biomass.

Electricity generated from standard technologies is bounded by the installed capacity for each standard power technology and state, whereas electricity generated by backup technologies has to

equal the installed backup capacity for each backup power technology and state to maintain the grid's reliability as follows:

$$GEN_{i,j}^{ST} \leq CAP_{i,j}^{ST} CF_{i,j} H \quad \forall i,j \tag{B.9}$$

$$GEN_{i,j}^{BU} = CAP_{i,j}^{BU} CF_{i,j} H \quad \forall i,j \tag{B.10}$$

where $CAP_{i,j}^{ST}$ is the standard capacity for power technology i in state j, $CF_{i,j}$ is the capacity factor for power technology i in state j, H is the total number of hours in a given year and $CAP_{i,j}^{BU}$ is the backup capacity for power technology i in state j.

Following the Environmental Protection Agency regulation where the current capacity of nuclear power plants cannot be expanded [55], the following constraint is imposed:

$$CAP_{i,j}^{ST} + CAP_{i,j}^{BU} = CAP_{i,j}^{CUR} \quad \forall j, i = nuclear \tag{B.11}$$

where $CAP_{i,j}^{CUR}$ is the total installed capacity of nuclear power plants in 2012.

To maintain the grid's reliability, half a unit of backup capacity from non-intermittent technologies is to be built for every unit of standard capacity from intermittent technologies as follows:

$$\sum_{i \notin IR} CAP_{i,j}^{BU} = BUC \sum_{i \in IR} CAP_{i,j}^{ST} \quad \forall j \tag{B.12}$$

$$CAP_{i,j}^{BU} = 0 \quad \forall j, i \in IR \tag{B.13}$$

where BUC is a parameter that donates the ratio of backup capacities of non-intermittent technologies to standard capacities of intermittent technologies. Intermittent technologies cannot be used as backup, as illustrated in constraint Eq. (B.13).

The generated electricity is traded only between neighboring regions as follows:

$$TRD_{j,j'}^{ORIG} = 0 \quad \forall j, j' \notin NU_j \tag{B.14}$$

$$TRDCAN_{j,k}^{ORIG} = 0 \quad \forall j, k \notin NC_j \tag{B.15}$$

where $TRD_{j,j'}^{ORIG}$ is the total exports from state j' to state j, NU_j is the set of neighboring states to state j, $TRDCAN_{j,k}^{ORIG}$ is the total exports from Canadian region k to state j and NC_j is the set of neighboring Canadian regions to state j.

Transmitted electricity between neighboring regions are vulnerable to losses that are a function of the transmission distance as follows:

$$TRD_{j,j'}^{ORIG} = TRD_{j,j'}^{DEST} + TRD_{j,j'}^{LOSS} \quad \forall j, j' \in NU_j \tag{B.16}$$

$$TRDCAN_{j,k}^{ORIG} = TRDCAN_{j,k}^{DEST} + TRDCAN_{j,k}^{LOSS} \quad \forall j, k \in NC_j \tag{B.17}$$

$$TRD_{j,j'}^{LOSS} = TRD_{j,j'}^{ORIG} DIST_{j,j'} TLF \quad \forall j, j' \in NU_j \tag{B.18}$$

$$TRDCAN_{j,k}^{LOSS} = TRDCAN_{j,k}^{ORIG} DISTCAN_{j,k} TLF \quad \forall j, k \in NC_j \tag{B.19}$$

where $TRD_{j,j'}^{DEST}$ is the actual amount of electricity received by state j from state j', $TRD_{j,j'}^{LOSS}$ is the transmission losses incurred due exporting electricity from state j' to state j, $TRDCAN_{j,k}^{DEST}$ is the actual amount of electricity received by state j from Canadian region k, $TRDCAN_{j,k}^{LOSS}$ is the transmission losses incurred due exporting electricity from Canadian region k to state j, $DIST_{j,j'}$ is the transmission distance between state j' and state j, TLF is a parameter that links the electricity transmission losses to the transmission distance and $DISTCAN_{j,k}$ is the transmission distance between Canadian region k and state j.

To maintain the market structure in the power sector, states are prevented from being transmission nodes where they import electricity just to export it later as follows:

$$\sum_{j} \sum_{k \in NC_j} TRDCAN_{j,k}^{ORIG} \leq CTB \sum_{j} DEM_j \tag{B.20}$$

$$\sum_{j' \in NU_j} TRD_{j,j'}^{DEST} + \sum_{k \in NC_j} TRDCAN_{j,k}^{DEST} \leq DEM_j \quad \forall j \tag{B.21}$$

where CTB is the largest share of demand for electricity that can be met by imports from Canadian regions and DEM_j is the demand for electricity in state j.

The total electricity generated from standard and backup capacities and net imports of electricity in a given state must meet its demand satisfaction condition as follows:

$$\sum_{i} GEN_{i,j}^{ST} + \sum_{i \notin IR} GEN_{i,j}^{BU} + \sum_{j' \in NU_j} TRD_{j,j'}^{DEST} + \sum_{k \in NC_j} TRDCAN_{j,k}^{DEST} - \sum_{j' \in NU_j} TRD_{j',j}^{ORIG} = DEM_j DSF \quad \forall j \tag{B.22}$$

where DSF denotes the demand satisfaction factor to maintain the reliability of the grid.

The summation of the LCOE and monetized endpoint indicators represents the objective function of ERCOM-LCIA, where the latter appears only in the ecological solution (S3), as follows:

$$COST^{TOT} = \sum_{j} COST_j + \sum_{e} LCAI_e M_e^{2030} \quad \text{(B.23)}$$

where $COST^{TOT}$ is the total cost of electricity that is to be optimized, $COST_j$ is the direct cost of electricity in state j, $LCAI_e$ is the life cycle endpoint indicator e of the US energy mix and M_e^{2030} is the adjusted monetization value to the year 2030 for each life cycle endpoint indicator e. Note the monetization value, M_e^{2030}, for the resource availability endpoint indicator is one because the latter is already expressed in a monetary term. Eq. (B.23) is the objective function of the ecological solution (S3). In the objective function of the Paris Agreement solution (S2), however, the second term in Eq. (B.23) is omitted.

The total LCOE is divided into capital, fixed, variable costs in addition to the cost of electricity imports from Canadian regions as follows:

$$COST_j = COST_j^{CAP} + COST_j^{FIX} + COST_j^{VAR} + COST_j^{CAN} \quad \forall j \quad \text{(B.24)}$$

$$COST_j^{CAP} = \sum_{i} \left((CAP_{i,j}^{ST} + CAP_{i,j}^{BU}) CO_{i,j}^{CAP} CF_{i,j} H \right) \quad \forall j \quad \text{(B.25)}$$

$$COST_j^{FIX} = \sum_{i} \left((CAP_{i,j}^{ST} + CAP_{i,j}^{BU}) CO_{i,j}^{FIX} CF_{i,j} H \right) \quad \forall j \quad \text{(B.26)}$$

$$COST_j^{VAR} = \sum_{i} \left((GEN_{i,j}^{ST} + GEN_{i,j}^{BU}) CO_{i,j}^{VAR} \right) \quad \forall j \quad \text{(B.27)}$$

$$COST_j^{CAN} = \sum_{k \in NC_j} TRDCAN_{j,k}^{DEST} CO^{CAN} \quad \forall j \quad \text{(B.28)}$$

Where $COST_j^{CAP}$, $COST_j^{FIX}$, $COST_j^{VAR}$ and $COST_j^{CAN}$ represent the total capital, fixed, variable and import costs, respectively, in state j, $CO_{i,j}^{CAP}$, $CO_{i,j}^{FIX}$ and $CO_{i,j}^{VAR}$ represent the unitary capital, fixed and variable costs, respectively, of power technology i in state j and CO^{CAN} is the unitary electricity import cost from neighboring Canadian regions.

The US energy mix total life cycle endpoint indicators are calculated as follows:

$$LCAI_e = \sum_{i,j} \left((GEN_{i,j}^{ST} + GEN_{i,j}^{BU}) EB_{i,j,e} \right) \quad \forall e \quad \text{(B.29)}$$

where $EB_{i,j,e}$ is the unitary environmental burden of life cycle endpoint indicator e per unit of energy generated by power technology i in state j .

Appendix C: Assumptions and data sources

Table C.1

Summary of the assumptions and data sources for the parameters used in ERCOM-LCIA. The work by Galán-Martín et al. [28] shows further details.

Parameter	Source	Description
BUC	Brown et al. [56]	The capacity ratio of backup dispatchable technologies to standard non-dispatchable technologies to support the grid, 50%
$CAP_{i,j}^{CUR}$	EIA [57]	2012 installed capacity in the United States
$CF_{i,j}$	EIA [57]	Capacity factor
CO^{CAN}	CEA [58]	Import price of Canadian electricity, 39 USD_{2013} per MWh
$CO_{i,j}^{CAP}$	BECCS: Algunaibet et al. [8]	Capital cost portion of the total levelized cost of electricity
$CO_{i,j}^{FIX}$	Others: EIA [29]	Fixed operating cost portion of the total levelized cost of electricity
$CO_{i,j}^{VAR}$		Variable operating cost portion of the total levelized cost of electricity
CTB	NERC [59]	Share of demand in each state that acts as an upper bound on electricity imports from neighboring regions in Canada, 5%
DEM_j	EIA [57]	Demand for electricity in each state
$DIST_{j,j'}$	Galán-Martín et al. [28]	Distance of transmission between regions in the United States
$DISTCAN_{j,k}$		Distance of transmission between states and neighboring Canadian regions
DSF	Short et al. [60]	Demand satisfaction factor, 1.05
$EB_{i,j,e}$	*Life cycle data:* Coal with CCS: Iribarren et al. [36]	Life cycle endpoint indicator per unit of electricity generated by technology and state
$GWP100_{i,j}$	Solar thermal: Corona et al. [37] Natural gas with CCS: Petrakopoulou et al. [38] BECCS: Oreggioni et al. [14] Remaining technologies: ecoinvent v3.4 [35]	100-year global warming potential per unit of electricity generated by technology and state
GDP^{1995}	World Bank Group [46]	United States gross domestic product per capita based on purchasing power parity in 1995
GDP^{2030}	EIA [47]	United States gross domestic product per capita based on purchasing power parity in 2030
$GEN_{i,j}^{POT}$	NERL [61]	Electricity generation potential by each technology and state
GEN_i^{POTGLO}		National electricity generation potential by each technology
M_e^{1995}	Weidema [34]	Monetization value for the life cycle endpoint indicator (i.e., human health and ecosystem diversity) calculated for the year 1995
$TARG$	UNFCCC [9]	United States target in 2030 under the Paris Agreement, 39% reduction relative to 2005 levels (i.e., 61% of 100-year global warming potential of the United States energy mix in 2005)
TLF	Fripp [62]	Losses due to electricity generation, 0.62% for every 100 km
ε_e	Human health: Viscusi [44] Ecosystem diversity: Jacobsen and Hanley [45]	Income elasticity of willingness-to-pay for the life cycle endpoint indicator (i.e., human health and ecosystem diversity)

Appendix D: Uncertainty analysis approach

In this appendix, we describe the uncertainty analysis approach used to evaluate the robustness of our conclusions against uncertainties in the three life cycle endpoint indicators and in the weights used to monetize the human health and ecosystem diversity indicators. We generated 350 scenarios using Monte Carlo sampling for each of the three solutions solved via ERCOM-LCIA in order to ensure that the Law and Kelton's test is passed [63] with a confidence level of 95% and a relative error of 5%. The uncertainty analysis was applied to the three solutions shown in this work (i.e., S1, S2 and S3). The resultant standard deviations are shown on the figures as error bars (i.e., each error bar represents one standard deviation).

Note that the BAU (S1) and Paris Agreement (S2) solutions are insensitive to these uncertainties, that is, the optimal mix that emerges in these solutions does not depend on the scenario, as these uncertainties do not appear in the objective function of the model. On the other hand, the ecological solution (S3) changes from one scenario to another, because it depends on the life cycle endpoint indicators and their corresponding monetization values. In all the cases, however, the cost of externalities varies between scenarios regardless of whether the mix changes or not across them; this happens because the externalities need to be recalculated for every scenario according to the outcome of the uncertain parameters. We next describe the distribution and sampling method for each uncertain parameter considered in this analysis.

The three life cycle endpoint indicators are assumed to follow lognormal distributions [31]. Each run is, therefore, associated with different values of the uncertain parameters obtained via Monte Carlo sampling on the underlying probability distributions. The geometric standard deviations are obtained using the Pedigree matrix [31] as follows:

$$\sigma_{i,j,e}^{geo} = \sqrt{e^{\sqrt{\begin{matrix}[\ln(U_{1,i,j,e})]^2+[\ln(U_{2,i,j,e})]^2+[\ln(U_{3,i,j,e})]^2+[\ln(U_{4,i,j,e})]^2+ \\ [\ln(U_{5,i,j,e})]^2+[\ln(U_{6,i,j,e})]^2+[\ln(U_{b,i,j,e})]^2\end{matrix}}}} \quad \forall i,j,e \tag{D.1}$$

where $\sigma_{i,j,e}^{geo}$ denotes the geometric standard deviation of the lognormal cumulative distribution function for each life cycle endpoint indicator e, technology i in state j, $U_{1,i,j,e}$ to $U_{6,i,j,e}$ represent the parameters defined by the Pedigree matrix for each life cycle endpoint indicator e, technology i in state j and $U_{b,i,j,e}$ is the basic uncertainty parameter for each life cycle endpoint indicator e, technology i in state j (description of the scores for all U's can be obtained from the SimaPro manual [33]).

We obtain the standard deviation of the life cycle endpoint indicators' natural logarithm via Eq. (D.2).

$$\sigma_{i,j,e} = ln\left(\sigma_{i,j,e}^{geo}\right) \quad \forall i,j,e \tag{D.2}$$

The mean of the three life cycle endpoint indicators' natural logarithm, $\mu_{i,j,e}$, is obtained as follows:

$$\mu_{i,j,e} = ln\left(E\left[EB_{i,j,e}\right]\right) - \frac{\left(\sigma_{i,j,e}\right)^2}{2} \quad \forall i,j,e \tag{D.3}$$

where $E\left[EB_{i,j,e}\right]$ is the expected life cycle endpoint indicator e, technology i in state j. Lastly, the random values of each uncertain life cycle endpoint indicator is obtained via the lognormal distribution alongside the calculated parameters in Eq. (D.2) and Eq. (D.3), $EB_{i,j,e} \sim lognormal(\mu_{i,j,e}, \sigma_{i,j,e}^2)$.

The monetization values for the human health and ecosystem diversity endpoint indicators are assumed to follow a uniform distribution with the following probability density function:

$$f(x_e^u) = \begin{cases} \dfrac{1}{(b_e - a_e)} & a_e \le x_e^u \le b_e \quad \forall e \in \{HH \cup ES\} \\ 0 & otherwise \end{cases} \tag{D.4}$$

where x_e^u is the random parameter corresponding to the uncertain monetization value of the life cycle endpoint indicator $e \in \{HH \cup ES\}$, which follows a uniform distribution, a_e corresponds to the lower bound in the uncertainty range of the monetization value for life cycle endpoint indicator $e \in \{HH \cup ES\}$, b_e corresponds to the upper bound in the uncertainty range of the monetization value for life cycle endpoint indicator $e \in \{HH \cup ES\}$, HH is the human health endpoint indicator in the set e and ES is the ecosystem diversity endpoint indicator in the set e.

Appendix E: Understanding the trade-off between the direct cost of electricity and externalities

To further understand and quantify the inherent trade-off between direct and indirect costs of energy mixes, we minimize the two of them simultaneously (i.e., direct cost of electricity and monetized life cycle endpoint indicators). Fig. E.1 shows the Pareto solutions of this bi-criteria problem, which were obtained via the epsilon constraint method, that is, by minimizing the direct cost of electricity for different bounds on the cost of externalities.

Solutions S1, S2 and S3 are shown in Fig. E.1. The BAU energy mix (S1) is clearly inefficient in 2030, as it can be improved simultaneously in the direct cost of electricity and externalities; consequently, the BAU mix should not be maintained. The Paris Agreement solution (S2) is efficient and shows the minimum direct cost of electricity, mainly due to the competitive LCOE of some renewables in the future (e.g., wind onshore) [29]. The ecological solution (S3) is also efficient and lies on the part of the Pareto set where further reductions in externalities would require a steep increase in the direct cost of electricity.

All the solutions on the Pareto front meet the Paris Agreement, that is, all the mixes in the Pareto set lead to carbon emissions below the US INDC commitment under the Paris Agreement 2 ˚C target. Indeed, among all the solutions that satisfy the Paris Agreement, there are many that reduce significantly the total cost compared to solution S2, highlighting the substantial potential economic benefits of going beyond the Paris Agreement in order to preserve human health, ecosystem diversity and resource availability.

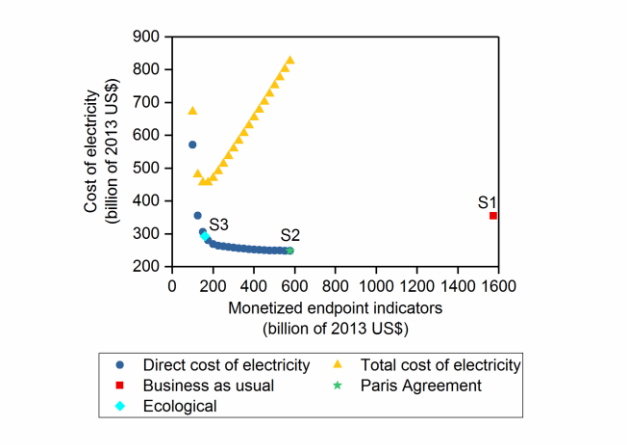


Fig. E.1. Pareto frontier of the direct cost of electricity and monetized life cycle endpoint indicators (i.e., indirect cost). The dark blue circles represent the direct cost of electricity as a function of the monetized endpoint indicators. The yellow triangles represent the total cost of electricity (i.e., the summation of the direct cost of electricity and monetized life cycle endpoint indicators resulted by the Pareto solutions) as a function of the monetized endpoint indicators. The red square represents the business as usual energy mix in the year 2030, solution S1, the green star represents the Paris Agreement mix in 2030, solution S2, and the light blue rhombus represents the ecological mix in 2030. The labeling of solutions is provided in Table 1.

Competing of interest

There are no competing of interests to declare.

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