Article:

Eufrasio, R.M., Kantzas, E.P. orcid.org/0000-0002-7610-1874, Edwards, N.R. et al. (5 more authors) (2022) Environmental and health impacts of atmospheric CO2 removal by enhanced rock weathering depend on nations' energy mix. Communications Earth & Environment, 3. 106. ISSN 2662-4435

https://doi.org/10.1038/s43247-022-00436-3

communications
earth & environment

ARTICLE

https://doi.org/10.1038/s43247-022-00436-3 OPEN

Environmental and health impacts of atmospheric CO_2 removal by enhanced rock weathering depend on nations' energy mix

Rafael M. Eufrasio[1,2✉], Euripides P. Kantzas[2], Neil R. Edwards[3,4], Philip B. Holden[3], Hector Pollitt[4,5], Jean-Francois Mercure[5,6], S. C. Lenny Koh[1] & David J. Beerling[2]

Enhanced Rock Weathering is a proposed Carbon Dioxide Removal technology involving the application of crushed silicate rocks, such as basalt, to agricultural soils with potential co-benefits for crops and soils, and mitigation of ocean acidification. Here we address the requirement of diverse stakeholders for informative studies quantifying possible environmental and health risks of Enhanced Rock Weathering. Using life-cycle assessment modelling of potential supply chain impacts for twelve nations undertaking Enhanced Rock Weathering deployment to deliver up to net 2 Gt CO_2 y^{r-1} CDR, we find that rock grinding rather than mining exerts the dominant influence on environmental impacts. This finding holds under both a business-as-usual and clean energy mix scenario to 2050 but transitioning to undertaking Enhanced Rock Weathering in the future with low carbon energy systems improves the sustainability of the Enhanced Rock Weathering supply chain. We find that Enhanced Rock Weathering is competitive with other large-scale Carbon Dioxide Removal strategies in terms of energy and water demands.

[1] Advanced Resource Efficiency Centre, Management School, University of Sheffield, Sheffield S10 1FL, UK. [2] Leverhulme Centre for Climate Change Mitigation, School of Biosciences, University of Sheffield, Sheffield S10 2TN, UK. [3] Environment, Earth and Ecosystems, The Open University, Milton Keynes MK7 6AA, UK. [4] Cambridge Centre for Energy, Environment and Natural Resource Governance, University of Cambridge, Cambridge CB3 9EP, UK. [5] Cambridge Econometrics Ltd, Covent Garden, Cambridge CB1 2HT, UK. [6] Global Systems Institute, Department of Geography, University of Exeter, Exeter, UK. ✉email: r.eufrasio@sheffield.ac.uk

Adoption of the 2021 Paris agreement by over 191 nations requires carbon emissions reductions and the development of environmentally safe, scalable and cost-effective Negative Emissions Technologies (NETs) to extract CO_2 from the atmosphere for climate stabilisation[1–3]. Enhanced Rock Weathering (ERW) is a NET strategy that aims to accelerate the natural geological process of CO_2 removal via the application of crushed calcium and magnesium-rich silicate rocks (e.g. basalt) to agricultural soils[4,5] with potential co-benefits for food security[6–8], soil health and mitigation of ocean acidification[9,10]. In soils, the crushed silicate rock undergoes dissolution to draw down CO_2 from the atmosphere by forming bicarbonate ions that are ultimately transferred to the oceans for long-term storage via runoff and/or lead to the formation of pedogenic carbonates[11].

The ERW supply chain processes include mining rocks, generally in open site quarries and/or utilising existing stockpiles of rock dust, haulage of raw materials to processing sites, grinding rocks into a fine powder and transportation to croplands where it is spread onto soils[4,5]. Due to the novelty of NETs, including ERW, Life Cycle Assessment (LCA) of their possible environmental impacts is limited[12]. Current LCA research on ERW mainly focuses on optimisation algorithms for supply chains[13,14], and analysis of ERW supply chains within regional deployment scenarios[15,16]. However, large-scale ERW deployment on croplands across twelve countries indicates the potential to extract up to net 2 Gt CO_2 yr^{-1} by 2050, with potentially substantial but unquantified environmental impacts[5,17,18]. Thus, a comprehensive LCA of the environmental and health impact of ERW supply chain processes is required as an important step towards understanding the sustainability of this nascent CDR technology.

Here, we utilise an LCA methodology to analyse the negative potential environmental impacts of ERW deployment across twelve nations to deliver up to 2 Gt CO_2 yr^{-1} CDR by 2050 (Supplementary Tables 1–7). Our LCA modelling includes ERW deployment under two future (2050) energy scenarios: one based on existing policies only and one with additional policy measures to meet the Paris Agreement 2 °C global warming target with ≥66% probability (Methods). We refer to these energy scenarios as Business-As-Usual (BAU) and 2 °C, respectively[19]. In the integrated performance ERW deployment modelling, these scenarios affect net CDR efficiency via CO_2 emissions associated with rock grinding and rock dust transportation, where rock grinding to a particular particle size is optimised for individual nations based on energy supply constraints[5]. LCA for the ERW supply chain across nations is defined here as the product of all the processes in the ERW supply chain (i.e. mining, processing and grinding, haulage and distribution of rock dust).

We comprehensively evaluate the supply chain life-cycle impacts of ERW per unit area of cropland (hectare) in each of the twelve nations, assuming a baseline application rate of 40 t ha^{-1} yr^{-1} of basalt rock dust, and then the total impacts per country (Supplementary Figs. 1–8). Process-based LCA was undertaken with a cradle-to-grave system boundary[20] using the ReCiPe assessment method[21,22]. This method delivers results for environmental impacts across air, water and land with 18 impact categories, denoted 'midpoint indicators'. Results are summarised with 'end-point indicators' which are the aggregated mid-point impact categories for resource scarcity (RE), ecosystems (EC) and human health (HH) (Supplementary Fig. 9). Both mid-point and end-point impact calculations are standard procedures aligned with ISO14040 standards[23].

Our results highlight that rock grinding rather than rock mining exerts the dominant influence on environmental impacts. Mining is the dominant contributor to natural land transformation impacts and water resource depletion, but these impacts are relatively minor, with ERW maximally resulting in <0.05% of agricultural land loss and <0.25% of annual freshwater withdrawals for any of the twelve nations considered. A comparison of the energy, water and land requirements of ERW with other CDR strategies shows that it is competitive in terms of sustainability. It has half the energy demand of DACS, avoids land-use competition of other land-based technologies (Bioenergy with Carbon Capture and Storage, afforestation/reforestation/biochar), and has a 10–100-fold lower water demand than these other CDR strategies. Our results offer a broad assessment of the suitability of nations for sustainable ERW deployment, where lower environmental impact equates to greater sustainability, and identify new areas of methodological development for making LCA of ERW more robust in future.

Results

End-point impacts of the ERW supply chain. End-point impacts per unit area (hectare), synthesising 18 mid-point environmental impact category results across all supply chain impacts, reveal the relative sustainability of ERW for each of the twelve nations considered in our analysis (Fig. 1, Table 1). Impacts are scaled from 0 to 120 points per hectare of cropland (points/ha) to assess the potential resource depletion (RE), ecosystems (EC) and human health (HH) impacts of the ERW supply chain involved with the extensive deployment on cropland of nations that collectively could deliver up to net 2 Gt CO2 yr^{-1} CDR. Increasing CDR goals translates into LCA impacts through the effects of increased mining, grinding and transportation of rock dust onto a larger cropland area.

Resource depletion (RE). Resource depletion end-point impacts (per unit area) quantify the degree of exhaustion of abiotic resources associated with increased extraction of metals and minerals, and depletion of primary energy carriers such as oil, gas and coal and water consumption embedded in the processes of the ERW supply chain (Table 1). Regardless of the energy scenario, Poland, Germany, India and China show the highest RE values, whereas Brazil, France, Canada and Spain have the lowest values (Fig. 1a–d). This pattern is generally consistent as the CDR goal rises from 0.5 Gt CO_2 yr^{-1} to 2.0 Gt CO_2 yr^{-1} and coincides with the electricity sector carbon emissions of each country (Supplementary Figs. 4 and 5) as metal and mineral depletion is higher for electricity grids that are more reliant on coal and gas. The transition from undertaking ERW with BAU to the 2 °C energy scenario reduces RE in most nations, with the exception of China. Reductions in RE follow from the adoption of low-carbon electricity grids and a cleaner future energy. Under the 2 °C scenario, however, China is assigned a higher contribution to the global CDR goal, due to its available cropland area and the electricity capacity for grinding[5]. This higher CDR goal is met by increasing grinding energy for smaller and more weathering-efficient particles at the cost of increased RE.

Ecosystem loss (EC). The ecosystem loss end-point indicator aggregates impact categories related to climate change, land use, acidification, ecotoxicity and eutrophication (Table 1). Our analysis indicates that EC impacts are generally lower than those for RE, with less variation between nations because the majority of EC mid-points (i.e. acidification, ecotoxicity and eutrophication) are not greatly affected by the constituent processes of ERW (Fig. 1e–h). Results indicate that the EC impacts of ERW supply chain processes are similar in the two energy scenarios, ranging from 24 to 61 points/ha for the BAU and 25 to 65 points/ha for the 2 °C scenarios, with average impacts of 42 and 45 points/ha for the BAU and 2 °C scenarios. These results suggest that

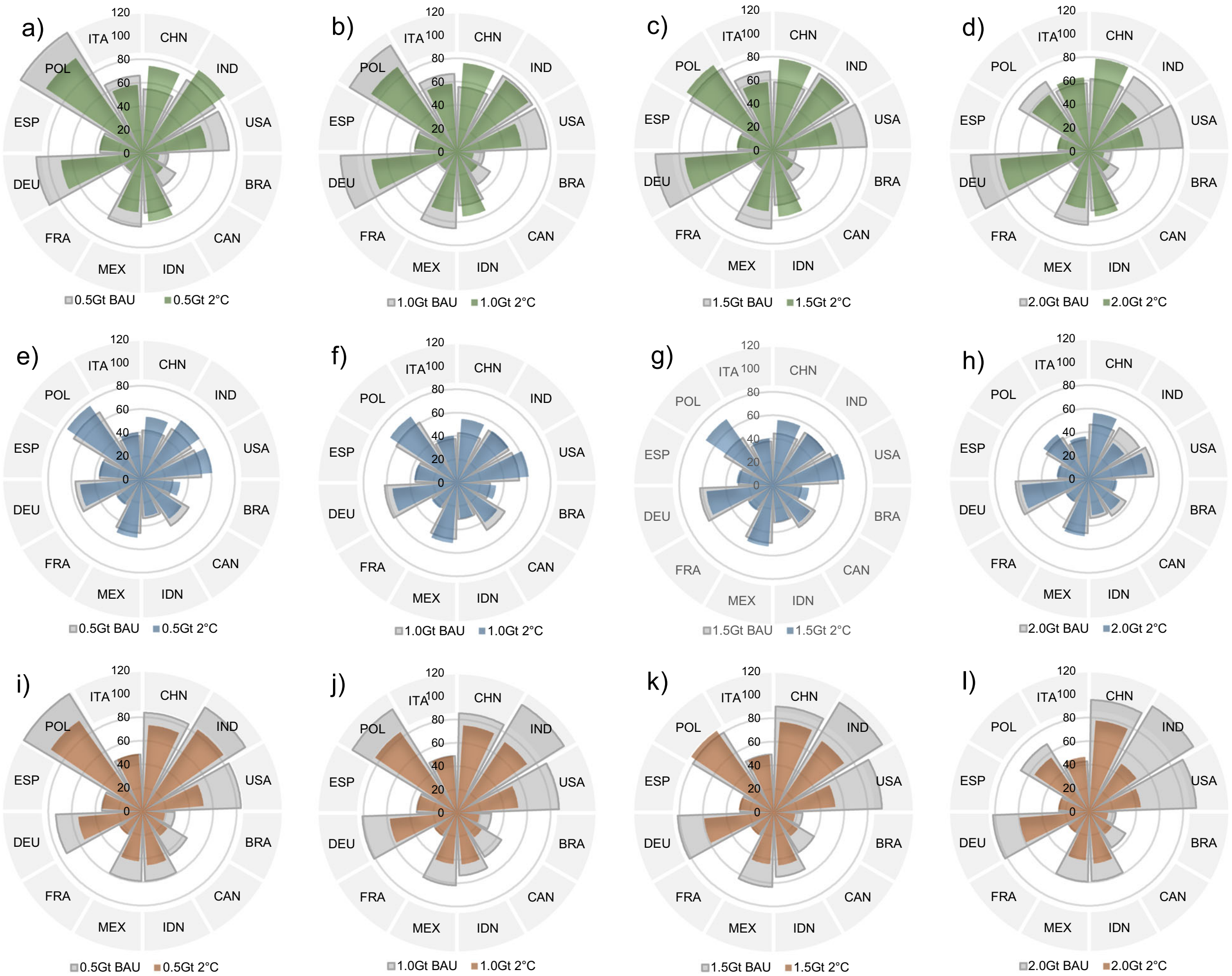

Fig. 1 End-point impacts of the enhanced rock weathering supply chain (per hectare) for 2050 under two energy scenarios. Plots display the three end-points **a**–**d** Depletion of natural resources, **e**–**h** Ecosystems and **i**–**l** Human health end-points for 12 nations with the collective potential to deliver net 0.5–2.0 Gt CO_2 yr^{-1} CDR under business-as-usual (BAU) and 2 °C energy policy scenarios. End-point impacts were calculated from 18 mid-point indicators with the LCA ReCiPe method based on 0–120 weighted units and points/ha functional unit. 120 represents highest impacts per hectare; 0 indicates no impacts.

transitioning to clean energy has only modest effects on ERW supply chain impacts, mainly because Global Warming Potential (GWP100; greenhouse gas emissions) is the only scenario-dependent mid-point that contributes to the EC end-point.

Human health (HH). Human health end-point impacts result from combining mid-point categories related to climate change, human toxicity, ionising radiation, ozone depletion, particulate matter formation and photochemical oxidation (Table 1)[22]. Here, HH represents the aggregated negative impacts linked to the ERW supply chain. (Fig. 1i–l) shows that HH impacts are greatest in India, USA, China, Poland and Germany, and smallest in France, Brazil, Spain, Indonesia, Italy and Canada. However, all HH impact scores are markedly reduced in the 2 °C scenarios for all nations, particularly the USA, India, Germany, Mexico, Canada and Indonesia, following the decarbonisation of their electricity supply. On average, HH values fall from 22–106 points/ha for the BAU to 18–80 points/ha for the 2 °C scenario, with average impacts of 62 and 47 points/ha for the BAU and 2 °C scenarios, respectively. As with RE, higher HH impacts point to the energy sectors of countries that rely on fossil fuels (Supplementary Figs. 4 and 5) due to the inclusion of the GWP100 mid-point. Nevertheless, Indonesia, despite ranking second in fossil fuel emissions per unit of energy behind India, ranks low in HH impacts, because its tropical climate and perennial crops favour higher weathering rates, meaning that less grinding is required to achieve an equivalent amount of CDR.

Synthesis. Nation-by-nation end-point LCA results indicate a consistent grouping of nations (Poland, Germany, India, USA and China) with the highest ERW supply chain environmental impacts per unit area, and another group of nations experiencing far lower impacts (France, Spain, Canada, Brazil). Resource Depletion and Human Health supply chain impacts are typically reduced by nations transitioning to cleaner, low-carbon energy for ERW deployment, as represented by our 2 °C scenario, whereas Ecosystem Loss impacts vary less between nations and are less affected by the choice of energy scenario.

Analysis of mid-point drivers. We next consider the mid-point LCA indicators for quantifying the environmental impacts of ERW supply chain processes per unit area (Supplementary Fig. 7), and their response to the transition from the business-as-usual (BAU) to the 2 °C energy scenario (Table 1). These mid-point indicators, expressed as 'potential' impacts, represent contributory drivers to the three end-point impact indicators (Resource Depletion, RD; Ecosystem Loss, EC; and Human

Table 1 Summary of Life Cycle Assessment drivers and results for enhanced rock weathering deployment across twelve nations.

Main drivers		CHN	IND	USA	BRA	CAN	IDN	MEX	FRA	DEU	ESP	POL	ITA
Average CDR contribution per country (%)[5]		27%	25%	21%	9%	3%	3%	3%	3%	3%	2%	1%	1%
Average reduction in silicate demand[5]	BAU to 2 °C	−4%	−18%	−10%	−7%	−29%	−13%	−11%	0.0%	−13%	0.0%	−8%	−9%
Electricity mix carbon coefficients reduction 2050, LCA based on[19]	BAU to 2 °C	−56%	−54%	−67%	−69%	−84%	−53%	−47%	10%	−21%	0%	−23%	−15%
Average energy increase (Pj) for rock grinding	BAU to 2 °C	107%	23%	50%	24%	−25%	83%	16%	0.1%	−14%	4%	0.4%	5%
Average supply chain energy demand (kwh/t) including average transport distances (LCA)	BAU 2 °C	210.5 338.0	245.5 334.7	283.5 368.4	186.4 215.8	256.5 265.6	250.1 295.1	283.5 368.4	386.5 386.9	307.3 302.1	275.3 281.1	326.5 350.7	270.7 297.1
Maximun Basalt Transport Distances per country for BAU and 2 °C scenarios	Roads km Rails km	1401 898	977 1246	1450 1692	1879 705	2217 1498	2024 218	1075 548	915 821	681 735	676 895	1034 1085	553 680

End-point indicators	Mid-point indicators	CHN	IND	USA	BRA	CAN	IDN	MEX	FRA	DEU	ESP	POL	ITA
Resource depletion	MDP	↑	↑	↑	↑	↔	↑	↑	↔	↔	↗	↑	↗
	FDP	↑	↔	↓	↓	↓	↗	↘	↔	↘	↔	↘	↘
	WDP	↗	↘	↗	↘	↘	↔	↘	↔	↘	↗	↔	↔
Ecosystems	TAP100	↓	↓	↓	↓	↓	↓	↓	↗	↓	↔	↘	↓
	FETPinf	↑	↑	↑	↑	↔	↑	↑	↔	↔	↗	↑	↗
	METPinf	↘	↓	↓	↘	↓	↓	↘	↔	↓	↔	↘	↔
	TETPinf	↑	↑	↑	↑	↔	↑	↑	↗	↔	↗	↑	↗
	FEP	↔	↓	↓	↓	↓	↘	↓	↘	↓	↔	↘	↘
	MEP	↘	↓	↓	↓	↓	↓	↓	↗	↓	↗	↘	↑
	ALOP	↑	↑	↗	↑	↗	↔	↔	↔	↔	↔	↑	↗
	ULOP	↑	↗	↘	↔	↘	↔	↘	↔	↘	↔	↔	↗
	NLTP	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
	GWP100	↘	↓	↓	↓	↓	↘	↓	↗	↘	↔	↘	↔
Human health	GWP100	↘	↓	↓	↓	↓	↘	↓	↗	↘	↔	↘	↔
	HTPinf	↘	↓	↓	↓	↓	↓	↓	↔	↓	↗	↘	↔
	IRP_HE	↑	↑	↑	↔	↔	↗	↑	↔	↑	↗	↔	↔
	ODPinf	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔
	PMFP	↘	↘	↓	↘	↘	↘	↘	↔	↘	↔	↘	↗
	POFP	↗	↘	↓	↓	↓	↘	↓	↔	↓	↔	↘	↔

We appropriate, results show the change from the business as usual (BAU) to the 2 °C energy scenario, averaged across the 0.5–2 Gt CO_2 yr^{-1} CO_2 draw-down goals. Effect of ERW on Mid-Point impact categories per hectare across the transition from BAU to 2 °C energy scenario is summarised for each country as follows: ↓ reduction >30%, ↘ reduction 5% and 30%, ↔ between 5% and −5%, ↗ increase 5% and 30% and ↑ increase >30%.

Health, HH) that provide relative indices of sustainability for the ERW supply chain of nations (Fig. 1).

Mid-point drivers for resource depletion (RE) impacts. Fossil fuel Depletion Potential (FDP) is highest in Poland and Germany and contributes to the high RE scores of these nations (Supplementary Fig. 7; Supplementary Table 8). In general FDP scores are lower in the 2 °C scenario than in the BAU energy scenario as a result of lower carbon emissions during mining and rock grinding. France has the lowest FDP impact of the twelve nations because nuclear energy reduces the depletion of fossil fuel resources across the ERW supply chain. Conversely, Metal Depletion Potential (MDP) is higher in the 2 °C energy scenario, reflecting the increased demand for raw materials for the electrification of transportation infrastructure[24]. The USA, Canada and Mexico have the highest MDP impacts per hectare, and Indonesia, China, Italy and France the lowest impacts (Supplementary Fig. 7; Supplementary Table 9). France has the highest Water Depletion Potential (WDP) values (Supplementary Table 10) because it has the largest proportion of nuclear energy in its electricity mix (Supplementary Fig. 4), which is deployed for comminution processes.

Mid-point drivers for ecosystems loss (EC) impacts. The EC end-point indicator is generally low and less variable between nations compared to the RE and HH impacts. EC environmental impacts result from three land-use impact indicators (Supplementary Fig. 7; Supplementary Tables 11–13): Natural Land Transformation Potential (NLTP), Agricultural Land Occupation Potential (ALOP) and Urban Land Occupation Potential (ULOP), whose impacts are dominated by mining (Supplementary Fig. 7). This analysis accounts for mining impact on hydrology and land-use change, in the case of mine tailings. All these mid-point environmental impact indicators are generally low, with small increases between BAU and 2 °C energy scenarios.

Additionally, the ERW supply chain processes contribute to EC through acidification of freshwater and marine ecosystems, as defined by Terrestrial Acidification Potential (TAP100) (Supplementary Table 14), and ecotoxicity of freshwater (FETPinf), marine and terrestrial (METPinf ecosystems) (Supplementary Tables 15–17). TAP100 values decrease by an average of 38%, METP by 29% and FETP by 30% with the transition from BAU to 2 °C (Supplementary Fig. 7), as averaged across CDR goals and countries. Eutrophication of freshwater (FEP; Freshwater Eutrophication Potential) and marine (MEP; Marine Eutrophication Potential) ecosystems, decreases by 30% when moving from BAU to 2 °C with the transition away from fossil fuels (Supplementary Fig. 7; Supplementary Tables 18–19). Ecosystem impacts are also driven by GWP100 which represents ERW supply chain CO_2 equivalent emissions. Averaged across all CDR goals, GWP100 is reduced by 25% in the transition from the BAU to the 2 °C scenario (Supplementary Fig. 7). However, GWP100 values are significantly higher in India, USA, Poland, and China than in other nations, and lowest in France and Brazil. These patterns reflect energy demand and mix, and relative rock dust transportation distances.

Mid-point drivers for human health (HH) impacts. Four mid-point impact categories contribute to the Human Health (HH) end-point indicator. Human Toxicity Potential (HTPinf) is reduced by 34% from BAU to 2 °C on average across our CDR goals (Supplementary Fig. 7), but with the greatest impacts in India and China (Supplementary Tables 20–25). In the case of Ionising Radiation Potential (IRP_HE), we predict an average increase of 32.4% from BAU to 2 °C scenarios driven by increased comminution and nuclear energy adoption under 2 °C. France has the highest IRP_HE, mainly as a consequence of nuclear power. Photochemical Oxidant Formation Potential (POFP) is reduced by 21% on average from BAU to 2 °C across CDR goals (Supplementary Fig. 7) and linked to comminution and transport. The maximum impacts are in Poland, with the lowest impacts in Brazil and France. Finally, Ozone Depletion Potential (ODP) increases by 30% from BAU to 2 °C. BRA scenarios also due to increased comminution demands.

Supply chain process impact contribution analysis. Mid-point potential environmental impacts from ERW supply chain processes are summed to give their cumulative contribution and expressed as a percentage for each category in each of the twelve nations and two energy scenarios (Supplementary Fig. 6). However, because values are relative, the contribution analysis is insensitive to the energy scenario.

We cover the nations with the largest CDR potential first: China, India and the USA. China's mid-point indicator categories are generally dominated by comminution processes, which account for 40–80% of the total impacts, except for ALOP and NLTP, where mining accounts for 90–100% of the total impacts. India and the USA have similar process contribution fingerprints for all mid-point indicators, but with a larger 20–40% contribution by road and rail transportation for 15 of the indicators (compared to China).

In the second bloc of nations, road and rail transportation for Canada contributes up to 60% of the total for some categories (e.g. MEP, ULOP, POFP), which reflects the long transport distances involved in ERW deployment there (a similar increase in the importance of transportation is also seen in the USA and India where quarry-to-field distances are large, Supplementary Fig. 3). In Brazil, comminution and mining processes tend to dominate total impact potentials. In Indonesia, where road and rail rock dust transportation distances are short, comminution processes dominate impact categories, accounting for 60–80% of the total impacts of each but with important relative contributions from rock dust spreading to total MDP and ODP impacts. Mexico and Germany have similar supply chain process contribution fingerprints with impact category totals mostly dominated by comminution. The European nations, Spain, France, Poland and Italy, also share similar contributions of supply chain processes to potential environmental impacts but with a higher proportional contribution of road and rail transport to mid-point indicators.

Overall, contribution analysis indicates that comminution processes, i.e. rock grinding, and transportation of rock dust from mines to fields, are the dominant contributors to potential environmental and health impacts for all twelve nations analysed. Rock grinding and transportation impacts are linked to energy and fuel requirements, respectively. These findings extend and support prior LCA studies for regional ERW deployment in Sao Paulo State, Brazil[16]. Mining, however, makes a consistently dominant contribution for all nations to the NLTP and ALOP categories.

National LCA impacts on the ERW supply chain. Technologies for CDR are primarily judged on their potential impacts on the overall carbon balance weighed against their demands for critical land and water resources, potentially in conflict with food production and other essential uses[25]. We therefore focus on area-integrated annual total impacts at the country level for Global Warming Potential (GWP100), Natural Land Transformation Potential (NLTP) and Water Depletion Potential (WDP), measured against their respective CDR/cropland contributions (Fig. 2).

Global warming potential (GWP100). We report national GWP100 values calculated as the increased radiative forcing over

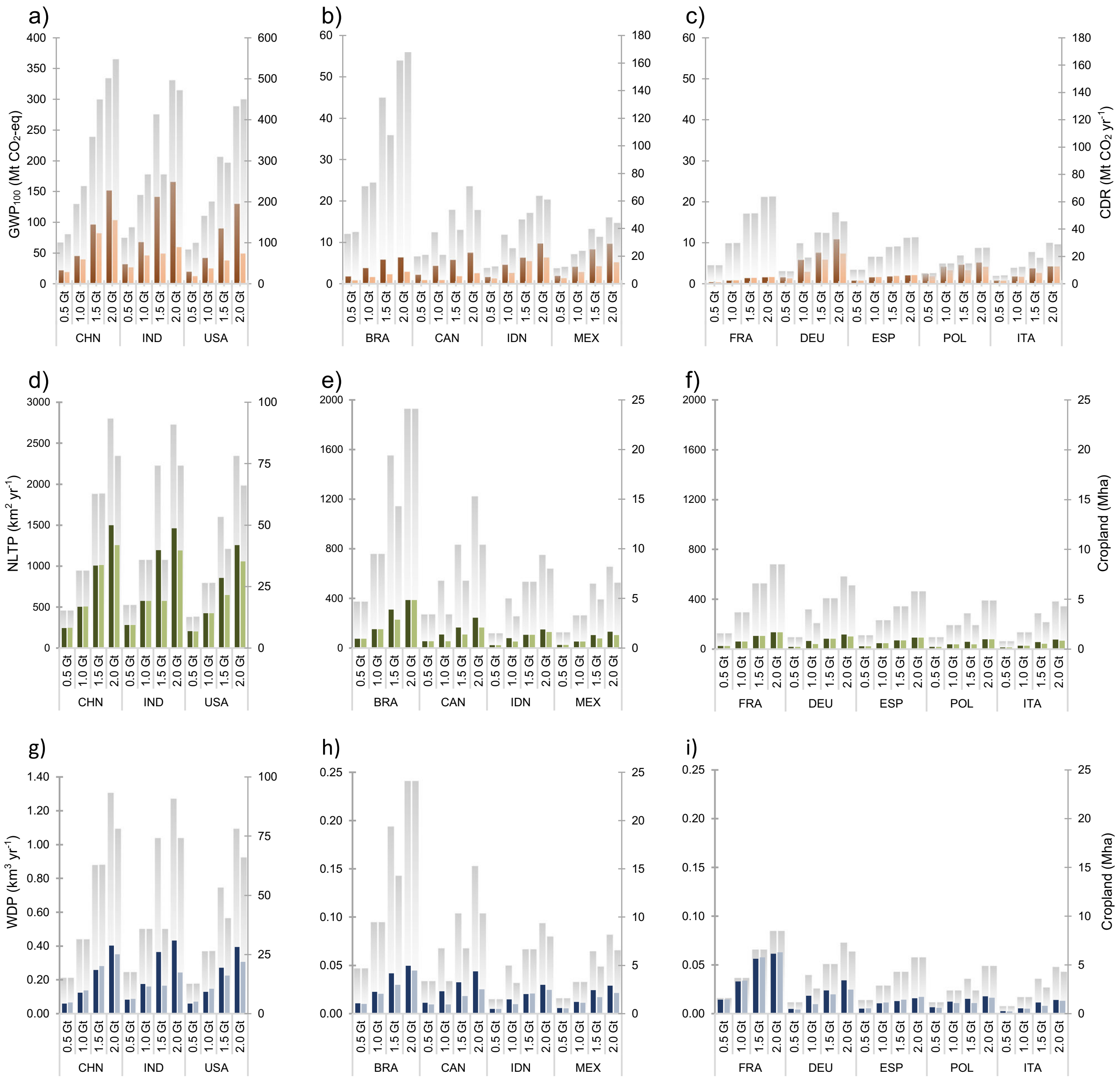

Fig. 2 Selected integrated national mid-point environmental impacts of the enhanced rock weathering supply chain for 2050 under two energy scenarios. Results are shown for **a**–**c** Global Warming Potential (GWP100) relative to net CDR potential for each of 12 nations; **d**–**f** Natural Land Transformation (NLTP) and **g**–**i** Water Depletion (WDP); NLTP and WDP are both displayed relative to cropland area used for ERW. Results are shown for 12 nations with the collective potential to deliver net 0.5–2.0 Gt CO_2 yr^{-1} carbon dioxide removal under business-as-usual (BAU) and 2 °C energy policy scenarios[5]. Countries are grouped into high (USA, IND, CHN), medium (MEX, CAN, IDN, BRA) and low fossil fuel CO_2 emitters (POL, ITA, ESP, DEU, FRA). IND India, MEX Mexico, CAN Canada, IDN Indonesia, BRA Brazil.

a 100-year time horizon for CO_2 and non-CO_2 greenhouse gas emissions associated with the ERW supply chain. GWP100 effectively represents the CO_2 equivalent footprint of cradle-to-grave captured CO_2. Figure 2 scales GWP100 (CO_{2eq} yr^{-1}) against the corresponding ERW net CO_2 removal potential of each nation to facilitate a comparative understanding of the relative impacts of LCA on ERW-based net CDR. Supply chain CO_2 emissions from mining, grinding and rock dust spreading derived by the LCA methodology are comparable to that accounted for previously[5].

The highest GWP100 values (i.e. supply chain CO_2 emissions) are associated with China, India and the USA, i.e. those nations with the largest CDR potential via ERW deployment (Fig. 2a–c). However, the GWP100 values of these nations fall markedly in the 2 °C scenario (compared with the BAU scenario) because of the transition away from fossil fuels (Supplementary Fig. 7), and subsequent reduction in comminution and transport emissions. GWP100 values for the second bloc of countries (Mexico, Canada, Indonesia and Brazil) and European countries (Poland, Italy, Spain, Germany and France) are lower and also reduced by moving to the 2 °C scenario rather than the BAU energy scenario. In terms of European nations, Poland and Germany have electricity sectors with the highest carbon emissions and consequently largest supply chain emissions, but also the greatest potential for improvement based on 2 °C energy decarbonisation pathways anticipated for 2050.

Natural land transformation potential (NLTP). NLTP refers to the change of land cover from one type to another[26,27] which, in the case of ERW, is mainly attributed to opening new mines. Thus, NLTPs for each country are roughly proportional to corresponding total rock demand, which scales with cropland area (rock application rate is kept constant at 40 t ha^{-1}) (Fig. 2d–f), with the USA, India and China having the highest values. NLTPs decrease by a factor of three in the second bloc of countries and by a factor of ten in European countries because of the lower corresponding cropland areas of these nations. As with GWP100, NLTP is reduced in the largest nations by transitioning from the BAU to the 2 °C energy scenario because cleaner electrical energy reduces the emission penalties of grinding smaller particle sizes, thus increasing weathering efficiency and allowing equivalent levels of CDR to be obtained with reduced area/rock requirements. This situation is not applicable to countries already constrained by electricity available for grinding such as Spain and Poland[5]. Taking the area-integrated NLTP in the context of maximum possible loss of agricultural land (Supplementary Table 26) due to increased rock extraction activities, we find that ERW linked NLTP could maximally result in <0.05% of agricultural land loss for any of the twelve nations considered, thereby supporting its sustainability.

Water depletion potential (WDP). WDP is the amount of water consumed by the ERW supply chain processes that are not available in the source of origin for humans or ecosystems. Across all twelve nations, WDP increases approximately proportionally with CDR potential. The USA, India and China are simulated to have WDP impacts ~10-fold higher than the other nations (Fig. 2g, h), which reflects the large cropland area utilised and the large amount of rock required to mine and crush for ERW deployment in these nations. Nevertheless, results indicate that there is significant potential for reducing WDP impacts following a transition to clean energy and a reduction in rock demand as weathering efficiency increases. Overall, we find that water depletion of ERW supply chain processes represents a very minor proportion of freshwater resources and annual freshwater withdrawals, in each of the 12 nations analysed (<0.25%) (Supplementary Table 27).

Synthesis. Area-integrated national environmental impacts of ERW indicate two general results that hold true across nations, energy supply scenarios and global CDR goals. First, national GWP, NLTP and WDP impacts scale by CDR, with the nations conducting ERW practices at the largest spatial scale simulated to have the greatest environmental impacts. Second, transitioning from BAU to 2 °C energy scenarios reduces these impacts. The lower electricity emissions allow for additional rock grinding to obtain smaller particle sizes, which increase weathering efficiency and reduce rock/land demand. This process eventually leads to lower impacts in all three categories, thus offering a pathway to increasing the sustainability of ERW deployment at scale.

Carbon capture efficiency of ERW. We quantify the performance of ERW by calculating the carbon removal efficiency (ηCO_2), defined by net CDR as a percentage of gross CDR, where net CDR is gross CDR minus supply chain CO_2 emissions. The results show that ERW-CDR efficiency scales linearly with the carbon footprint of projected electricity supply for 2050 across the twelve nations (Fig. 3). Nations with large ERW-CDR potential and high CO_2 emissions from electricity generation (China, India and the USA) have scope for increasing ηCO_2 by 10–20% by transitioning from the BAU to 2 °C scenario with a less carbon-intensive energy mix. Without making that transition, these nations have ηCO_2 values of around 0.75, in-line with earlier estimates of the carbon penalty from supply chain processes[5,11,17]. Nations with relatively low CO_2 emissions from power generation under the BAU energy mix already have high ηCO_2 and limited scope for further improvement. These nations include Brazil, France and Canada - each of which has dominant low-carbon power source (hydro, nuclear and natural gas, respectively) (Supplementary Fig. 4).

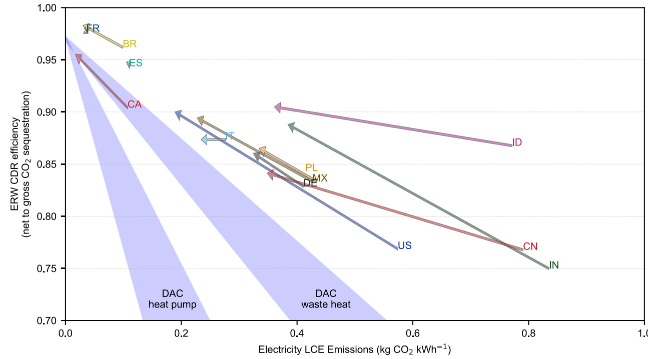

Fig. 3 Efficiency of carbon dioxide removal by enhanced rock weathering scales with the CO_2 emissions of electricity. For each nation, efficiency of ERW-CDR is shown for ERW deployment under business-as-usual (BAU) (vector tail for each nation) and 2 °C energy policy scenarios for 2050 (vector head). Shaded areas denote CDR efficiency of direct air capture plants powered by geothermal heat or waste heat[28].

Across a wide range of national electricity CO_2 emissions, ηCO_2 is generally higher for ERW than for direct air capture, regardless of whether the electricity to power DAC is supplied by geothermal energy or waste heat from incineration plants[28] (Fig. 3). With a low electricity footprint, however, the efficiency of the two CDR strategies converges; the DAC plants in Hellisheiði and Hinwil have the potential to reach ηCO_2 values of 93.1% and 85.4%, respectively[28].

Comparison of ERW with other NETs. Analysis of the ERW supply chain potential impacts provides a basis for a wider comparison with other NETs deployed to deliver CDR across the same range (0.5–2.0 Gt CO_2 yr^{-1})[29]. Direct comparison is complicated by a lack of consistency in impact categories and methods used[30] but can nevertheless be attempted for standardised metrics of energy, land-use and water-use requirements (Fig. 4). Across all three metrics, literature values are linear functions of CDR. Our analysis differs by showing the diminishing CDR returns as the geographical deployment of ERW increases and prime cropland areas suitable for high ERW decrease.

In terms of energy requirements, our ERW estimates are consistent with the mid-range of earlier ERW studies[11], increasing from 3 to 10 EJ yr^{-1} across the 0.5–2 Gt CO_2 yr^{-1} CDR range (Fig. 4a). In comparison, Direct Air Capture (DAC) has double the energy demand of ERW to achieve the same CDR range[29]. Other NETs, such as Bioenergy with Carbon Capture and Storage (BECCS), not shown here, have a positive net energy balance[29].

The land-use requirement (cropland) for ERW can be calculated as the sum of the NLTP from our LCA results, mainly resulting from mining activities, and the cropland area required for deployment (Fig. 4b). However, only the former should be considered as an additional land requirement. An important advantage of ERW over other land-based CDR strategies is that carbon sequestration is achieved without competing with other land uses (e.g. crop production) and avoids the loss of natural

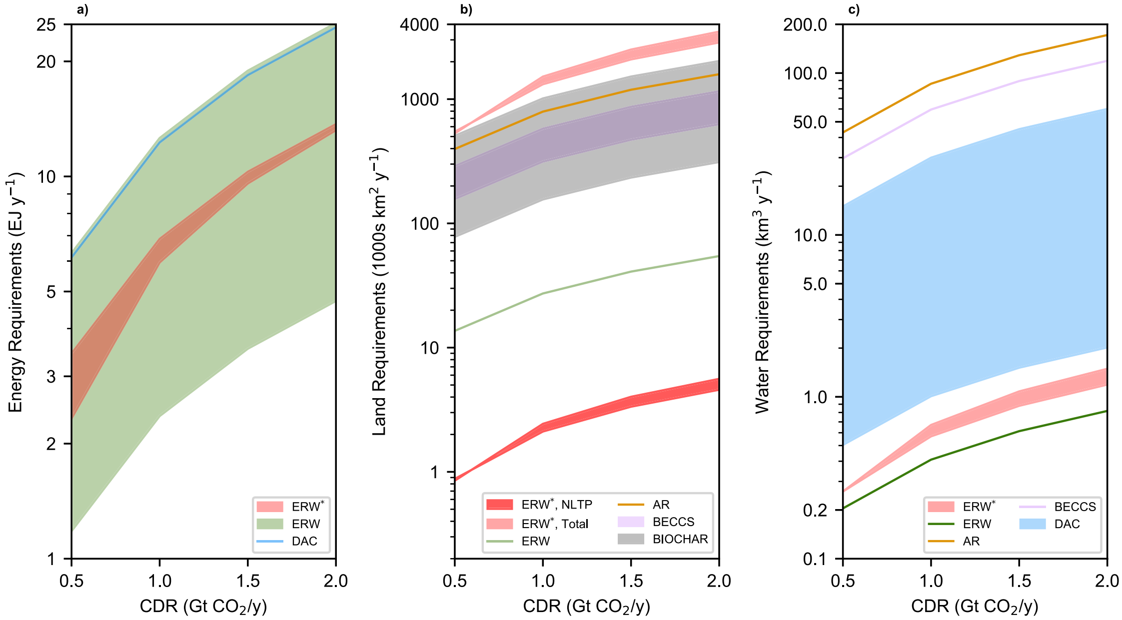

Fig. 4 Comparison of resource requirements of carbon dioxide removal (CDR) strategies. **a** Energy, **b** land and **c** water requirements for a range of CDR strategies across a comparable CDR range. Enhanced rock weathering (ERW*) this study, ERW prior work[11], Afforestation (AR), Direct Air Capture (DAC), Bioenergy with Carbon Capture and Storage (BECCS)[29,31]. In **b** cropland area is show for comparison only, given ERW deploys on existing land no additional land is required.

habitats and associated biodiversity[6,25,27]. Focusing only on the NLTP, ERW requires less area than all the other NETs. DAC is not a directly comparable land-based CDR technology but still requires land to site the industrial-scale CO_2 removal units, and for additional power production to drive the DAC systems and storage. Large-scale deployment of DAC to capture ~0.36 Gt CO_2 yr^{-1} requires 29 km^2 to site the 3683 DAC units and additionally between 445 km^2 (wind) and 4450 km^2 (photovoltaics) of land for electricity generation, depending on the energy source[28]. Additionally, as with Biochar[31] but unlike DAC and BECCS, ERW requires no complex industrial infrastructure development to capture, transport and store the CO_2 in sub-surface reservoirs, which all generate supply chain environmental impacts[28].

Our results show that annual water consumption for ERW deployment resulting from LCA is higher than previous estimates lacking LCA quantification[11,29]. Nevertheless, our estimates are substantially lower than those for AF/RF, BECCS and DAC, respectively, across equivalent CDR goals (Fig. 4c). These alternative NETs require large quantities of water to support tree and bioenergy crop biomass production, while DAC has a moderate-to-high water demand with substantial uncertainty. Other NETs, such as biochar and soil carbon sequestration, have very limited requirements for water.

In summary, our comparison of the energy, water and land requirements of ERW for CDR show that ERW is competitive in terms of sustainability. ERW requires half the energy demand of DACS. It needs more land than other land-based technologies (BECCS/AF/RF/biochar), but avoids land-use competition. ERW also has a 10–100-fold lower water demand than these other CDR strategies.

Discussion

The emergence of nascent CDR technologies has increased the demand for informative studies on their potential environmental impacts from diverse stakeholders, including the public, civil society, scientists and policymakers[12,14,32]. We have attempted a first detailed LCA quantification of the possible environmental and health impacts of ERW supply chain processes (mining, grinding, distributing and spreading rock dust) for twelve nations with the potential to achieve up to net 2 Gt CO_2 yr^{-1} CDR[5]. Our analyses consider on-site and off-site resource use, pollutant emissions and land use associated with ERW supply chain processes, and include an impact assessment of ERW deployment for nations under two future energy scenarios: business as usual (BAU) and 2 °C for 2050.

Calculating national impact indices, taken as the average of the three end-point (per hectare) indicator scores (Resource Depletion, RE; Ecosystem Loss, EC; Human Health, HH) (Fig. 1), shows that the transition to clean energy has a marked capacity to increase sustainability for all twelve nations considered (Fig. 5a, b). Area-integrated impact indices scale the impact index with cropland area and rank the relative ERW sustainability of the USA < India < China (Fig. 5c,d). As with the per hectare impact index, the area index shows that the environmental and health impacts caused by the ERW supply chain are reduced in nations where deployment is undertaken under a 2 °C energy scenario compared with that in the BAU case (Fig. 5b). This finding reflects the societal benefits of transitioning from fossil fuels to clean low-carbon energy for rock grinding and the electrification of rail and road transportation systems. For China, however, the impact index remains similar across both energy scenarios, but CDR increases by 10% in the 2 °C case (Fig. 5a). This outcome is a consequence of increased energy production under the 2 °C scenario allowing ERW practices to be undertaken on less land but with more finely ground rock that undergoes faster chemical weathering and yields higher CDR efficiency, and sustainability.

Among the second bloc of nine nations, Brazil is exceptional. It has a low impact index but 2.6-fold higher CDR potential than any of the other countries. This is due to energy generation with a high proportion of hydropower, extensive croplands suitable for rock dust amendment being co-located with the Parana flood basalts[16] and a warm climate that accelerates ERW processes[5] (Fig. 5b). Other nations in this bloc have similar low index values, with the exception of France which has predominantly nuclear energy production driving efficient ERW and thus CDR gains.

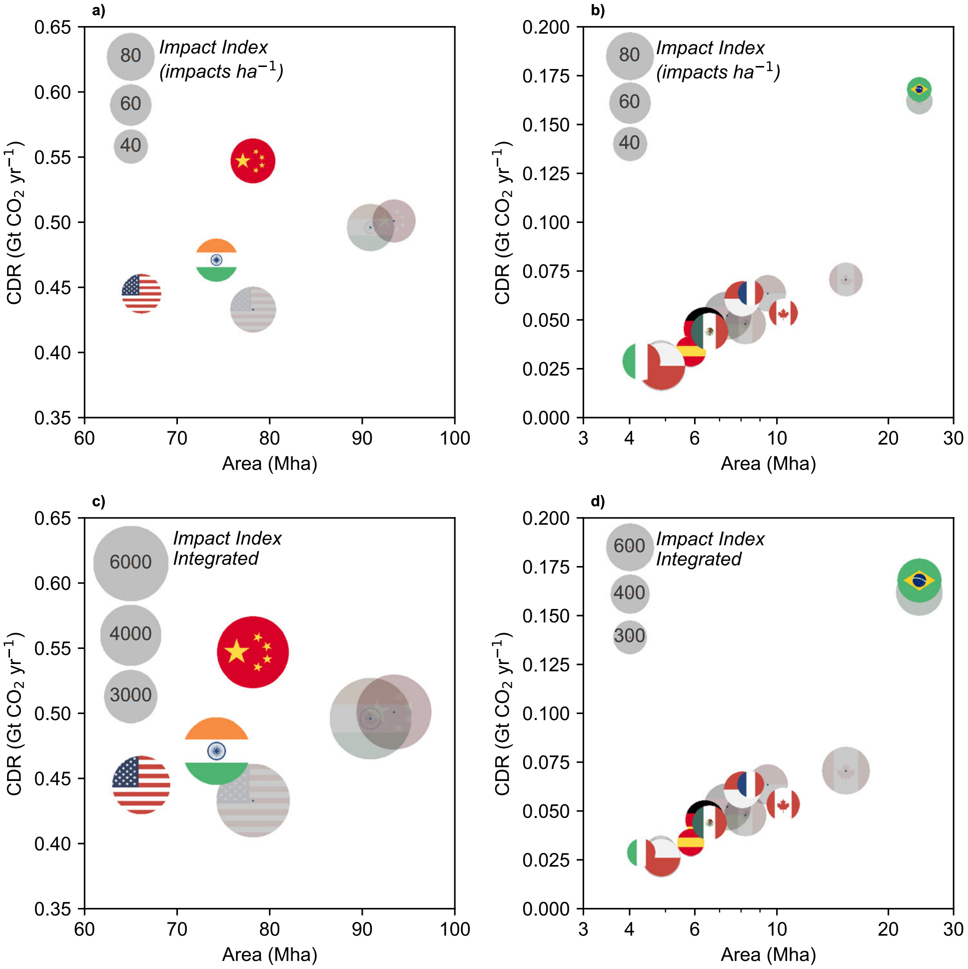

Fig. 5 Sustainability of the enhanced rock weathering supply chain scales with carbon dioxide removal potential. Sustainability index (SI, per hectare) calculated as the mean of the three end-point scores (see Fig. 1) for **a** China, India and the USA and **b** 9 other countries (see listing in Table 1) relative to the cropland area of ERW deployment and carbon dioxide removal (CDR) potential. Panels c and d show the area-integrated sustainability index for the same nations as in **a** and **b**, respectively, (i.e. SI × cropland area used for ERW deployment). For each nation, we highlight results for ERW with under business-as-usual (BAU) (bright flags) and 2 °C energy policy scenarios (shaded flags).

We caution that inherent uncertainties in LCA methodologies exist when adopted for agroecosystems[33] and CDR technologies[12]. These limitations are additional to those relating to the accuracy of the primary and secondary data sources used in analysing supply chain impacts. Limitations of LCA in capturing the suite of environmental impacts are exemplified by organic agriculture, in which, for example, land use, soil quality and soil function are not fully represented[33]. These areas of weakness in LCA methodology are directly relevant to ERW. Amendment of soils with a multi-element silicate rock, such as basalt, has the potential to rebuild soils, reverse soil acidification and resupply depleted pools of plant-essential nutrients, including phosphorus (P) and (K) potassium[4,6,8,34]. These effects of ERW can improve soil health and increase crop production, as shown in mesocom experiments and field trials[6,8,35,36]. The release of P and K lowers the demand for expensive P and K fertilizers derived from finite rock resources[34], while the release of silica from basalt can protect crop plants from pests and pathogens, thereby reducing pesticide requirements. Reducing agricultural demand for fertilizers and pesticides, which themselves have substantial environmental footprints, by substituting with crushed basalt, has yet to be assessed.

Methodological advances are also required to integrate better greenhouse gas removal functions into LCA for CDR technologies[12,14], including ERW practices driving CO_2 sequestration and mitigation of soil nitrous oxide emissions[37]. We also need to know how a carbon-neutral or less-toxic economy and environment will be influenced by a combination of gains in ERW and CDR efficiency and sustainability[38]. Additional uncertainties relating to CDR technologies include the political, social and economic considerations affecting the degree to which nations deploy ERW practices[12,14].

Our LCA analyses deal with ERW practices on agricultural lands using mined crushed basalt, but carefully screened and processed calcium silicates from construction and demolition (C&D) waste, and stockpiles for crushed basalt, may also have the potential for CDR and could greatly reduce the demand for mining and grinding[5,39]. Forecast increases in the production of C&D waste materials over the next few decades for China, India and the USA are substantial with a combined total exceeding 30 Gt yr^{-1} by 2100[5]. The use of recycled C&D waste can lower greenhouse gas emissions by 65% compared with aggregates obtained from raw crushed stone material[40] and is consistent with the concept of the circular economy in converting waste to resources and prolonging the cycle life of materials[41]. Innovative ERW utilisation of C&D waste, and rock dust stockpiles, to lower the requirement for mining and grinding, requires separate LCA analyses to understand likely reductions in resource depletion, and environmental and health impacts.

Conclusions

Negative ERW supply chain environmental and health impacts increase with national CDR potential across all twelve nations considered in our analysis. However, transitioning to undertaking ERW in the future (2050) with a clean, low-carbon energy mix and the electrification of transportation systems, as represented in our 2 °C energy scenario, significantly improves the sustainability of the ERW supply chain. Nation-by-nation end-point LCA on a per hectare unit area basis highlights consistently a grouping of nations with the highest ERW supply chain environmental impacts per unit area (Poland, Germany, India, the USA and China), and another group of nations with lower impacts (France, Spain, Canada and Brazil). We find that the carbon footprint for the captured CO_2 depends on the carbon footprint of the electricity supply. In terms of energy, land and water requirements, ERW is found to be competitive with other large-scale CDR strategies and holds additional advantages over some of them by requiring less energy (e.g. direct air capture) and less water (e.g. afforestation), while supporting agricultural production rather than competing with it (e.g. bioenergy crops). We identify LCA future research and methodological advances that are required to improve impact assessments of ERW and other land-based CDR NETs in the future.

In addition to our quantitative results that have utility in defining quantitative pathways towards achieving net-zero emissions targets, we highlight the following key policy-related messages from our results, aligned with IPCC AR6 recommendations[42] in terms of the supply chain environmental impacts of the large-scale CDR strategies considered here.

(1) Our LCA outputs weigh the sustainability of the ERW supply chain against other CDR technologies to assist policymakers in combining CDR solutions to achieve national net-zero targets and aid decision making for investment and adoption of CDR strategies.
(2) Our derived national impact indices (Fig. 5) translate to a nation's suitability to employ ERW. These results provide an initial basis for nations to consider ERW as a possible CDR strategy, or even remap and distribute national CDR targets from high to low impact countries to balance capture efficiency and sustainability impacts in their supply chains.
(3) Obtained national end/mid-points impacts (e.g. resource/water depletion, natural land transformation) can offer nation-specific CDR solutions by allowing policymakers to forecast and alleviate impacts while at the same time avoiding combining CDR technologies with overlapping demands. Results can play a major role in countries prioritisation of sustainable CDR solutions mix to mitigate climate change whilst protecting biodiversity and the planet.

Methods

Cropland carbon dioxide removal with ERW. We use the global ERW-CDR goals for 2040–2050 apportioned to nations reported in ref. [5]. Those analyses are based on a detailed 1-D vertical reactive transport model for rock weathering with the steady-state flow, and a source term representing rock grain dissolution within the soil profile[5]. The 1-D model profile modelling accounts for changing dissolution rates with soil depth and time as grains dissolve, chemical inhibition of dissolution as pore fluids approach equilibrium with respect to the reacting basaltic mineral phases and the formation of pedogenic calcium carbonate mineral in equilibrium with pore fluids[5]. Simulations considered generic basalts exhibiting relatively slow- versus fast-dissolution rates due to differing mineralogy. Basaltic minerals undergo dissolution at different rates, with some minerals continuing to undergo dissolution and capture CO_2 after the first year of application. Thus the model calculates mean rates of basaltic rock dust weathering and CDR following annual applications by tracking cohorts of particles applied over a 10-year time horizon and their mineral composition. Reported annual CO_2 removal rates are decadal averages (2040–2050) derived from repeated basaltic rock dust applications for a baseline application rate of 40 tonnes per hectare yr^{-1}.

Net CDR is defined as the difference between CO_2 capture by ERW as dissolved inorganic carbon and soil (pedogenic) carbonate and the sum of CO_2 emissions for logistical operations. Carbon emissions per unit mass of ground rock depend on particle size, the CO_2 emissions per kilowatt hour of electricity generated from component energy sources (fossil fuels, nuclear and renewables), as well as the carbon costs of sourcing and transporting the silicate materials. Rock grinding to reduce particle size and maximise CDR is the primary energy-consuming operation in ERW. Country-specific electricity production and the forecast fractional contributions to electricity production by different energy sources (coal, natural gas, oil, solar photovoltaics, concentrated solar power, hydropower, wind, marine) for 2050 are based on BAU, that is, currently implemented energy policies, and energy projections consistent with a 2 °C warming scenario[19]. Assessment of basalt transport from source regions to croplands is based on road and rail network analyses to calculate distances, costs and carbon emissions for each scenario. The 1-D model[5] is driven by high spatial resolution global datasets for soil pH, soil temperature, soil hydrology and crop productivity.

Life-cycle assessment (LCA) methodological framework

Goal and scope. The first step in LCA methodological framework is defining the goal and scope of the analysis[21,22]. The purpose of this study is to estimate the potential environmental impacts associated with the potential scaling up of ERW in 2050 according to four CDR goals (0.5, 1.0, 1.5, 2.0 Gt CO_2 yr^{-1}) and two energy scenarios (BAU and 2 °C). The justification for these goals and scenarios was outlined in our previous study[5]. We followed an extended bottom-up approach, where the incorporation of projections in the energy mix of twelve countries for BAU and 2 °C scenarios were modelled with openLCA software[43] through the modification of current life-cycle inventories from the ecoinvent database[44]. Simulated carbon coefficients from these scenarios were used to estimate the impacts of all the processes involved in the supply chain of ERW (Supplementary Figs. 1, 2).

Data. The second step within the LCA methodological framework is to source large-scale data input. Given the complementary nature of this study, input data were inherited from our major techno-economic work, along with additional data from different sources. Specifically, we used maximum and minimum energy requirements for grinding and transportation processes in ERW supply chain[5], while energy requirements for mining and spreading processes in ERW supply chain were taken from the literature[11,17] and calculated with ecoinvent datasets[44]. Nations' energy coefficients per kWh in BAU and 2 °C scenarios were derived from ref. [19].(Supplementary Figs. 4-5). The E3ME model[19] uses a simulation-based energy-economy approach related to carbon cycle climate scenarios and grid transformation technologies. The ERW model contains geographical information related to crop areas, rock demand and energy requirements for ERW processes (mining, grinding, transport and spreading) which were essential to perform our spatial life-cycle inventory.

Inventory. The third step in this LCA methodological framework is to perform a detailed spatial inventory analysis of available resources to identify optimal target cropland application areas in the twelve countries[5]. Although this has been described[5], for this life-cycle inventory, we highlight the following two additional points: (a) for sources of basalt rock, we used a high resolution global lithological map database (GLiM), which identifies the physical, mineralogical and geochemical properties of rocks, thereby allowing the analysis of earth surface processes at global scales[45]. This database has been used recurrently in previous studies[46]; however, considering the restrictions on mining in natural protected areas, we have included in this analysis the world database on protected areas, which is managed by the Environment World Conservation Monitoring Centre of the United Nations[47]. Therefore, an availability restriction model created in ArcGIS model builder has been incorporated during this inventory analysis phase to avoid potential damages by mining on natural protected areas, rivers and archaeological zones (Eq. 1).

$$S = \sum_{i-1}^{n} w_i c_i \left(r_{Pa} \times r_{Rl} \times r_{As} \right) \quad (1)$$

Where:
$S =$ Suitability for rock mining
$w_i =$ Weight for a criteria i (Ci)
$C_i =$ Criteria for suitability
$r_{Pa} =$ Restriction related to protected areas
$r_{Rl} =$ Restriction related to river locations
$r_{As} =$ Restriction related to archaeological sites

We also identified optimised service areas between rock demand in crops and supply sources of the supply chain. Modelled with a transport network analysis, the network analyst tool established the costs of meeting the annual demand of products (basalt rock powder in this case) at a specific site from a number of geographically disperse available supply points[48]. Therefore, the use of this approach in this study takes the form of an optimisation model for the transportation systems[49].

For the transport analysis, we created the cost friction raster per country based on its road[50] and rail network infrastructure using the ArcGIS' OD Cost Matrix analyst tool[49]; thus the cost matrix enabled the selection of identified cropland areas in order to find the three (self-defined) least-cost routes for basalt suppliers. In the friction raster, transport emissions are calculated as follows; Transport fuel efficiency by carbon emissions per fuel type. This number is then multiplied by transport distance and then divided by the transport payload capacity in order to obtain the tonnes of CO_2 emitted from transport (Eq. 2). The estimations of detailed energy requirements, transport distances and annual trips were incorporated in our LCA to calculate the rest of the environmental impacts associated with the ERW supply chain.

$$Te = \frac{(Tf) \times (Fe) \times l}{pc} \quad (2)$$

Where:
Te = Transport emissions as $kgCO_2$-tonne-km
Tf = Transport fuel efficiency as litre/kWh per Km
Fe = Fuel type carbon emissions as $kgCO_2$ per litre/ kWh
l = Distance in km
pc = Transport payload capacity in tonnes

The CDR goals and the two energy-economy scenarios for 2050 represent, respectively, a future in which technology continues to evolve according to system dynamics already in train, but without additional climate policies (BAU) and a scenario in which a range of additional policy instruments, already in discussion or planning, on energy, transport and other areas, are introduced to avoid exceeding 2 °C temperature increase with 75% probability. Scenarios were derived from the dynamic macro-econometric integrated model[19].

LCA method. We adopted and performed process-based LCA with a cradle to grave systems boundary within this S-LCA methodological framework. We derived our database by modifying datasets from the ecoinvent 3.6 database;[51] whilst the allocation and cut-off were achieved through the classification with mid-points and end-points from the selected LCA method[22]. We used the ReCiPe assessment method in LCA (Supplementary Fig. 9), which considers three different cultural perspectives, namely Individualist (I), Hierarchist (H) and Egalitarian (E). From these, we selected H given that it is often considered the default model for scientific studies and aligned with the most common policies for medium time horizons impact assessments[23].

Functional unit. Within this LCA methodological framework, the functional unit for this assessment was based on the annual deployment of rock dust per hectare of cropland, thus, like other studies, the first set of environmental impacts caused by ERW was displayed in this unit area[16], followed by the impacts per country considering their cropland areas and impacts across all CDR goals. The application rate was 40 tonnes of basalt rock powder per hectare of cropland per year (40 t $ha^{-1}yr^{-1}$ or 4 kg m^{-2} yr^{-1}).

Life-cycle impact assessment (LCIA). In this step within the LCA methodological framework, carbon emissions of countries' energy mixes were modelled and estimated, with results aligned with other studies[52], then 18 mid-point impacts indicators for the proposed functional unit (hectare) were analysed. This round of results was useful for a direct comparison of the set of impacts by the ERW supply chain between the analysed countries. The accumulated annual life-cycle environmental impacts in each indicator were then estimated with respect to the contribution of each country according to the established CDR goals and scenarios. To simplify the interpretation of this analysis and according to the environmental impact categorisation of the ReCiPe assessment method, we weighted the 18 mid-point impacts indicators results (Eq. 3) into 3 end-point (Eq. 4) impacts indicators results per hectare[22].

For mid-point characterisation the formula is:

$$I_m = \sum_i Q_{mi} m_i \quad (3)$$

Where:
m_i = is the magnitude of intervention i,
Q_{mi} = is the characterisation factor that connects intervention i with mid-point impact category m,
I_m = is the indicator result for mid-point impact category m.

For end-point characterisation the formula is:

$$I_e = \sum_m Q_{em} I_m \quad (4)$$

Where:
I_m = is the indicator result for mid-point impact category m
Q_{em} = is the characterisation factor that connects mid-point impact category m with end-point impact category e
I_e = is the indicator result for end-point impact category e.

Uncertainty. Given the exploratory approach of this analysis and the predictive requirement for LCA[53], uncertainty was incorporated in this study through a stochastic method with 1000 runs of Monte Carlo simulations per impact category in Excel spreadsheets by considering a 95% confidence interval (Supplementary Fig. 8). For the interpretation of comparative results in S-LCA, we used the Impact Category Relevance (ICR) and the Modified Null Hypothesis Significance Testing (NHST) approaches. While the ICR approach is not anticipated to calculate statistical significance, but to evaluate the trade-offs in using a relevance parameter; the NHST approach aims to confirm whether the mean or median of the relative impacts of two alternatives are or are not statistically significantly different from each other[54].

LCA mid-point impacts. CO_2 emissions and non-CO_2 greenhouse gas emissions expressed as Global Warming Potential (GWP100), i.e. over a 100-year time horizon, are direct indicators for the increase of infrared radiative forcing into the atmosphere[55]. In terms of land use, which is an indicator for occupation and time-integrated land transformation, the breakdown of impact categories is split into Natural Land Transformation Potential (NLTP), Agricultural Land Occupation Potential (ALOP) and Urban Land Occupation Potential (ULOP). Transformation refers to a permanent change of one type of land cover to another, while occupation refers to the use of a land cover for a certain period[26,27].

Water, fossil, metal and ozone are the depletion of natural resources included in our life-cycle impact assessments, however, ozone is also considered within human health factors. Water Depletion (WDP) is the amount of water that has been consumed for production purposes and neither available anymore in the source of origin for humans nor ecosystems[22]. Fossil depletion (FDP) is an indicator of the scarcity and consumption of fossil fuels as a non-biological resource[56]. Ozone depletion (ODPinf) estimates the potential decrease of this gas in the stratosphere, with potential effects on human health as the increased risk of skin cancer[57]. Metal depletion (MDP) accounts for the decrease of metals (kg Iron (Fe) equivalents per hectare)[22]. Freshwater Eutrophication (FEP) is an indicator that accounts for the potential increase of Phosphorus (P) equivalent emissions as a nutrient in freshwater while Marine Eutrophication (MEP) considers equivalent emissions of nitrogen (N)[58].

Following the deposition of nutrients, terrestrial acidification (TAP100)[59] considers potential changes in the chemical properties of soil, expressed as equivalent emissions of sulphur dioxide (kg SO2-Eq/ha). Freshwater (FETPinf), marine (METPinf) and terrestrial ecotoxicity (TETPinf) are a set of indicators that account for the potential impact of toxic substances on ecosystems, where the standard unit is based on kilograms of dichlorobenzene-equivalents (kg 1,4-DCB-Eq/ha)[60]. Human Toxicity (HTPinf) measures the effects of toxic substances on the human environment, as human toxicity increases the risk of cancer increases. The human health impact of ERW supply chain is also based on the units of dichlorobenzene-equivalents released[61]. In LCIA, Particulate Matter Formation (PMFP) is considered an essential environmental factor contributing to the global human health problem, which is measured in units of kg PM_{10}-Eq/ha)[62]. Ionising Radiation (IRP_HE) measured by kg Uranium-235 equivalents (kg U_{235}-Eq/ha) assesses human health damages related to man-made routine releases of radioactive material to the environment in the supply chain[63]. Photochemical Oxidant Formation (POFP) measured by kg NMVOC/ha accounts for reactive substances (mainly ozone), and it is harmful to human health, ecosystems and crops directly[64].

End-point impacts. Mid-point categories are aggregated into: Implications for human health (HH), ecosystem loss (EC) and resource depletion (RE).

Data availability

The GLiM v1.0 dataset used to identify rock sources is available at https://www.geo.uni-hamburg.de/en/geologie/forschung/aquatische-geochemie/glim.html. Dataset with 5 min resolution on global crop production and yield area to identify cropland is available at http://www.earthstat.org/harvested-area-yield-175-crops/. Datasets on LCA impact factors used for projections modelling are available within Ecoinvent 3.6 at https://ecoinvent.org/. Datasets on roads and rails vector data used for countries transport network analysis are available at http://www.diva-gis.org/gdata. Datasets on Natural Protected areas used for spatial analysis and restrictions to mine in natural protected areas are available at https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA. Underlying data for the main figures of the manuscript and Supplementary Information are included as a Supplementary Data 1-6 and are available at https://doi.org/10.6084/m9.figshare.19298963.

Code availability

Life-cycle assessment analyses performed here used the standard open source software package: openLCA v. 1.1 (2007-2019) (https://www.openlca.org/download/). Transport network and spatial analysis used a Geographical information system: ArcGIS 10.7.1 at https://www.arcgis.com/index.html.

Received: 17 August 2021; Accepted: 13 April 2022;
Published online: 05 May 2022

References

1. Framework Convention on Climate Change. *Nationally determined contributions under the Paris Agreement, Synthesis report by the secretariat, Conference of the Parties serving as the meeting of the Parties to the Paris Agreement*. Third session, Glasgow. (Framework Convention on Climate Change, 2021).
2. Intergovernmental Panel on Climate Change (IPCC). *Global Warming of 1.5 °C. An IPCC Special Report on the Impacts of Global Warming of 1.5 °C Above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways.* (World Meteorological Organization, 2018).
3. Hansen, J. et al. Young people's burden: requirement of negative CO2 emissions. *Earth Syst. Dyn.* **8**, 577–616 (2017).
4. Hartmann, J. et al. Enhanced chemical weathering as a geoengineering strategy to reduce atmospheric carbon dioxide, supply nutrients, and mitigate ocean acidification. *Rev. Geophys.* **51**, 113–149 (2013).
5. Beerling, D. J. et al. Potential for large-scale CO2 removal via enhanced rock weathering with croplands. *Nature* **583**, 424–248 (2020).
6. Beerling, D. J. et al. Farming with crops and rocks to address global climate, food and soil security. *Nat. Plants* **4**, 138–147 (2018).
7. Kantola, I. B. et al. Potential of global croplands and bioenergy crops for climate change mitigation through deployment for enhanced weathering. *Biol. Lett.* **13**, 20160714 (2017).
8. Zhang, G. et al. Review and outlook for agromineral research in agriculture and climate change mitigation. *Soil Res.* **56**, 113–122 (2018).
9. Taylor, L. L. et al. Enhanced weathering strategies for stabilizing climate and averting ocean acidification. *Nat. Clim. Change* **6**, 402–406 (2015).
10. Köhler, P., Hartmann, J. & Wolf-Gladrow, D. A. Geoengineering potential of artificially enhanced silicate weathering of olivine. *Proc. Natl Acad. Sci. USA* **107**, 20,228–20,233 (2010).
11. Renforth, P. The potential of enhanced weathering in the UK. *Int. J. Greenhouse Gas Control* **10**, 229–243 (2012).
12. Terlouw, T., Bauer, C., Rosa, L. & Mazzotti, M. Life cycle assessment of carbon dioxide removal technologies: a critical review. *Energy Environ. Sci.* **14**, 1701–1721 (2021).
13. Aviso, K. B. et al. Fuzzy optimization model for enhanced weathering networks using industrial waste. *Clean Tech. Environ. Pol.* https://doi.org/10.1007/s10098-021-02053-8 (2021).
14. Tan, R. R. & Aviso, K. B. On life-cycle sustainability optimization of enhanced weathering systems. *J. Cleaner Product.* **289**, 125836 (2021).
15. Bodénan, F. et al. Ex situ mineral carbonation for CO_2 mitigation: evaluation of mining waste resources, aqueous carbonation processability and life cycle assessment (Carmex project). *Minerals Eng.* **59**, 52–63 (2014).
16. Lefebvre, D. et al. Assessing the potential of soil carbonation and enhanced weathering through life cycle assessment: a case study for Sao Paulo State, Brazil. *J. Cleaner Product.* **233**, 468–481 (2019).
17. Moosdorf, N., Renforth, P. & Hartmann, J. Carbon dioxide efficiency of terrestrial enhanced weathering. *Environ. Sci. Technol.* **48**, 4809–4816 (2014).
18. Fuss, S. et al. Negative emissions—Part 2: Costs, potentials and side effects. *Environ. Res. Lett.* **13**, 063002 (2018).
19. Mercure, J. F. et al. Macroeconomic impact of stranded fossil fuel assets. *Nat. Clim. Change* **8**, 588–593 (2018).
20. Goucher, L., Bruce, R., Cameron, D. D., Koh, S. C. L. & Horton, P. The environmental impact of fertilizer embodied in a wheat-to-bread supply chain. *Nat. Plants* **3**, 1–5 (2017).
21. ISO. *Environmental Management, Life Cycle assessment, Goal and Scope definition and inventory analysis* (ISO.org, Switzerland, 1998).
22. Huijbregts, M. A. J. et al. *ReCiPe 2016 A harmonized life cycle impact assessment method at midpoint and endpoint level. Report I: Characterization. National institute for Public Health and the Environment*. (Ministry of Health, Welfare and Sport, 2016).
23. Finkbeiner, M., Inaba, A., Tan, R., Christiansen, K. & Klüppel, H.-J. The New International Standards for Life Cycle Assessment: ISO 14040 and ISO 14044. *Int. J. Life Cycle Assess.* **11**, 80–85 (2006).
24. Herrington, R. Mining our green future. *Nat. Rev. Mater.* **6**, 456–458 (2021).
25. Smith, P. et al. Land-Management options for greenhouse gas removal and their impacts on ecosystem services and the sustainable development goals. *Annu. Rev. Environ. Resour.* **44**, 255–286 (2019).
26. de Baan, L., Alkemade, R. & Koellner, T. Land use impacts on biodiversity in LCA: a global approach. *Int. J. Life Cycle Assess.* **18**, 1216–1230 (2013).
27. Curran, M., Hellweg, S. & Beck, J. Is there any empirical support for biodiversity offset policy? *Ecol. Appl.* **24**, 617–632 (2014).
28. Deutz, S. & Bardow, A. Life-cycle assessment of an industrial direct air capture process based on temperature–vacuum swing adsorption. *Nat. Energy* **6**, 203–213 (2021).
29. Smith, P. et al. Biophysical and economic limits to negative CO2 emissions. *Nat. Clim. Change* **6**, 42–50 (2015).
30. Goglio, P. et al. Advances and challenges of life cycle assessment (LCA) of greenhouse gas removal technologies to fight climate changes. *J. Cleaner Product.* **244**, 118896 (2020).
31. Smith, P. Soil carbon sequestration and biochar as negative emission technologies. *Glob. Change Biol.* **22**, 1315–1324 (2016).
32. Cox, E., Spence, E. & Pidgeon, N. Public perceptions of carbon dioxide removal in the United States and the United Kingdom. *Nat. Clim. Change* **10**, 744–749 (2020).
33. van der Werf, H. M. G., Knudsen, M. T. & Cederberg, C. Towards better representation of organic agriculture in life cycle assessment. *Nat. Sustain.* **3**, 419–425 (2020).
34. Lewis, A. L. et al. Effects of mineralogy, chemistry and physical properties of basalts on carbon capture potential and plant-nutrient element release via enhanced weathering. *Appl. Geochem.* **132**, 105023 (2021).
35. Swoboda, P., Döring, T. F. & Hamer, M. Remineralizing soils? The agricultural usage of silicate rock powders: a review. *Sci. Total Environ.* **807**, 150976 (2022).
36. Kelland, M. E. et al. Increased yield and CO2 sequestration potential with the C4 cereal Sorghum bicolor cultivated in basaltic rock dust-amended agricultural soil. *Glob. Change Biol.* **26**, 3658–3676 (2020).
37. Blanc-Betes, E. et al. In silico assessment of the potential of basalt amendments to reduce N2O emissions from bioenergy crops. *GCB Bioenergy* **13**, 224–241 (2021).
38. Acquaye, A. A. et al. Identification of 'carbon hot-spots' and quantification of GHG intensities in the biodiesel supply chain using hybrid LCA and structural path analysis. *Environ. Sci. Technol.* **45**, 2471–2478 (2011).
39. Renforth, P. The negative emission potential of alkaline materials. *Nat. Commun.* **10**, 1401 (2019).
40. Hossain, M. U., Poon, C. S., Lo, I. M. C. & Cheng, J. C. P. Comparative environmental evaluation of aggregate production from recycled waste materials and virgin sources by LCA. *Resour. Conserv. Recycl.* **109**, 67–77 (2016).
41. Awasthi, A. K., Li, J., Koh, L. & Ogunseitan, O. A. Circular economy and electronic waste. *Nat. Electronics* **2**, 86–89 (2019).
42. Masson-Delmotte, V. et al. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* (Cambridge University Press, 2021).
43. openLCA v. 1.1, GreenDelta, open source software licensed under the Mozilla Public License, MPL 2.0, https://www.openlca.org (2007–2019).
44. Wernet, G. et al. The ecoinvent database version 3 (part I): overview and methodology. *Int. J. Life Cycle Assess.* **21**, 1218–1230 (2016).
45. Hartmann, J. & Moosdorf, N. The new global lithological map database GLiM: a representation of rock properties at the Earth surface. *Geochem. Geophys. Geosyst.* **13**, Q12004 (2012).
46. Strefler, J., Amann, T., Bauer, N., Kriegler, E. & Hartmann, J. Potential and costs of carbon dioxide removal by enhanced weathering of rocks. *Environ. Res. Lett.* **13**, 034010 (2018).
47. Bingham, H. C. et al. Sixty years of tracking conservation progress using the World Database on Protected Areas. *Nat. Ecol. Evol.* **3**, 737–743 (2019).
48. Sánchez-García, S. et al. A GIS methodology for optimal location of a wood-fired power plant: quantification of available woodfuel, supply chain costs and GHG emissions. *J. Cleaner Product.* **157**, 201–212 (2017).
49. Rotaru, A. S. et al. Modelling a logistic problem by creating an origin-destination cost matrix using GIS technology. *Bull. UASVM Hortic.* **71**, 152–156 (2014).
50. Bethesda, M. *CO: USGS Information Services The Agency; Denver.* https://webapp1.dlib.indiana.edu/virtual_disk_library/index.cgi/4911752 (2000).
51. Ruize, E. M. et al. *Ecoinvent 3.5, Documentation of changes implemented in ecoinvent database v3.5.* (Ecoinvent, 2018).
52. Vandepaer, L., Treyer, K., Mutel, C., Bauer, C. & Amor, B. The integration of long-term marginal electricity supply mixes in the ecoinvent consequential database version 3.4 and examination of modeling choices. *Int. J. Life Cycle Assess.* **24**, 1409–1428 (2019).
53. Antwi, V. *Use of Monte Carlo Analysis in Life Cycle Assessment: Case Study – Fruits processing plant in Ghana Doctor of Philosophy thesis.* (Kwame Nkrumah University of Science and Technology, 2010).
54. Mendoza Beltran, A. et al. Quantified uncertainties in comparative life cycle assessment: what can be concluded? *Environ. Sci. Technol.* **52**, 2152–2161 (2018).
55. Stranddorf, H. K., Hoffmann, L. & Schmidt, A. *Impact categories, normalisation and weighting in LCA*. Environmental news No. 78. (Danish Ministry of the Environment, 2005).
56. Althaus, H. J. et al. *Implementation of life cycle impact assessment methods*, 33–40 (Ecoinvent centre, St Gallen, 2010).
57. WMO. *Scientific assessment of ozone depletion: 2010, Global Ozone Research and Monitoring Project-report no.52.* (World Meteorological Organization, 2011).

58. Helmes, R. J. K., Huijbregts, M. A. J., Henderson, A. D. & Jolliet, O. Spatially explicit fate factors of phosphorous emissions to freshwater at the global scale. *Int. J. Life Cycle Assess.* **17**, 646–654 (2012).
59. Roy, P.-O. et al. Characterization factors for terrestrial acidification at the global scale: a systematic analysis of spatial variability and uncertainty. *Sci. Total Environ.* **500-501**, 270–276 (2014).
60. van Zelm, R., Huijbregts, M. A. J. & van de Meent, D. USES-LCA 2.0—a global nested multi-media fate, exposure, and effects model. *Int. J. Life Cycle Assess.* **14**, 282–284 (2009).
61. Keller, D., Wahnschaffe, U., Rosner, G. & Mangelsdorf, I. Considering human toxicity as an impact category in life cycle assessment. *Int. J. Life Cycle Assess.* **3**, 80–85 (1998).
62. Fantke, P. et al. Health effects of fine particulate matter in life cycle impact assessment: findings from the Basel Guidance Workshop. *Int. J. Life Cycle Assess.* **20**, 276–288 (2015).
63. Frischknecht, R., Braunschweig, A., Hofstetter, P. & Suter, P. Human health damages due to ionising radiation in life cycle impact assessment. *Environ. Impact Assess. Rev.* **20**, 159–189 (2000).
64. Walid. *Comparative Life Cycle Assessment of WALiD Technologies and Processes Handbook* (Smithers Rapra & Smithers Pira Ltd, 2017).

Acknowledgements

This research was funded with a Leverhulme Research Centre Award (RC-2015-029) from the Leverhulme Trust. The University of Sheffield Institutional Open Access Fund supported the Open Access of this paper.

Author contributions

R.M.E.E., E.P.K., D.J.B. and S.C.L.K. conceived the study. LCA analyses were conducted by R.M.E.E. E.P.K. provided CDR, cropland area and ERW energy data and additional analysis. P.H., H.P., N.R.E. and J.F.M. provided the national energy data. R.M.E.E., E.P.K., N.R.E., S.C.L.K. and D.J.B. wrote the manuscript with input and discussion from all other authors.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s43247-022-00436-3.

Correspondence and requests for materials should be addressed to Rafael M. Eufrasio.

Peer review information *Communications Earth & Environment* thanks Jie Bu and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editors: Joe Aslin.