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Article

Keywords:

Posted Date: September 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11011048/v1>

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Additional Declarations: There is **NO** Competing Interest.

Reducing water stress from mining battery materials

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Main Text:

Text: 2666 words (excluding abstract, methods, references, tables and figure captions)

Methods: 1615 words

Figures: 4

Tables: 0

Supplementary Information:

Supplementary Figures 1 to 8

Supplementary Tables 1 to 2

Supplementary Text 1

Extended Data Figures 1 to 8

Abstract

Rising demand for lithium-ion batteries is expanding mining activity, with local environmental impacts tied to scarce water resources. Although high water requirements in mining are a known concern, opportunities for cost-effectively reducing these impacts have not been systematically assessed. Here, we use a global, spatially-explicit capacity expansion model to evaluate the future water impacts of mining for four battery minerals (copper, nickel, cobalt, and lithium). We find that it is possible to greatly reduce water stress by prioritizing mining where more water is available. Roughly 50% of stress-weighted water use could be avoided at 10% higher cost, primarily by relocating lithium and copper extraction. Reducing primary mineral demand, by efficiency improvements or through recycling, might reduce water stress at even lower costs, and desalination could prevent water stress at additional cost. Priorities include shifting extraction to water abundant basins, adopting desalination, and maximizing copper recovery rates.

Lithium-ion batteries, and the copper, nickel, cobalt and lithium they contain, are critical components of electric vehicles¹ and energy storage in electricity systems with high shares of variable generation (e.g., solar and wind)². Moreover, copper is also a critical component of transmission lines, buildings and electronics³. As a result, demand for these materials has surged in recent years (e.g., lithium extraction grew 25%/yr 2015-2025)⁴ and is projected to continue growing steadily as countries' progressively decarbonize their energy systems⁵⁻⁷. But although a number of studies have investigated the availability of needed mineral resources and mining capacity⁷⁻¹⁰ and the global climate benefits they provide^{11,12}, the local environmental impacts of such mining has received comparatively less and narrower attention¹³ despite important implications for local communities¹⁴; food, health and water security¹⁵⁻¹⁸; the integrity of forests and biodiversity^{16,19-23}; and the social license underpinning the energy transition and climate mitigation generally²².

The impacts of mining on water resources are particularly acute given the considerable and multiple water requirements of extraction and beneficiation processes, including pit dewatering, dust suppression, slurry transport, flotation and thickening circuits, equipment cooling, tailings management^{24,25}, and the fact that some of the richest deposits of battery minerals are located in water-stressed regions²⁶ (which is indeed mechanistic in the case of copper and lithium)^{17,27,28}. Prior research has assessed water overconsumption for mineral extraction in a small set of fixed scenarios²⁹, but without a systematic analysis of the trade-off between costs and water stress. Our research goal is to identify cost-effective actions to minimize water stress from battery minerals extraction across a range of demand, technology and biodiversity-protection scenarios.

We develop a spatially- and temporally-explicit capacity expansion model^{9,10} to estimate total extraction costs (operational and capital) and related water use (consumption) between 2025 and 2050 for mining of copper, nickel, cobalt, and lithium across a large number of possible futures. We first combine data on resource magnitude, ore grade, extraction costs, and operational status for 1,108 deposits from the S&P Metals and Mining Database³⁰ with estimates of water use per unit of processed ore compiled from literature. We then explore the Pareto frontier of cost and water impacts across a range of IEA mineral demand projections³¹ by modelling minimum and near-optimal total costs subject to constraints of meeting assumed global demand, not exceeding per-deposit maximum production, and minimizing stress-weighted water use³². Water stress is quantified as current water availability minus current water demand relative to the global average in 2019 watersheds worldwide (9,406 basins from the AWARE “Available Water Remaining” method)³³. We further test the implications of adding a more specific ecological constraint to avoid mining in watersheds with high fish biodiversity³⁴.

Spatial distribution of mineral resources and water stress

Terrestrial mineral and water resources are unevenly distributed across the globe, but major lithium and copper deposits are especially concentrated in water-stressed basins of North and South America (blue and green circles; Fig. 1). In contrast, nickel resources are in areas where water is more abundant, such as Australia, Brazil, Indonesia, and the Philippines (grey circles; Fig. 1). Cobalt is primarily extracted as a co-product of nickel and/or copper mining (see Supplementary Fig. 1), especially in the Democratic Republic of the Congo (purple circles; Fig. 1) where fish biodiversity is high (Extended Data Fig. 1). Although known mineral resources are sufficient to meet even high projected demand through 2050 (Supplementary Fig. 2), the location of these resources could substantially compound water stress and degrade basins with exceptionally high biodiversity. While the physical intersection of mineral, water, and fish biodiversity is mostly fixed, it may also be possible to minimize the environmental impacts of mining by reducing primary mineral demand, relocating extraction, or improving mining processes.

The cost of reducing water stress

Figure 2a shows the trade-off between the total cost of battery minerals extraction and stress-weighted water use across a range of future demand scenarios. When cost is minimized, stress-weighted water use is highest (the gray star at the right end of the orange “Net-zero” curve; Fig. 2a), but such water stress can be greatly alleviated at relatively low cost increases by sourcing minerals from different locations (i.e. moving left along the curves and contours in Fig. 2a). For

every percentage point reduction in primary demand we observe a decrease in 1.9% of costs and 2.2% in stress-weighted water use, but shifting sources could cut stress-weighted water use by ~50% with a cost increase of ~10% regardless of demand level (Fig. 2a). The slope of contours (Pareto frontiers) in Figure 2a reflect the cost per water stress reduction, which can be compared to other interventions to reduce basin water stress, like desalination (which make cost and water fungible). The red and white circles and dashed arrows in Figure 2a thus show the point at which desalination becomes more cost-effective, at a system level, than shifting sources assuming costs of \$0.25 and \$0.50 per m³ of desalinated water, respectively.

Importantly, copper and lithium account for virtually all stress-weighted water use: copper dominates future demand of these materials by mass and the low-cost of lithium from brines drives supply in water-stressed basins (Fig. 2b, Supplementary Fig. 2). Notably, the lower water consumption per ton of metal in deposits with high ore grade is cancelled by a higher water stress factor (Extended Data Fig. 4 shows deposit cost curves and water intensity). Mineral-specific Pareto curves thus highlight substantial opportunities for avoiding water stress by shifting sources of lithium and copper (Figs. 2c and 2d), but not for either nickel or cobalt production (Figs. 2e and 2f; Extended Data Fig. 5). However, as biodiversity is greater where water is abundant, there will be an inherent trade-off across water stress prevention and biodiversity protection. For example, avoiding extraction in basins where fish biodiversity is high systematically shifts the Pareto frontier towards higher cost and water scarcity (Extended Data Fig. 6), largely due to the substantial overlap between cobalt resources and fish-rich zones (Extended Data Fig. 1). Indeed, aggressively protecting fish biodiversity could lead to unmet cobalt demand (Extended Data Fig. 7).

Country-level changes

Figure 3 explores the implications of sourcing shifts at the country-level, showing changes between 2025 and 2050 in stress-weighted water use (horizontal axes) and revenue (using the spot price of relevant metal in 2025; vertical axes), such that the quadrants reveal losers and winners in each dimension. Where mineral sources shift to reduce water stress up to an aggregate cost increase of 5%, stress-weighted water use decreases worldwide (black arrow) with revenue loss in Chile (-\$ 243B over 25 years), Mexico (-\$42B), Iran (-\$24B), Armenia (-\$15B), and the U.S. (-\$8B), shifting revenues to countries such as Russia (+\$61B), Peru (+\$59B), China (+\$55B), Canada (+\$44B), Mongolia (+\$25B), Serbia (+\$23B), the Democratic Republic of the Congo (D.R.C., +\$8B), and Kazakhstan (+\$7B; Fig. 3a). These shifts are especially economically relevant in places like Chile, Peru, the D.R.C., and Mongolia where battery minerals currently represent >5% of GDP.

Further constraining extraction to avoid basins with high fish biodiversity paradoxically sacrifices reductions in stress-weighted water use despite further reducing the globally average revenue of mining these materials (black arrow in Fig. 3b), still shifting extraction to Canada (+\$142B), Indonesia (+\$101B), the U.S. (+\$88B) Serbia (+\$82B), Russia (+\$74B), Mongolia (+\$28B), and Kazakhstan (+\$20B) but also Australia (+\$69B) and Mexico (+\$56B)—and not Peru, the D.R.C. or China. Yet assuming the option to desalinate at \$0.50/m³ of water alters global and country-level outcomes dramatically, increasing the overall revenues of mining battery minerals, and increasing Chilean extraction (+\$255B) at the expense of Mexico (-\$183B), Peru (-\$34B), Pakistan (-\$31B), Iran (-\$30B), Australia (-\$28B), and Armenia (-\$15B), and; (Figs. 3c and 3d).

Key sensitivities

Because our model depends on uncertain quantities such as water use per kg metal, basin-specific water stress, desalination costs, primary metal demand, and mine productivity, we perform 10,000 Monte Carlo simulations to determine the importance of each variable for our estimates of stress-weighted water use. The bars in Figure 4a show the relative importance of different variables grouped according to the total level of water stress entailed. The location of mineral extraction is consistently the most important factor for water stress, followed in order of importance by the feasibility of desalination, copper mining process efficiency, and mineral demand (Fig. 4a). Focusing on each of these key variables, total costs and stress-weighted water use vary substantially across all our simulations, but there is robustly a large potential to reduce water impacts of mining battery materials at relatively small additional global cost, including cost savings in many of our simulations (0% (increase of cost allowed) shaded area in Fig. 4b). Moreover, such desirable outcomes are not contingent on the feasibility of desalination, but feasible desalination does prevent undesirable outcomes where stress-weighted water use does not decline much even as costs increase (Fig. 4c; and also dramatically affects country-specific outcomes, Fig. 3). Best case increases in copper recovery per mass of mined ore (recovery rates) and decreases in water consumption per ton of processed ore allows substantial reductions in water stress and cost savings across almost all our simulations (Fig. 4d). Similarly, keeping total battery mineral cumulative demand 2025-2050 to <1000 Mt ensures total cost and water stress reductions (Fig. 4e). More targeted, absolute constraints could be much more challenging, though. For example, an analogous sensitivity analysis shows that avoiding extraction in basins with high fish biodiversity risks cobalt shortfalls even where water desalination is feasible and cobalt recovery rates increase (Extended Data Fig. 8).

Discussion

Trade-offs in the energy transition are inevitable, but we can recognize them and plan accordingly to prevent sub-optimal outcomes³⁵. The fact that mining impacts vary enormously depending on the type and grade of resources, extraction techniques, and natural resources proximity, opens the possibility to actively manage them to ensure the sustainability of the energy transition. Here, in consideration of the outsized impacts of mines on local water resources, we have quantified the trade-off between the cost of extracted battery minerals and stress-weighted water use, finding that it is possible to greatly reduce related water stress with limited increases in extraction costs. But we also demonstrate that some constraints could make it difficult to meet future demand, like cobalt if we avoid mining in basins with high fish biodiversity.

The success of water impact reduction strategies will depend on technologic, economic, social and geopolitical factors. Relocation of mineral extraction, crucial to reduce water stress, may not be fully possible due to economic and political considerations: government dependence on rents from mineral extraction, endowment of resources, quality of ore, labor access, long lead times and metal prices²⁹. Social and geopolitical factors act in both directions, local opposition increases business costs to open new mines³⁶, but existing water conflicts in South America may favor relocation strategies³⁷ or desalination adoption³⁸. The global trend on critical mineral security may favor domestic mining over cost or environmental impact criteria. Moreover, countries with a high dependence on mining revenue, will likely enact policies to protect their industry, even at the expense of water stress. Other factors may prevent mining investments altogether, such as difficulties in the business environment⁹ or civil unrest risk in Congo, which may trigger a cobalt supply shortfall unless there is further substitution of cobalt in lithium-ion batteries.

Water desalination could prevent mining revenue loss, and it is already being adopted in water-stressed areas to mitigate competing water conflicts with local communities³⁸. Our analysis shows that at current costs of \$0.5-1.0 per m³, desalination is a convenient option especially in water-stressed zones, with even further adoption if costs decrease to \$0.3-0.5 per m³ in the next decade³⁹. Pumping freshwater from the ocean to high altitude deposits may be energy and cost prohibitive, however there is the opportunity of synergies on lithium extraction and desalination from the same brine⁴⁰, which tend to be located in water-stressed zones (e.g. northern Chile with major lithium and copper resources (Fig. 1)).

Reducing primary demand prevents the expansion of mining activities and their associated socio-environmental impacts⁹, yet it may be hard to attain in practice given the growing applications for lithium-ion batteries. Driven by decreasing battery costs⁴¹, there is increasing usage

to complement intermittent energy generation (e.g., solar and wind)⁴², and if the trend towards larger vehicles continues worldwide⁴¹ and range expectations are not met by efficiency gains, then battery packs will get bigger. Reducing vehicle size and shifting travel to public transport depends on infrastructure, pricing and regulation rather than voluntary individual change alone⁴³. Circular economy actions reduce demand by extending battery life in first and second uses (e.g. from EVs to stationary storage) and through mineral recovery at end-of-life, and will reduce trade risks⁴⁴. However, even ambitious recycling targets will take decades to substantially replace primary mineral demand^{9,45}, given the expected long life of lithium-ion batteries; and recycling at scale will require policy support to overcome barriers in costs, access to feedstock and low mineral value in new chemistries⁴⁶.

Our study is subject to several important limitations. Perhaps most importantly, we assume mines can only consume surface water within their own basin; the water stress indicator we use explicitly excludes groundwater consumption³³. This may lead us to overestimate the cost of water use reduction, but we find those costs to be quite low over large and long-term reductions in stress-weighted water use. Moreover, the economic and ecological costs (and timelines) of large-scale water projects are large⁴⁷, and the use of groundwater is unlikely to be sustainable over the long term in acutely water-stressed basins⁴⁸. Relatedly, we assume static and marginal factors over the simulation period, even as climate scenarios may alter hydrological dynamics and water availability⁴⁹, and relocating mineral extraction may alter basin's water balance and water stress. However, there is yet substantial uncertainty as to the magnitude and sign of regional precipitation changes in the coming decades⁵⁰, so we chose to test the sensitivity of our main results to a wide range of assumed water use intensity of metal production and projected changes in basin water availability⁵¹. Our analysis is also focused on freshwater requirements of mining cathode battery materials, and we do not model in detail the interventions that might reduce such water use. For example, we do not assess water requirements and impacts elsewhere in the battery life cycle, we exclude graphite for lithium-ion battery anodes (which may use synthetic graphite produced from needle coke), and we do not consider costs related to the transport of desalinated water, improvements in recovery rates, or decreases in ore grade over time. We also model only known existing, conventional, and legal mineral resources, neglecting future discoveries, the potential for deep-sea mining or tailings extraction, and (largely untracked) artisanal mining. Similarly, our capacity expansion model assumes a central planning agent with unrealistically perfect market foresight. Future work could assess the effects of uncertain futures and the long lead-times required for mining expansion, related to factors such as permitting, community opposition, corruption, lack of access to financial capital or lack of human capital. Finally, our study focuses primarily on the

volume of water used in water-stressed basins, and to a lesser extent the fish biodiversity in those basins. But mining has historically also impacted the quality of water resources (e.g., by acid drainage and through downstream runoff), driving additional deforestation fronts, air pollution, and greenhouse gas emissions related to energy and land use⁵². Future research could thus extend our approach to analyze some or all of these other impacts.

The ongoing energy transition is expected to generate large benefits for society, but it will also entail an expansion of mineral mining with unavoidable impacts on water and ecological resources. There is no silver bullet to reduce water stress impacts from mining. However, we show that it may be possible to substantially and cost-effectively mitigate the water impacts of mining for battery minerals by a combination of strategic sourcing, desalination, and improved mining processes. Trade-offs are almost inevitable, but our results suggest that strategic planning and policymaking could successfully protect the most vulnerable water resources while meeting future demand for battery materials.

Methods

We build a capacity expansion model to meet future mineral demand based on deposit-level data that includes economic and geological characteristics. We estimate stress-weighted water use considering current water stress at each basin.

Mineral demand

We use the mineral demand forecast from the IEA Global Critical Minerals Outlook 2025-2050, which includes all clean technologies and other uses for copper, nickel, cobalt and lithium (Supplementary Figure 2). We interpolate linearly to fill year gaps. As our supply model for nickel considers only class 1 (high purity) deposits, we adjusted nickel demand by assuming 100% of clean technology demand and 30% of other uses is class 1⁵³. We present the three IEA scenarios of stated policies (SPS), announced pledges (APS) and net zero emissions (NZE), the latter one used as reference in the main body figures.

Mining deposits

We obtained deposit level data from the Metals and Mining database from S&P³⁰. We retrieved data for each deposit on location, total known resources (tons of ore), grade ore (%), development stage, mine type, installed capacity (tons ore per year), projected capacity (until 2032), recovery rate (%), operational costs (per ton of processed ore) and capital expenditure costs. We consider only terrestrial deposits with existing estimates of ore resources and ore grade, and with an active or on hold status, resulting in a final database of 1,108 deposits, which accounts for 99%, 98%, 98% and 86% of global resources for copper, nickel, cobalt and lithium, respectively.

We filled missing points in costs by constructing predictive models. For operational costs we fit a regression model based on region and resource type (Supplementary Figure 3 for lithium) or a random forest based on region and primary mineral (Supplementary Figure 4 for other minerals). For capital expenditure costs we fit a linear regression of installed capacity and cumulative investments to obtain the initial investment (intercept) and expansion cost (slope) (Supplementary Figure 5 for lithium and Supplementary

Figure 6 for other minerals). For lithium hard rock resources we consider an operational conversion cost from spodumene to lithium carbonate of \$2,500 per ton of lithium carbonate equivalent (LCE)⁵⁴.

Deposits of copper, nickel and cobalt extract co-products as part of their operation, which influence mine exploitation economics⁵⁵. We allocate cost to our minerals of interest based on revenue share, considering zinc, gold, silver, platinum and palladium as potential co-products and using the 2021-2025 average metal prices³⁰. We assume a minimum joint 50% cost share for copper, nickel and cobalt as a conservative assumption to prevent cheap extraction driven only by co-products high prices.

Water impacts of mining

We consider two impact pathways on water of mining: it deprives water available for other potential uses, and it affects aquatic biodiversity. The impact of mining on water scarcity depends on: (i) quantity of extracted ore, (ii) mining extraction processes, and (iii) water stress level of the basin (characterization factors (CF)):

$$Stress - weighted\ water\ use[m^3 - eq] = \sum_{d,t} Ore\ extraction_{d,t} [ton] \times Water\ intensity_d \left[\frac{m^3}{ton} \right] \times CF_d \left[\frac{m^3 - eq}{m^3} \right] \quad (1)$$

We estimate water intensity from ore processing with a regression of literature values (see Supplementary Table 1, Supplementary Figure 7 for lithium and Supplementary Figure 8 for other minerals). We add one m³ of water to lithium brine deposits (per m³ of brine) to account that removing brine water affects the flows of freshwater that recharge the aquifer⁵⁶.

To characterize stress-weighted water use at basins we follow the AWARE proposed factors and methods³³. AWARE estimates remaining water availability (after human and ecosystems requirements) at basin level and compares it to the world average, thus producing an indicator that compares water scarcity of each basin relative to historical global conditions. The CF are restricted to 0.1 to 100 m³ world-eq/m³, where a factor of 100 indicates that one cubic meter consumed in that basin is equivalent to the consumption 100 cubic meters worldwide. The CF allows us to convert raw water consumption to stress-weighted water use.

To characterize aquatic biodiversity, we calculated a fish index based on previous ecological species biodiversity threat index⁵⁷. We obtained the ranges for 14,911 different fish species³⁴ and overlap them spatially with the water basins³³. The index for each basin is estimated as the sum of the fractions of the species range area intersected by the basin. Thus, a high index represents a basin that has a high number of different species and a high overlap with their range, and hence endemism.

$$Fish\ Index_b = \sum_s \frac{Area(b \cap s)}{Area(s)} \quad (2)$$

To avoid inflated values due to outliers we scale the index to the 0-100 range by dividing by 150 (corresponding to the 99.9 percentile) and setting any number above 150 to 100. The resulting fish index was used as a scenario constraint where we avoid extraction in basins above certain fish index threshold.

Forecast mine production and expansion

We extended previous dispatch optimization models for mining capacity expansion developed for lithium⁹ and copper¹⁰ by adding a second objective to minimize stress-weighted water use. Based on OPEX and CAPEX cost minimization, the model determines the opening, expansion and production of each mineral

deposit for every year. The ore processed determined by the model is multiplied by the grade for each mineral in the deposit to determine mineral production, handling co-production jointly in the model.

The first objective function contains costs of opening, capacity expansion and extraction:

$$\min_{x_{d,t}, y_{d,t}, w_{d,t}, z_{m,t}} \sum_t (\sum_d (Cost^{Open}_{d,t} \times W_{d,t} + Cost^{Expansion}_{d,t} \times Y_{d,t} + Cost^{Extraction}_{d,t} \times X_{d,t}) + \sum_m (Cost^{Curtail}_{m,t} \times Z_{m,t})) \quad (3)$$

Decision variables are indexed by deposit (d), year (t) or mineral (m). $X_{d,t}$ is the processing of ore (in tons); $Y_{d,t}$ is the additional capacity added to the deposit that year (tons ore/year); $W_{d,t}$ is a binary variable that indicates the opening of the deposit; and $Z_{m,t}$ indicates mineral demand curtailed in year (t) for mineral (m) (tons/year). We follow similar assumptions as previous capacity expansion models⁹: omission of transportation costs across locations, no market power of mines to influence price, perfect foresight of mineral demand and resources availability, no resource discovery, and 7% discount rate for the mine industry⁵⁸ (costs presented in all results are discounted to 2025). We delay short-term production depending on status: 2 years if under development, 5 years under economic studies and 8 years under exploration. Curtailment costs represents the opportunity cost of not meeting mineral demand, which we set at 50% higher than the historical maximum price for each metal: \$21,000 per ton copper, \$72,000 per ton nickel, \$123,000 per ton cobalt, and \$102,000 per ton of lithium carbonate ($LiCO_3$) (all in USD)³⁰. To avoid a horizon effect in 2050, opening and expansion costs include a salvage credit based on the remaining mine life (set at 15 years), assuming a non-recoverable fraction of 20%. Costs, mine conditions and water impacts are static in the model horizon, so our results are projections given current global conditions.

The model has the following constraints, besides non-negativity for decision variables:

(1) **Demand satisfaction:** Mineral production surpasses demand at every period considering curtailed demand when cost is too high; considering ore grade (g) by deposit and recovery rate (r) by mineral from current production averages: 80% for copper and evaporative brine lithium, 70% for nickel, cobalt and other lithium resources.

$$Demand_{m,t} \leq \sum_d (X_{d,t} \times g_{m,d} \times r_m) + Z_{m,t}, \forall t, m \quad (4)$$

(2) **Capacity Constraint:** Production at each mine cannot exceed installed capacity, including initial capacity and announced expansions.

$$X_{d,t} \leq \sum_{\tau=1}^t (Y_{d,\tau}) + Initial\ Capacity_{d,t}, \forall d, t \quad (5)$$

(3) **Resource depletion:** Cumulative extraction cannot exceed known resources

$$\sum_t X_{d,t} \leq Ore\ Resources_d, \forall d \quad (6)$$

(4) **Maximum capacity:** Capacity can only be added to previously opened mines, and there is an upper bound on the maximum production capacity, set at 4% depletion rate⁵⁹ (25-year mine life), except at 2% for lithium evaporative brines.

$$\sum_{\tau=1}^t (Y_{d,\tau}) + \text{Initial Capacity}_{d,t} \leq (\sum_{\tau=1}^t W_{i,\tau}) \times \text{Max. Capacity}_d, \forall d, t \quad (7)$$

(5) **Single opening.**

$$\sum_t W_{d,t} \leq 1, \forall d \quad (8)$$

(6) **Ramp-up limit:** Annual capacity expansion is bound to a 4-year ramp up.

$$Y_{d,t} \leq \frac{\text{Max. Capacity}_d}{4}, \forall d, t \quad (9)$$

(7) **Basin water availability:** Total water consumption by all deposits within a basin (b) (includes withdrawals in upstream sub-basins³³) cannot exceed available water remaining (AWR).

$$\sum_{d \in I(b)} X_{d,t} \times \text{Water Cons}_d \leq \text{AWR}_{b,t}, \forall b, t \quad (10)$$

Once the cost-optimal (C^*) solution is found, the model follows a second objective to minimize total stress-weighted water use subject to remains near the cost-optimal solution (ϵ -constraint method), which constructs the Pareto frontier³². The curtail decision variable is fixed to explicitly avoid additional curtailment, as its original intend in the model is to allow demand feasibility under short-term production constraints, rather than on exogenously determining the water-cost trade-off.

$$\min_{X_{d,t}} \sum_t \sum_d X_{d,t} \times \text{Water Cons}_d \times \text{Water Factor}_d \quad (11)$$

We tested scenarios for fish-rich basins protection by not allowing production in deposits inside basins (or connected to downstream basins) with a fish index above certain threshold. Our desalination sensitivity scenario allows the model to obtain water at a fixed cost with zero impact on scarcity, consistent with the AWARE method treatment of ocean water³³.

Sensitivity analysis

To assess variable importance we conducted a global sensitivity analysis across key model input parameters (see Supplementary Table 2), including water consumption per ton of ore, stress-weighted characterization factors, desalination cost, total mineral demand, lithium iron phosphate (LFP) battery share and battery chemistry Ni–Co ratio (see Supplementary Text 1), maximum production rate, fish-index protection threshold, recovery rate, and cost parameters (OPEX and CAPEX). Parameter values were sampled independently from uniform distributions over plausible ranges to ensure full exploration of the input space. We employed Sobol quasi-random sequence to generate 10,000 parameter combinations, providing efficient space-filling coverage in the multidimensional domain. For each sample, the optimization model was solved at multiple cost relaxation levels ($\epsilon = 0\%, 1\%, 5\%, 10\%, 25\%$) to capture near-optimal trade-offs between cost and water scarcity. We use light gradient boosting machine (lightGBM) to explain water scarcity results based on input data sampling variability and shapley additive explanations (SHAP) to estimate parameter importance. We build density regions for simulation results across cost and stress-weighted water use using kernel density estimation (KDE).

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Acknowledgments

P.B., J.C. and S.J.D. were supported by STEER at Stanford University.

Author contributions

S.D., A.K., J.C., K.B. and P.B. designed the research, conceptualization and methodology. P.B., S.H. and K.B. collected the data. P.B. conducted the research, analyzed the data and created the figures with input from all authors. P.B. wrote the paper. All the authors reviewed and approved the final version of the paper.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data used in this study comes from proprietary and non-proprietary sources. Proprietary sources include S&P Mineral Intelligence for deposit level characteristics and for historical metal prices. Non-proprietary data include: IEA Global Critical Minerals Outlook 2025 for mineral demand projections (available at <https://www.iea.org/reports/global-critical-minerals-outlook-2025>), AWARE 2.0 for water characterization factors at basin level (<https://wulca-waterlca.org/aware/download-aware-factors/>), International Union for the Conservation of Nature for fish species ranges (<https://www.iucnredlist.org/resources/spatial-data-download>), World Bank for GDP (<https://data.worldbank.org/indicator/NY.GDP.MKTP.CD>). All public data is consolidated in the repository: <https://github.com/pmbusch/sustainable-mining>.

Code availability

Data analysis was conducted in R 4.5.1 and Julia 1.12.1. All the code developed in this study is publicly available at <https://github.com/pmbusch/sustainable-mining>.

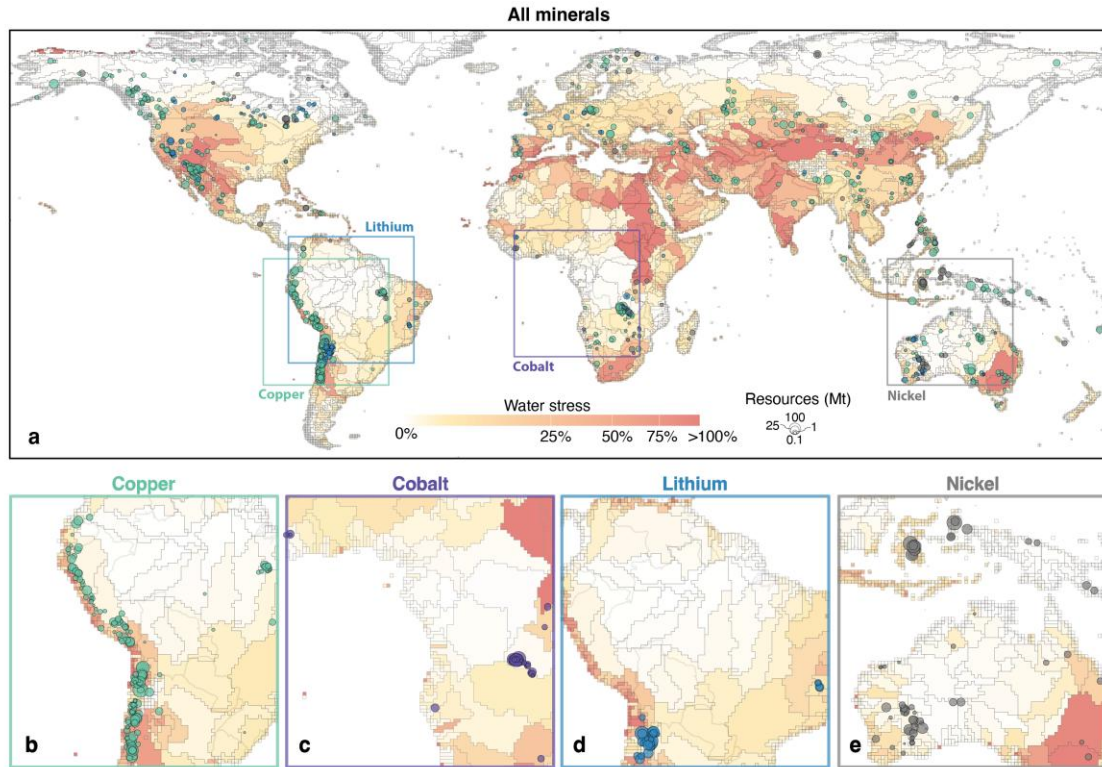


Figure 1 | Battery mineral resources (in million tons metal) overlap with basins with high water stress. (a) Shows all minerals, while each panel shows the 40° x 40° area with the highest quantities of mineral resources for (b) copper, (c) cobalt, (d) lithium and (e) nickel. Mineral co-production is common between copper, nickel and cobalt, panel (a) colors each deposit with the main mineral (highest ore grade), while mineral panels show mineral of interest. Water stress is calculated as current water demand divided by gross freshwater available in each basin³³. Data source for deposit characteristics is Metals and Mining database from S&P³⁰.

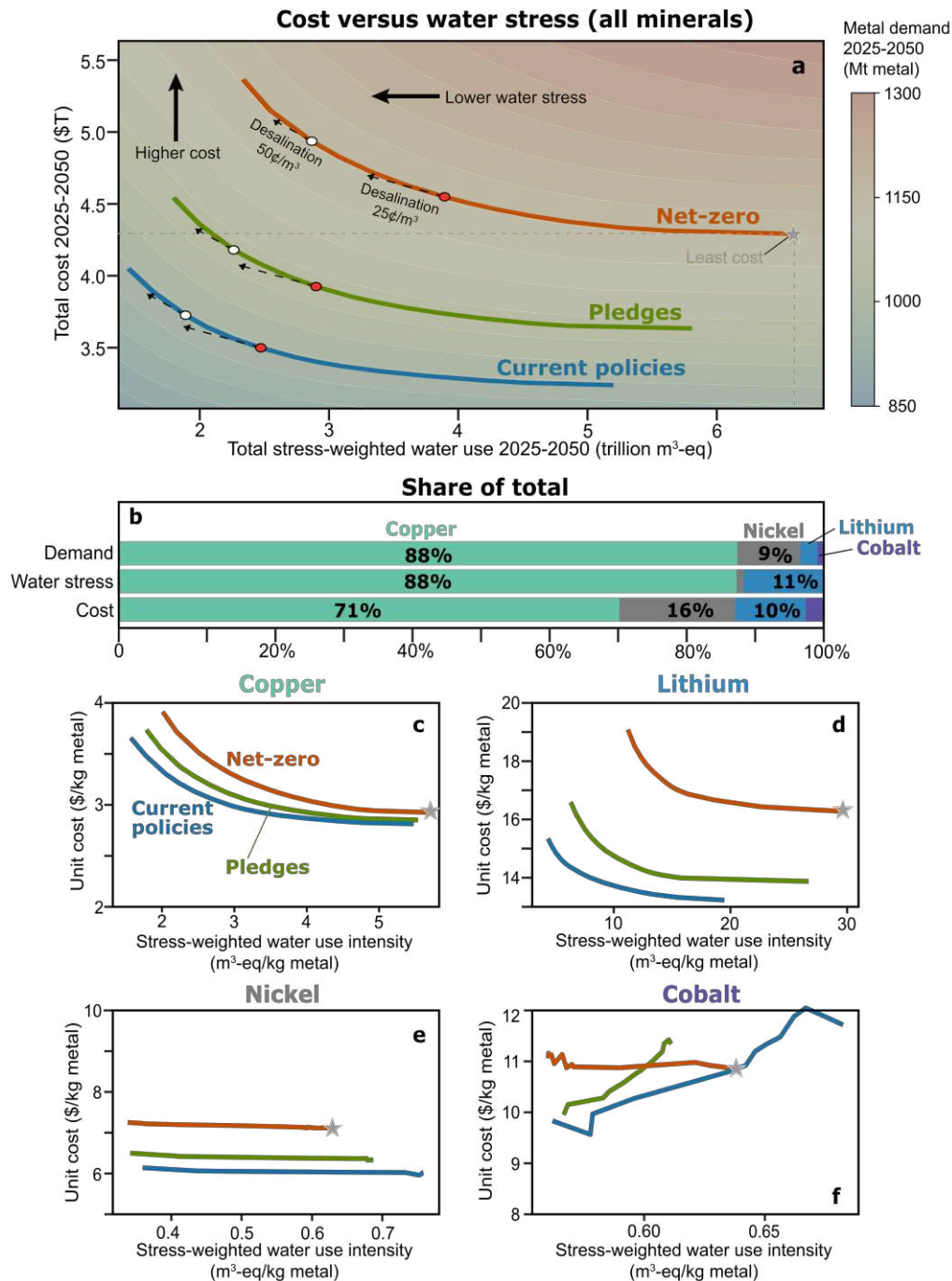


Figure 2 | Pareto trade-off curves between 2025-2050 stress-weighted water use (trillion m³ world eq.) and extraction cost (trillion USD). (a) Pareto curves for mineral demand levels (copper + nickel + cobalt + lithium), highlighting the three International Energy Agency (IEA) demand scenarios³¹ (contour levels are interpolations across IEA scenarios). The grey star shows the least cost solution for the Net-zero scenario. The red and white circles and dashed arrows show the point at which desalination becomes more cost-effective than moving along the Pareto curve, assuming desalination costs of \$0.5 and \$0.25 per m³ of freshwater. (b) Share of total demand, stress-weighted water use and cost by mineral. Unitary Pareto curves for the three IEA demand scenarios for (c) copper, (d) lithium, (e) nickel, and (f) cobalt. All costs are discounted to 2025.

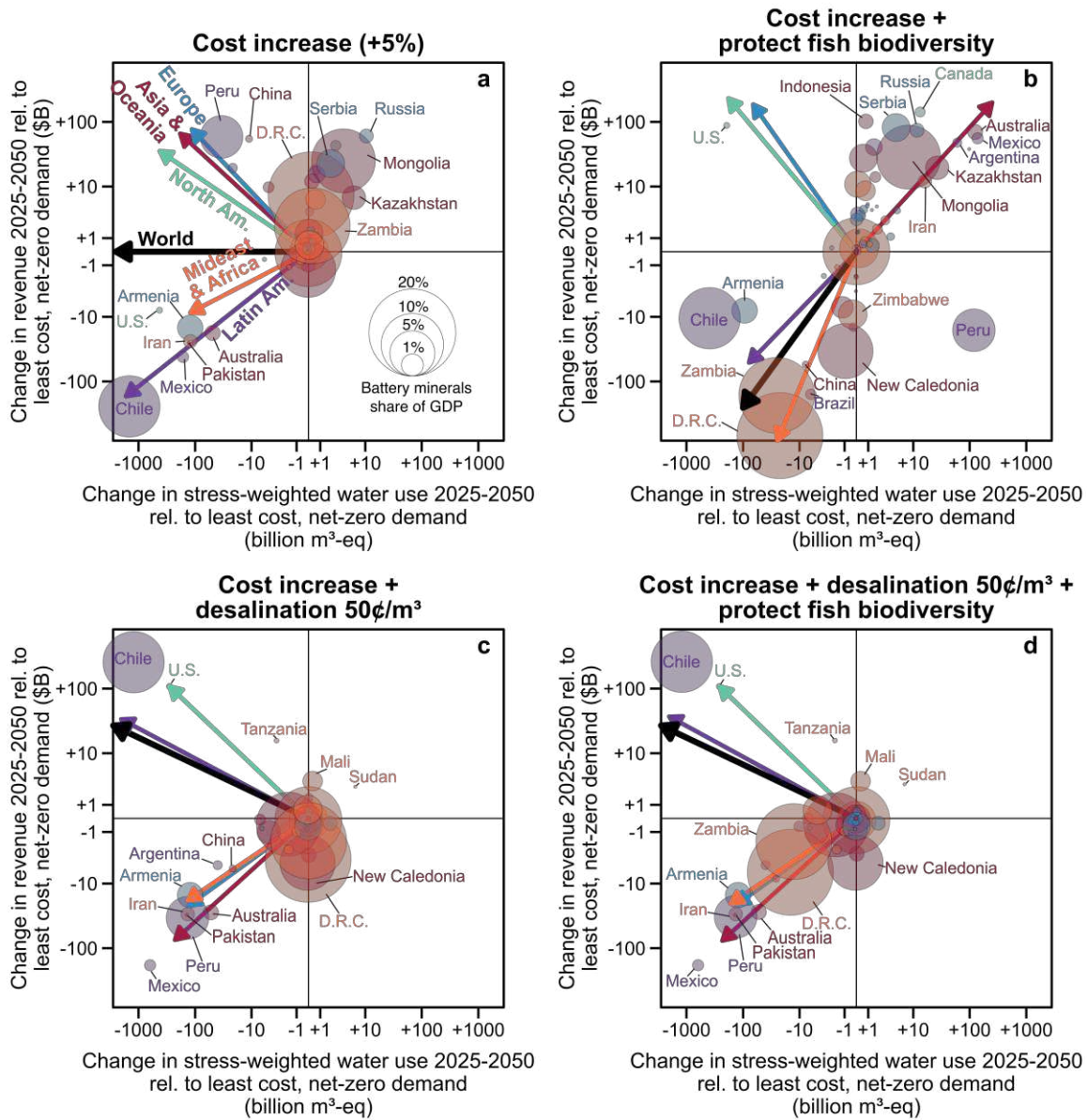


Figure 3 | Country-level changes in revenue (billion USD) and stress-weighted water use (billion m³ world eq.) relative to the least cost solution for the Net-zero demand scenario. Bubbles show countries, with the size showing 2025 revenue from copper, nickel, cobalt and lithium as share of their gross domestic product (GDP)⁶⁰. Revenue is calculated using 2025 average mineral spot price³⁰. Arrows indicate regional total change. **(a)** Scenario where a 5% increase in total costs is allowed to reduce stress-weighted water use. **(b)** 5% cost increase and protecting basins with a fish biodiversity index above 70. **(c)** 5% cost increase and water desalination available at \$0.5 per m³ of freshwater. **(d)** 5% cost increase, protecting basins with fish biodiversity index above 70, and water desalination at \$0.5 per m³. GDP: Gross domestic product. Costs and revenues are discounted to 2025.

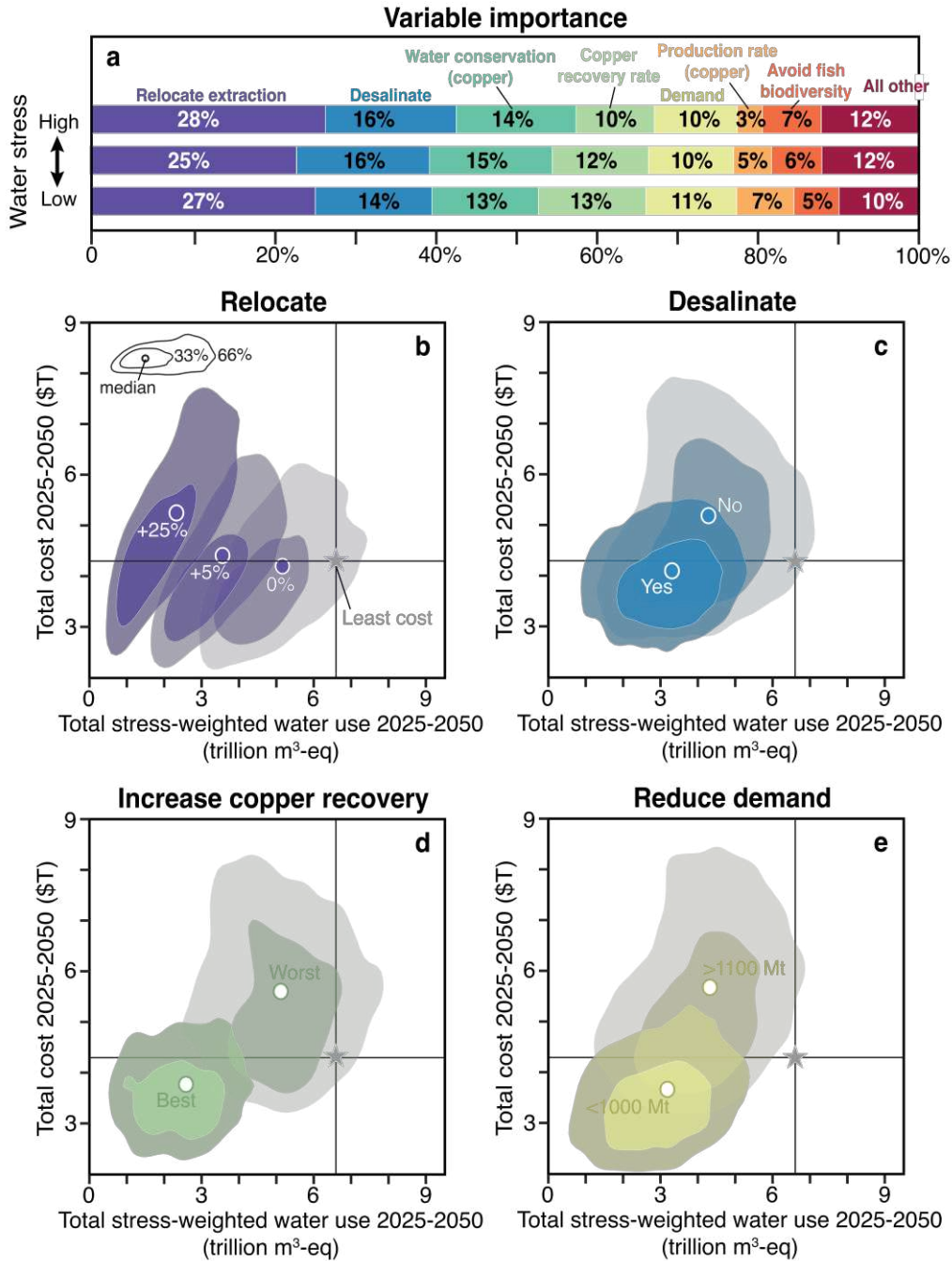


Figure 4 | Cost and stress-weighted water use sensitivities across 10,000 Monte Carlo simulations. (a) Relative importance of variables for different levels of stress-weighted water use, estimated through a light gradient-boosting machine and SHAP (shapley additive explanations). Each subsequent panel focuses on the main variables identified, showing the median for all simulations within each condition, along high-density regions containing 33% and 66% of the simulations (estimated using kernel density). The grey star shows the least cost solution for the Net-zero demand scenario. **(b)** Total cost increase allowed. **(c)** Water desalination available (at different costs) or not. **(d)** Copper recovery process, high recovery (>85%) and low water consumption per ton of ore (<25th quantile) and low recovery (<70%) and high-water consumption (>75th quantile). **(e)** Total primary mineral demand 2025-2050. All costs are discounted to 2025.

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