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Materials-Related Challenges of Energy Transition

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ABSTRACT

Transition from fossil fuels to clean energy technologies (CETs) is critical, but material shortages threaten to hinder progress. This study analyzes the potential deficits in 14 key materials – such as lithium, nickel, and cadmium – based on capacity projections for CETs by eight Integrated Assessment Models (IAMs) for 2020-2050. It focuses on technologies including battery storage, concentrated solar power (CSP), electrolyzers, solar photovoltaics (PV), and wind turbines. Our findings show that these materials could face shortages of up to 97% by 2050. To meet rising demand, material production rates must increase sharply, with some materials like cadmium, selenium, and tellurium requiring about 31% increases, peaking in this decade. Immediate actions are needed to accelerate production and improve recycling efforts. However, recycling targets, such as 325% for lithium, seem highly challenging to achieve. Without these measures, material shortages could delay CET deployment, risking Paris Agreement goals. To prevent these disruptions, we call for: (i) revising CET capacity projections, (ii) urgent planning for mining expansion, and (iii) a significant increase in recycling infrastructure to ensure a sustainable energy transition.

Keywords: Energy transition, Clean Energy, Integrated Assessment Models, Material Requirements.

INTRODUCTION

Clean energy technologies are pivotal in reducing fossil fuel consumption, mitigating greenhouse gas (GHG) emissions, and enhancing energy security. However, as CET deployment accelerates, resource extraction grows, presenting significant challenges to meeting the energy sector's rising material demands.

The capacity requirements for CETs are a central focus of climate policies shaped by IAMs [1]. These models are used for guiding policy strategies, driving climate change mitigation, and informing global initiatives [2]. However, IAMs have faced criticism overlooking key factors such as human behaviour [3], socio-technical insights [4], and political neutrality [5]. A particular concern is the absence of materials availability to scale CETs. This undermines the credibility of their capacity projections.

This study evaluates the feasibility of CET capacity projections across 25 scenarios from eight widely used IAMs, aligned with the Paris Agreement temperature target. These scenarios, covering diverse assumptions, increase the reliability of our findings. We assess capacity projections for stationary and Electric Vehicle (EV) batteries, electrolyzers, CSP systems, PV panels, and wind turbines against realistic capacities based on the availability of 14 materials, including critical minerals, rare earth elements, and platinum group metals. Then, we develop an optimization model to identify the gap between IAM projected capacities and realistic estimates constrained by material availability. Also, we calculate the recycling rates required to meet IAM-projected capacities.

Methodology

First part of this section focuses on estimating the material demand, while the second part introduces a model to evaluate the effect of material unavailability.

Assessing the feasibility of IAM projections

The materials demand estimation is based on the projected capacity for each technology from 2020 to 2050, using data from 25 scenarios provided by eight widely used IAMs [6], discussed in the following.

Overview of selected IAMs

Recognizing that each IAM employs unique scenario designs and technological assumptions, our analysis incorporates multiple IAMs to provide a comprehensive range of perspectives and account for differences in modelling approaches. Specifically, we include the following IAMs: GCAM 4.2, IMAGE 3.0.1, MERGE-ETL 6.0, MESSAGE-GLOBIOM 1.0, MESSAGEix-GLOBIOM 1.0, POLES ADVANCE, REMIND-MAgPIE 1.7-3.0, and WITCH-GLOBIOM 4.4. These models collectively represent 25 scenarios explained in Rostami et al. [7].

Throughout this study, references to IAMs specifically pertain to the eight models and their respective scenarios selected for analysis.

Accounting for technology variations

IAMs provide data at a general, archetypal technology level, but in reality, technology designs – and their material requirements – vary significantly. To account for this, our analysis includes seven battery types, three CSP types, two electrolyzer types, three PV panel types, and six wind turbine types. We allocate IAM capacity projections across different technology types using two market contribution scenarios [8]: ***Continued***, which assumes a gradual evolution of existing technologies; and ***Technological Change***, which considers the potential for rapid advancements and shifts in technology design. These scenarios predict how various technology designs will contribute to the overall market. The specific selected technology types and market contribution values are detailed in supplementary information. Furthermore, we will highlight the technology types that are most recommended under materials availability constraints.

Materials demand estimation

Material consumption per gigawatt (GW), known as material intensity, was sourced from the literature for each technology type [8], [9]. We used two material intensity scenarios: ***Current,*** reflecting present-day intensities; and ***Learning curve,*** accounting for technological advancements that may reduce intensities over time.

The material intensity values used for each technology type are available in supplementary information.

To estimate material demand, we multiplied the projected technology capacities from each of the 25 IAM scenarios by two market contribution trends (*k:"Continued"* and *"Technological Change"*) and two material intensity scenarios (*i:"Current"* and *"Learning Curve"*). This approach, illustrated in Equation 1, results in a total of 100 potential outcomes, providing a comprehensive assessment of material demand under varying assumptions.

$$MD^{T}_{m,t,n,s,k,i} = CC^{T}_{n,s} \cdot MC_{t,n,k} \cdot MI_{m,t,n,i} \qquad (1)$$

$$\forall m,n,s,k,i,\ t \in TT_T,\ T=\{BAT, CSP, ELECTZ, PV, WIND\}$$

Here, $MD^{T}_{m,t,n,s,k,i}$ [ton] represents the demand for material *m*, driven by technology type *t* within the broader technology category *T*, for year *n* as determined by IAM scenario *s*, market trend *k*, and material intensity *i*. $CC^{T}_{n,s}$ [GW] denotes the installed capacity for technology category *T* in year *n* according to IAM scenario *s*, while $MC_{t,n,k}$ [%] is the market contribution of technology type *t* in year *n* according to market trend *k*. The relationship between technology types *t* (e.g., crystallin silicon PV panels) and technology categories *T* (e.g., PV panels) is given by set TT_T, which specifies the types *t* that belong to category *T*. $MI_{m,t,n,I}$ [ton/GW] is the material intensity *i* (*"Current"* or *"Learning Curve"*) of material *m* used in type *t* of technology *T* in year *n*.

To assess the potential material shortages, we compared the material demands estimated over time with their prospective market availability, calculated projecting their current production rates. The details of these comparisons are explained in Equation 2.

$$MSh_{m,n,s,k,i} = \frac{\left([PR_{m,20} \cdot (1+\alpha)^{r} \cdot Sh^{CETs}_{m,20}] - \sum_{t,T} MD^{T}_{m,t,n,s,k,i}\right).100}{\sum_{t,T} MD^{T}_{m,t,n,s,k,i}} \qquad (2)$$

$$(\forall m,n,s,k,i,t \in TT_T, r = 0,1,\dots,30)$$

In Equation 2, the first term in the numerator calculates the market availability of material *m* in year *n* for CET development [ton]. Our estimation is based on the production rates for 2020 ($PR_{m,20}$) sourced from the literature [7]. The production rate might remain constant (*α=0*) or grow annually. To account for its variations, we assume an annual growth rate of *α=2.7%*, reflecting the average growth in metal mining [10]. Notably, *r* is the counter of the years in the projection period, starting at *r=0* for 2020 and increasing to *r=30* for 2050. Since materials are not solely used for CET development (i.e., they are also needed in other sectors), we limit the allocation of each material for CETs by applying the 2020 share of CET-driven demand ($Sh^{CETs}_{m,20}$). It represents the proportion of each material´s total production used for CETs in 2020 [%]. This calculation gives the market availability of material *m* for CETs in year *n*. From this, we then subtract the total demand for each material *m* in year *n*, derived by IAM scenario *s*, market trend *k*, and material intensity scenario *i* across all technology types *t* within each category *T* [ton]. The resulting difference, divided by total demand for desired material, provides the shortage in its availability for CETs development ($MSh_{m,n,s,k,i}$).

The required growth rates for material production to meet the IAM capacity projections are determined by forcing the numerator of Equation 2 to be zero, and solving the resulting equation for α.

Estimating technology capacity shortfalls

To evaluate the impact of material shortages on CET deployment, we aim to estimate the achievable capacities of CETs. This involves developing an optimization model, formulated and solved in General Algebraic Modeling System (GAMS), to minimize the gap between the capacities projected by IAMs and the realistic capacities constrained by material availability. In the model, variables are *italicized*, and parameters are presented in standard font for clarity throughout the equations.

$$\mathrm{Min} \sum_{\mathrm{T,n,s}} Diff_{n,s}^{T} \tag{3}$$

$$\text{s.t:} \quad Diff_{n,s}^{T} = CC_{n,s}^{T,Opt} - \mathrm{CC}_{\mathrm{n,s}}^{\mathrm{T,IAMs}} \tag{4}$$

$$\forall n,s,T=\{BAT, CSP, ELECTZ, PV, WIND\}$$

$$Diff_{n,s}^{T} \geq 0 \tag{5}$$

$$\forall n,s,T=\{BAT, CSP, ELECTZ, PV, WIND\}$$

$$\sum_{k,t,T} CC_{n,s}^{T,Opt} \cdot \mathrm{MC_{t,n,k}} \cdot \mathrm{MI_{m,t,n}} \leq \mathrm{PR_{m,n}} \cdot \mathrm{SHARE_{m,2020}^{CETs}} \tag{6}$$

$$\forall m,s,\ n=2021, \ldots, 2050$$

$$\sum_{n,k,t,T} CC_{n,s}^{T,Opt} \cdot \mathrm{MC_{t,n,k}} \cdot \mathrm{MI_{m,t,n}} \leq \mathrm{Res_m} \quad \forall m,s \tag{7}$$

$$Diff_{n,s}^{T},\ CCI_{t,n,s}^{T,Opt} \in \mathrm{R}^{+} \tag{8}$$

The objective of the model (Equation 3) is to minimize capacity disparities across technology categories *T* (e.g., PV), IAM scenarios *s*, and years *n*, as denoted by $Diff_{n,s}^{T}$. These disparities are defined in Eq. 4 as the difference between the capacities projected by IAMs ($\mathrm{CC_{n,s}^{T,IAMs}}$) and the "realistic" capacities estimated by the model ($CC_{n,s}^{T,Opt}$). For each technology, this difference should be positive to prevent situations where surplus capacity in one technology category offsets deficits in another (Eq. 5). The values for $\mathrm{CC_{n,s}^{T,IAMs}}$ are obtained from IAMs, for the corresponding scenario *s* and year *n*. In this context, as discussed in Equation 1, the left-hand side of Equation 6 calculates the demand for material *m* driven by all types of technology *T* developed in year *n*. By incorporating multiple technology types into our models, we can determine which technologies are preferentially selected. The right-hand side reflects the portion of the realistic production rate for material *m* in year *n* ($\mathrm{PR_{m,n}}$) allocated to CET manufacturing. Indeed, the shares observed in 2020 ($\mathrm{SHARE_{m,2020}^{CETs}}$) are used to limit the amount of each material available for CET manufacturing. Notably, production rates for 2020 ($\mathrm{PR_{m,2020}}$) are sourced from the literature [7]. Future production rates ($\mathrm{PR_{m,n}}$) are obtained by applying an annual growth rate of α = 2.7%, reflecting the historical average annual growth rate of metals mining [10]. This rate was adjusted to 0.7% and 4.7% for sensitivity analysis, representing the average growth ± 2%. Finally, Equation 7 is used to constrain the cumulative demand for material *m* by year *n,* driven by all the technologies, to remain within the limits of its available reserves ($\mathrm{Res_m}$), as given in literature [11].

To estimate the minimum recycling rates needed to address CET material shortages and achieve IAM capacity projections, we developed a secondary optimization model, deriving from this one. The objective of this second model is to calculate the minimum required recycling rates. The model uses constraints similar to those in the primary model but incorporates recycling as an additional supply source (i.e., recycling is added as a new variable to the right-hand sides of Eqs. 6–7). Due to space limitations, we avoid detailed explanation of this model. Further details can be found in Rostami et al. [7].

For each of the 25 IAM scenarios, we ran the model 12 times, using different combinations of two market trends, two material intensity projections, and three annual production rates (α). This results in a total of 300 (i.e., 25×12) estimates for each material´s recycling rate. Current recycling rates, sourced from various references [11], [12], are used to contextualize the results.

Results and discussion

Material shortage

Figure 1 illustrates the potential material shortages for CET development, shown as negative values (red shadow), and the necessary annual production growth rates to address these shortages, represented by positive values (blue shadow). The lines inside each shadow present the median results across 100 scenarios.

The red lines highlight significant material shortages, with materials such as cadmium, graphite, indium, lithium, nickel, and tellurium projected to fall short by up to 97% of demand. Materials like dysprosium, iridium, neodymium, silver, and terbium face comparatively lower deficits, still their shortages remain significant. The steep decline in the red curves indicates that the most severe shortages are likely to occur within this decade, followed by a moderate worsening trend in next decades. An exception is iridium, where based on the median values, shortages are mainly expected after 2040, aligning with the large-scale deployment of electrolyzers. However, when considering all the scenarios (i.e., the red shadow), we might face an iridium shortage starting this decade. Overall, these commodities markets will be so tight that the deployment of CETs at the pace and scale envisioned by IAMs seems impossible. It will likely translate into higher cumulative emissions, which might prevent us from meeting Paris agreement targets.

Addressing these deficits requires urgent and worthy action. Incremental production increases, such as the 2.7% annual growth shown by thin red lines (reflecting historical averages of metal mining annual growth rate), are clearly insufficient. For instance, this growth only marginally reduces lithium shortages from 97% to 93%. Without addressing these material deficits, achieving CET capacities at the scale envisioned may not be feasible. This underscores the importance of integrating material constraints into IAMs to ensure realistic projections.

For most materials, the blue lines, representing the median of necessary annual production growth rates, start at low values in 2020 and rise sharply during the early years (2020–2025). Materials like cadmium, gallium, indium, selenium, silver, and tellurium exhibit high starting points in 2020, reflecting their early and intensive use in PV panels. Since production of these materials has not increased as necessary in recent years, we expect a challenging period, indicating that more effort will be required in the future to compensate for these shortages and achieve the CET projected capacities by 2050.

Overall, after 2025, the rate of increase slows but remains positive, suggesting that while the urgency for scaling production decreases, steady growth remains necessary. Factors such as technological maturity and improved material intensity likely contribute to this trend. Even in the long term, annual growth rates remain above 5.6%, with this median observed for iridium in 2050.

Furthermore, in the early 2030s, a second peak in the production of cobalt, graphite, and lithium will be necessary to develop batteries for EVs at the projected scale. Similarly, unachieved targets before 2030 will exacerbate the situation beyond that point, if we want to catch up the projections at some point. It is important to note that mine expansion is time-intensive, meaning that material production might not ramp up at the necessary pace in the short term. This highlights the urgency of planning for mining expansion.

Alternatively, CET development could be adjusted to require a steadier material production rate over time. Implementing this requires adjustments in CET projections and offers significant long-term benefits by ensuring more stable material production. For example, it reduces the risk of supply chain bottlenecks, provides more time to incentivize investments in recycling infrastructure, decreases market volatility and price fluctuations, and benefits industries dependent on these materials.

CET shortfalls and required material recycling

Figure 2 highlights the shortfalls in CET capacities based on IAM scenarios and after implementing constraints on materials availability. Meeting IAM projections for batteries and PV panels is challenging. For batteries, persistent material deficits are expected starting this decade (see cobalt, graphite, lithium, and nickel in Figure 1), potentially resulting in a 94% shortfall, equating to 11.1 TW below the 2050 targets. Similarly, PV panels capacity may fall short by 1.6 TW (94% of projections) due to cadmium, gallium, indium, selenium, and tellurium, shortages.

Electrolyzer deployment appears more feasible under median scenarios. However, under pessimistic condition, iridium shortages could limit output by 752 GW. CSP faces a moderate shortfall, with a median capacity deficit of 10.4 GW by 2050. Still, under ambitious scenarios, the entire 169 GW projected capacity may be unattainable. Wind turbine deployment could also be hindered by dysprosium, neodymium, and nickel shortages, resulting in a median shortfall of 88 GW (54% below the 2050 target). All these highlight the urgent need to modify IAMs by incorporating material availability constraints.

Raw materials are unevenly distributed across the globe, which inherently creates vulnerabilities in supply chains. For instance, a substantial share of gallium reserves is concentrated in China. Therefore, geopolitical

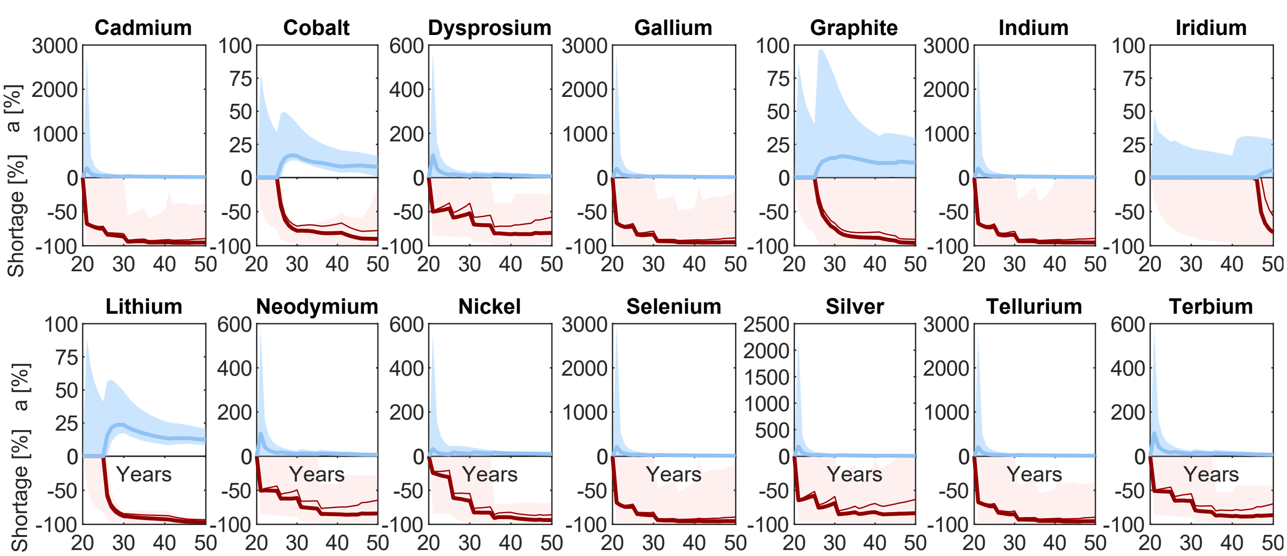

Figure 1: Material shortages and required annual production growth rates across 100 evaluated scenarios. The red thick line shows median material shortages (% of annual demand) based on current production rates, while the red thin line reflects shortages assuming a 2.7% annual increase in production. The blue line represents the median of required annual production growth rates. Timeframes: 20 (2020), 30 (2030), 40 (2040), and 50 (2050).

factors may further compound the challenge of securing sufficient raw materials for CETs. In the event of political conflicts, trade restrictions, or economic sanctions, these imbalances could be exacerbated, further reducing the attainable capacity of CETs or driving up their costs.

In Figure 2, the narrow bars above the panels indicate the technology types selected by the model. The findings demonstrate that, due to their unique designs and material requirements, technology types face varying levels of material shortage challenges. While some types are not selected at all, others, such as lithium ferro phosphate batteries, dominate, indicating these designs are strongly favored under materials availability constraints. For the list of technology names, refer to the supplementary information.

The data from Figure 3 underscore the magnitude of the challenge. For materials like lithium, iridium, and terbium, the recycling rates required to meet IAM projections are dramatically higher than current recycling rates. For example, based on median values, by 2050, lithium's recycling rate must reach 325% of its annual production, which indicates the amount of lithium needed for recycling would far exceed what is produced in a single year, pointing to the need for large-scale, long-term strategies for material recovery. This required a massive effort to dismantle existing infrastructure, including outdated technologies, in a feasible and sustainable way.

Materials such as dysprosium, graphite, iridium, and terbium also require substantial increases in recycling rates. For instance, for iridium it should rise from the current 17% to 64%, which highlights the significant gap between current capabilities and future needs.

Conclusion

This study emphasizes the severe challenges posed by material shortages in the development of CETs, highlighting the urgent need to revise IAM capacity projections and take proactive measures in material production and recycling. The analysis reveals that critical materials such as lithium, nickel, cadmium, indium, and iridium are projected to experience substantial shortages, with some deficits reaching up to 97% of the required demand by 2050, based on IAM projections. For example, lithium shortfalls potentially lead to a deficit of more than 11 TW, which accounts for 94% of the projected battery capacity. Similarly, PV panel deployment could fall short by 1.6 TW (94% of projections) due to the scarcity of materials like cadmium, gallium, and tellurium. The availability of

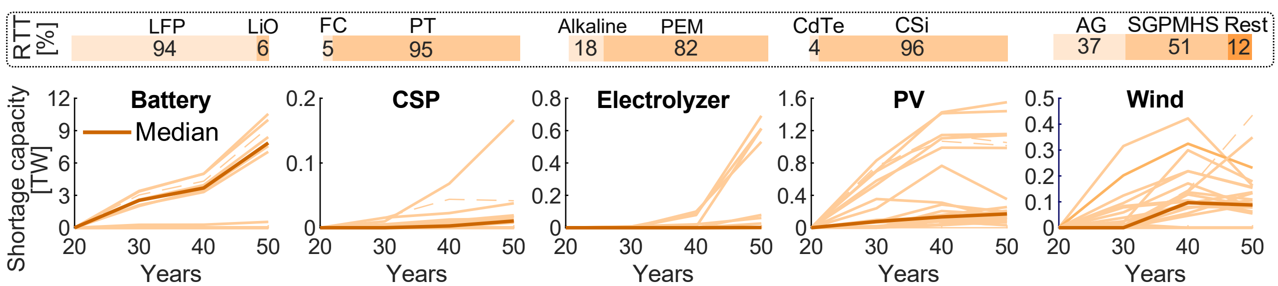

Figure 2: Annual shortage in CET capacities based on the 25 IAM scenarios. RTT:Recommended Technology Type.

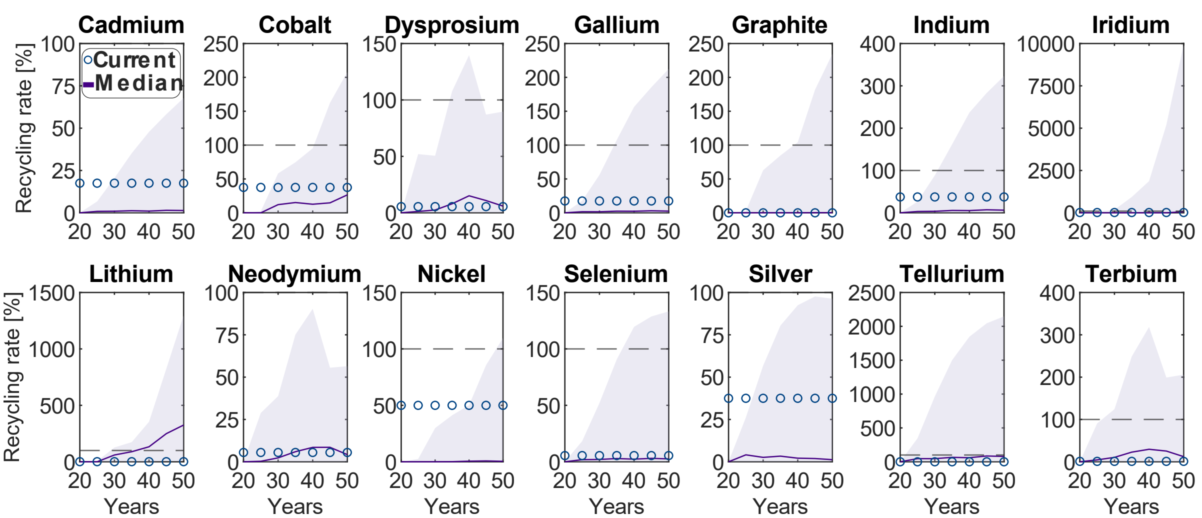

Figure 3: Recycling rates required to meet IAM capacity projections. The shaded area represents the range of recycling rates derived from 300 scenarios. Timeframes: 20 (2020), 30 (2030), 40 (2040), and 50 (2050).

materials for electrolyzers, CSP, and wind turbines could also be severely impacted, hindering their development.

To meet the growing material demands for CETs, production rates must increase significantly. Materials such as cadmium, selenium, and tellurium are expected to see a sharp rise in their production rate. However, the pace of production growth may not be able to keep up with this demand, emphasizing the need for immediate and strategic planning to expand mining capacity.

The unequal distribution of raw materials gives countries with domestic access a strategic advantage while disadvantaging others. This underscores the need for a free and open global market, combined with strong international collaboration, to mitigate supply chain risks and ensure that the transition to a sustainable clean energy future is not derailed by geopolitical tensions.

Investing in recycling infrastructure and circular economy initiatives helps to reduce reliance on raw material extraction. For example, by 2050, recycling rates for lithium and iridium will need to reach 325% and 64% of their annual production, respectively – an ambitious target, asking for extra efforts.

Overall, this calls for adjustment of IAMs so as to account for the availability of raw materials, enabling them to provide more realistic guidance for policy makers.

DIGITAL SUPPLEMENTARY MATERIAL

Supplementary information with record ID: LAPSE:2025.0006 is available in https://psecommunity.org/LAPSE:2025.0006.

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