Hundreds of dams have been proposed throughout the Amazon basin, one of the world’s largest untapped hydropower frontiers. While hydropower is a potentially clean source of renewable energy, some projects produce high greenhouse gas (GHG) emissions per unit electricity generated (carbon intensity). Here we show how carbon intensities of proposed Amazon upland dams (median = 39 kg CO2eq MWh−1, 100-year horizon) are often comparable with solar and wind energy, whereas some lowland dams (median = 133 kg CO2eq MWh−1) may exceed carbon intensities of fossil-fuel power plants. Based on 158 existing and 351 proposed dams, we present a multi-objective optimization framework showing that low-carbon expansion of Amazon hydropower relies on strategic planning, which is generally linked to placing dams in higher elevations and smaller streams. Ultimately, basin-scale dam planning that considers GHG emissions along with social and ecological externalities will be decisive for sustainable energy development where new hydropower is contemplated.
Hydropower has been promoted as a climate-friendly alternative to meet the world’s growing electricity demand. Globally, hydropower dam construction is expected to reach unprecedented rates in the coming decades, especially in countries with emerging economies. One hotspot for future hydropower expansion is the Amazon, the world’s largest river basin. Although dams have already been built in several regions of the basin, the Amazon hydropower potential remains largely untapped, and electricity generation is the primary motivation for new dam construction. Existing evidence suggests that most global hydropower projects have total greenhouse gas (GHG) emissions per unit electricity generated (also known as carbon intensity, Table 1) within the range of other renewable energy sources like solar and wind power. However, about 10% of the world’s hydropower facilities emit as much GHGs per unit energy as conventional fossil-fueled power plants. Some existing dams in the lowland Amazon have been shown to be up to ten times more carbon-intensive than coal-fired power plants. In light of the expected boom in construction of new hydropower dams in the Amazon basin, it is critical to identify whether future dams will produce low-carbon energy.

GHG emissions from reservoirs stem primarily from the decomposition of organic matter that is either flooded, transferred to the reservoir via runoff and river input, or produced within the reservoir as aquatic plant and algal biomass. Although part of the emissions would occur under natural pre-impoundment conditions, reservoirs generally result in net increases of both carbon dioxide ($\text{CO}_2$) and methane ($\text{CH}_4$) emissions to the atmosphere, and should thus be considered anthropogenic GHG sources. $\text{CH}_4$ is the most important GHG produced in reservoirs and originates from bacterial decomposition of organic matter in anoxic water and sediment environments created by impoundment. GHG emissions (Table 1) from reservoirs vary substantially over space and time, being positively correlated with temperature and aquatic primary production, and negatively correlated with reservoir age. Since total GHG emission is proportional to flooded area, the electricity generation capacity (installed capacity) per unit of reservoir flooded area, or power density (Table 1), is a key determinant of carbon intensity. Hence, projects with low GHG emission (e.g., oligotrophic reservoirs) can still have high carbon intensities if they produce low amounts of electricity per unit flooded area (i.e., low power density).

Environmental impact studies for new dams rarely consider GHG emissions, especially in developing countries where hydropower is currently expanding. The problem is compounded by the piecemeal nature of these studies where each project is evaluated independently without considering the integrated effect of all existing and planned dams on basin-wide emissions. Here, we use a database of GHG fluxes for existing tropical and subtropical reservoirs to calculate the range of carbon intensities expected for 351 proposed and 158 existing Amazon hydropower dams. To incorporate the time-related radiative forcing effect of $\text{CH}_4$, a potent GHG with an approximate atmospheric residence time of only about a decade, we conducted analyses of carbon intensities considering 20-year and 100-year time horizons. We found that carbon intensities vary by over two orders of magnitude from the lowest to the highest emitting dam, with projects in lower elevations and larger rivers being associated with higher emissions per unit electricity generated. Using a basin-wide optimization approach, we show that strategic dam planning could minimize aggregate carbon intensity as hydropower generation expands. Our approach can be adapted to different scales and could help Amazonian countries achieve their energy goals more sustainably.

### Results and Discussion

#### Carbon intensities of proposed dams

We estimate that existing Amazon hydropower reservoirs collectively emit 14 Tg $\text{CO}_2$ per year over a 100-year time horizon (95% confidence interval (CI): 10–19), or ~2% of the current total annual GHG emission from reservoirs globally; if all 351 proposed dams are built, annual emissions from Amazon reservoirs would increase approximately fivefold (Supplementary Table 1). The carbon intensities of reservoirs that would be created by proposed dams differ markedly depending on whether dams are built in upland (>500 m a.s.l.) or lowland reaches (Fig. 1).

Based on projections of the sustainable development scenario of the International Energy Agency’s (IEA) World Energy Outlook 2017, we consider 80 kg $\text{CO}_2$ eq MWh$^{-1}$ as a reference carbon intensity for sustainable electricity generation. This value is consistent with achieving the energy-related goals of the United Nations 2030 Agenda for Sustainable Development (2030 Agenda), which would reduce the collective carbon intensity of the global electricity sector from the current ~500 kg $\text{CO}_2$ eq MWh$^{-1}$ to ~80 kg $\text{CO}_2$ eq MWh$^{-1}$ in 2040. Our analysis indicates that most proposed upland dams (92% for a 100-year time horizon and 60% for a 20-year time horizon) would likely result in carbon intensities below 80 kg $\text{CO}_2$ eq MWh$^{-1}$ (Fig. 1b, c). By contrast, only a minority of lowland dams would be expected to emit less than 80 kg $\text{CO}_2$ eq MWh$^{-1}$ (36% for a 100-year time horizon and 14% for a 20-year time horizon). In fact, over a 20-year time horizon about 25% of the proposed lowland dams would likely be more carbon-intensive than coal-fired power plants (Fig. 1b).

Lowland dams have significantly higher carbon intensities due to their typically larger reservoir areas and innately lower power densities, whereas the steeper topography of high-elevation areas affects the strong link between energy density and carbon intensity. A critical question is whether the projected boom in hydropower expansion is compatible with achieving the long-term carbon intensity goals set by the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement.

### Table 1 Metrics commonly used to evaluate GHG emissions in hydropower projects

| Metric                | Units       | Description                                                                 |
|-----------------------|-------------|-----------------------------------------------------------------------------|
| GHG flux              | kg $\text{CO}_2$ eq km$^{-2}$ d$^{-1}$ | The exchange of GHG, in $\text{CO}_2$ equivalents, at the reservoir air-water interface per unit of surface area over a certain time period. The direction of GHG flux can be from water to atmosphere (emission or efflux; positive value) or from atmosphere to water (uptake or influx; negative value). |
| Total GHG flux        | Tg $\text{CO}_2$ eq | GHG flux over a reference time period multiplied by the total reservoir area. The reference times considered here are a day and 1, 20, and 100 years (1 Tg = 10$^{12}$ g). |
| Power density         | MW km$^{-2}$ | The ratio of electricity generation capacity to reservoir flooded area. This metric reflects the strong link between GHG emissions and flooded area and is often used as a simple proxy for carbon intensity. Also known as emission intensity or emission factor. CO2-equivalent emissions produced per unit electricity generated. This metric is used to compare emissions performance across projects of different sizes, and also among electricity sources. |
favors hydropower projects with higher power densities. This explains why the largest number of Amazon dams with high carbon intensities occurs in Brazil, a predominantly lowland country, whereas dams with lower carbon intensities are concentrated in mountainous parts of Bolivia, Ecuador, and Peru (Fig. 1c). Notably, while it has recently been suggested that dams can mitigate natural GHG emissions from downstream floodplain wetlands by reducing the extent and duration of inundation, hydropower dams that can regulate inundation of downstream wetlands are typically those in lowland reaches, which generally implies lower power density and hence high carbon intensities for such projects. In addition, it is critical to understand whether lowland dams are more likely to create reservoirs enriched in nutrients such as phosphorus and nitrogen, which would increase aquatic primary production and consequently GHG emissions, thereby increasing their carbon intensities.

Achieving low-carbon hydropower with strategic planning. Our findings suggest that Amazon hydropower must be developed strategically on a basin-wide scale to achieve low-carbon energy goals. We therefore performed a multi-objective optimization to determine the Pareto-optimal frontier, which defines the set of solutions (i.e., dam portfolios) that minimizes total basin-wide GHG emissions while satisfying varying hydropower generation goals (Supplementary Fig. 1). Our computational framework adapts and parallelizes previously proposed algorithms to compute the exact (provably optimal) Pareto frontier for possible combinations of proposed Amazon dams in very fast computational time (Supplementary Fig. 2).

Our multi-objective optimization indicates that if future hydropower dams are selected optimally, it will be possible to develop ~80% (75 GW) of the total proposed electricity generation capacity while creating a portfolio of new dams with an aggregate carbon intensity below 80 kg CO₂eq MWh⁻¹ over a 100-year time horizon (Fig. 2a, b). Conversely, uncoordinated planning may result in portfolios of new dams with collective carbon intensities incompatible with sustainable energy goals (Fig. 2a, b). For instance, suboptimally exploiting about 15 GW of the total proposed installed capacity—which is equivalent to the current installed capacity of the entire electricity sector of Bolivia, Ecuador and Peru—could result in hydropower portfolios as carbon-intensive as equivalent electricity generation by fossil-fuel sources (Fig. 2a, b, e). Optimal planning, however, would allow the exploitation of 15 GW through a portfolio of new dams emitting < 25 kg CO₂eq MWh⁻¹ for a 100-year time horizon, which is below the carbon intensity of a typical solar power plant. Thus, the ability of hydropower to mitigate climate change relies critically on strategic dam portfolio planning so as to avoid carbon-intensive projects, especially over short time horizons (Fig. 2a).

Building dams without basin-wide coordination has led to a current Amazon dam portfolio with a collective carbon intensity of ~200 kg CO₂eq MWh⁻¹ (20-year time horizon) and ~90 kg CO₂eq MWh⁻¹ (100-year time horizon) (Fig. 2c, d). Optimal selection of future dams can lead to significant improvements, lowering the overall carbon intensity of Amazon hydropower (Fig. 2c, d). After ~75 GW of the proposed Amazon hydropower potential is tapped, however, it will not be possible to add extra dams without increasing the corresponding carbon intensity of the portfolio (Fig. 2c, d). This would occur because all of the most efficient proposed projects would have been selected; thus, tapping more energy thereafter implies selecting more dams on higher-order streams at lower elevations, which tend to have higher carbon intensities (Fig. 3).

The need for strategic planning to balance energy and water management benefits provided by dams with associated social and environmental externalities is becoming increasingly apparent. For instance, a study in a large tributary basin to the Mekong River, the largest river in Southeast Asia, has
Climate-friendly hydropower projects. Because the carbon intensity of hydropower dams is strongly linked to power density, \(^9,20,21\), power density is the criterion employed by the Clean Development Mechanism of the UN Framework Convention on Climate Change to finance and grant carbon credits to hydropower projects. Projects with power densities above 4 MW km\(^{-2}\) are eligible for credits and GHG emissions from candidate projects with power densities above 10 MW km\(^{-2}\) are assumed to be negligible over 100-year horizons. While power density may provide a convenient sustainable energy metric, natural variability in GHG emissions observed in reservoirs can lead to differences in carbon intensities for dams with comparable power densities. We plotted power densities against our predicted carbon intensities to examine what densities may satisfy sustainable energy goals (i.e., <80 kg CO\(_2\) eq MWh\(^{-1}\)). For a 100-year time horizon, power densities above 6.7 MW km\(^{-2}\) (95% CI: 4.5–9.5) were associated with projects emitting <80 kg CO\(_2\) eq MWh\(^{-1}\) (Fig. 4a). The lower bound of the 95% CI (4.5 MW km\(^{-2}\)) suggests that the Clean Development Mechanism lending criterion of 4 MW km\(^{-2}\) avoids most carbon-intensive projects. The more conservative upper bound of the 95% CI indicates that projects are very likely to emit <80 kg CO\(_2\) eq MWh\(^{-1}\) only when power densities exceed 9.5 MW km\(^{-2}\); about half of the proposed Amazon dams have power densities below 9.5 MW km\(^{-2}\) (Fig. 4a). Considering a 20-year time horizon for carbon intensities causes approximately a threefold increase in the power density threshold for designating climate-friendly projects (Fig. 4b). On a basin scale, prioritizing projects with high power densities can attenuate carbon intensities of future hydropower dam portfolios. However, mitigation measures can also reduce the carbon intensities of individual projects. Tackling internal and external sources of organic matter supporting CH\(_4\) production in reservoirs is key. Previous studies suggest that reducing nutrient inputs to reservoirs\(^{12,36}\) and clearing terrestrial vegetation prior to flooding\(^{20}\) can significantly decrease carbon intensities of hydropower projects. In addition, project-scale improvements to power densities can make future hydropower projects less carbon-intensive\(^{20}\), including alternative project designs that sacrifice a fraction of power generation to favor disproportionately smaller reservoir flooded areas, which would increase power density and hence reduce carbon intensity. Finally, retrofitting existing hydropower turbines with more efficient designs can increase electricity generation by up to 30% without requiring additional flooded area\(^{31}\), thus contributing to lower carbon intensities in the hydropower sector.
Moving forward. Our findings point to the complexities of utilizing hydropower as an energy source compatible with climate change mitigation. Integrated regional assessments of GHG emissions can help identify portfolios of dams that are consistent with low-carbon energy goals. Although our study has focused on Amazon dams, our approach can be adapted to other regions where hydropower is rapidly expanding, including the Balkans and major river basins such as the Congo, the Mekong, the Ganges-Brahmaputra, and the Yangtze².

Carbon intensity is a key criterion for sustainable energy planning. However, we emphasize that hydropower dams have a wide range of additional interactions with social and ecological systems, and some dams may have other purposes such as water supply, flood control, and recreation. Dam construction can lead to social disruptions³⁷ and seriously compromise a variety of ecosystem services and processes³⁸ including altered natural flow and flood regimes³⁹,⁴⁰, reduced sediment³³ and nutrient⁴¹ supply to downstream waters, blockage of fish migrations³, deterioration of habitat connectivity⁴²,⁴³, and loss of biodiversity⁴²–⁴⁴. Ultimately, a broader suite of criteria including consideration of alternative energy sources will be needed to fully integrate the social and ecological externalities into strategic hydropower planning, ideally using a multicriteria optimization framework building on the approach we employed in this study.

**Methods**

**Amazon dams database.** Geographic location, elevation and technical data including installed capacity and flooded area for proposed and existing dams were obtained from published databases on existing and proposed Amazon dams³⁴⁵. Our database incorporated information from recent national government databases for countries where updated inventory data were readily available⁴⁶,⁴⁷. We calculated the level of branching in the river network using the Strahler stream order method⁴⁸.

There are 158 existing dams, either operating or under construction, with over 1 MW of installed capacity in the Amazon basin, totaling 32,608 MW of electricity generation capacity with an average of 206 MW per dam (range: 1–11,233 MW). We identified 351 proposed dams in various stages of inventory, planning and licensing (installed capacity >1 MW). The proposed dams have a combined electricity generation capacity of 91,887 MW, on average 262 MW per dam (range: 1–6133 MW). Watershed areas above each dam were estimated from a digital elevation model of the region. Existing and proposed dams were categorized as upland or lowland using a cutoff of 500 m a.s.l.⁴⁹. In some cases (26% of dams), information on flooded areas was unavailable. For existing reservoirs without

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**Fig. 3** Characterization of optimal dam configurations as electricity generation increases. **a,** Carbon intensity outcomes (100-year time horizon) of optimal dam portfolios for different values of installed capacity considering the 351 proposed Amazon dams; squares indicate six example reference portfolios spanning increasing installed capacity (P) from 15–90 GW. The mean (±s.e.m.) elevation (**b**) of dams decreases, and stream order at dam locations (**c**) increases, as optimal portfolios target greater total installed capacity and subsequently include more dams in lowland areas of the Amazon basin (**d**). Stream order is a metric used in hydrology to indicate the level of branching in a river network, where increasing stream order correlates with increasing channel size and discharge.
reported flooded areas, we quantified flooded areas from satellite imagery (Google Earth Pro 7.3.2.5776). For proposed dams with missing information, we used available flooded areas as a training dataset to develop a multiple regression model including country, watershed area, installed capacity, and elevation as covariates to estimate flooded areas (Supplementary Fig. 3a). The predictive power of the regression model was high; however, we also ran sensitivity analyses to confirm that our main conclusions were robust to the inclusion of estimated flooded areas for the subset of dams with missing data (Supplementary Fig. 3b).

Time horizon of the analyses. To compare the radiative forcing effects of GHGs with different warming potentials and atmospheric residence times, we index the so-called Global Warming Potential (GWP) of 100 years, but shorter time frames are particularly appropriate for interpreting the climate effects of certain activities when short-lived gases are to be prioritized. This is the case of CH4, which remains in the atmosphere for approximately a decade but has a large radiative forcing effect. Therefore, all of our analyses also consider a 20-year time horizon in addition to the commonly used 100-year time horizon. In terms of radiative forcing, CH4 is the predominant GHG emitted from hydropower reservoirs, and the general temporal pattern of GHG emissions from dams indicates that emissions peak in the first decade after damming and then fall to lower levels that remain somewhat constant over time. Therefore, the high potential of dams to cause warming over short timescales gets underrepresented when the GHG footprint of dams is assessed only over long time horizons. We converted CH4 emissions to CO2-equivalents using a GWP of 84 over 100 years and 25 over 20 years.

Carbon intensity estimates. The carbon intensity (also referred to as emission intensity or emission factor) of power sources measures the net GHG emission per unit electricity generated (kg CO2eq MWh-1). We combined project-specific data on flooded areas and installed capacity from our Amazon dams database with 48 CO2 and 38 CH4 published flux estimates for tropical and subtropical reservoirs to calculate carbon intensity ranges for all existing and proposed Amazon dams. To calculate the carbon intensity of a given dam, we first calculated total GHG flux as follows:

\[ \text{TE}_{\text{dam}} = \text{A}_{\text{dam}} \times (\text{netCO}_2 \times F_{\text{CO}_2,\text{dam}} + \text{netCH}_4 \times F_{\text{CH}_4,\text{dam}} + \text{GWP}_{\text{CH}_4}) \times (1 + R_{\text{atmosphere}}) \]  

where \( \text{TE}_{\text{dam}} \) is the total GHG flux (kg CO2eq d-1), with positive values denoting emission (water-to-atmosphere flux) and negative values denoting uptake (atmosphere-to-water flux); \( \text{A}_{\text{dam}} \) is the reservoir flooded area (km2); \( F_{\text{CO}_2,\text{dam}} \) is the CO2 flux (kg CO2 km^-2 d^-1); \( F_{\text{CH}_4,\text{dam}} \) is the CH4 flux (kg CH4 km^-2 d^-1); \( \text{GWP}_{\text{CH}_4} \) is a conversion factor for the global warming potential of CH4 over the corresponding time horizon (20 or 100 years) to transform CH4 km^-2 d^-1 to kg CO2 eq km^-2 d^-1; \( R_{\text{atmosphere}} \) is a constant representing the ratio of downstream emissions to reservoir-surface emissions, estimated to be 17%-33%. We multiplied CO2 fluxes by a discount factor of 0.25 (netCO2) and CH4 fluxes by 0.90 (netCH4) to account only for the net (anthropogenic) change in GHG emissions associated with reservoir creation (see details below). We then calculated total electricity generation as follows:

\[ \text{EG}_{\text{dam}} = \text{Cap}_{\text{dam}} \times 24 \times P_{\text{Cap}} \]  

where \( \text{EG}_{\text{dam}} \) is the total electricity generation of a given dam over a day (MWh d^-1); \( \text{Cap}_{\text{dam}} \) is the installed capacity (MW), which was multiplied by 24 to obtain the energy output in 24 h and to have numerator and denominator units of Eq. (3) in the same time unit; and \( P_{\text{Cap}} \) is a constant representing the capacity factor (0.5727), which denotes the effective electricity generation as a proportion of installed capacity, and was derived from an empirical relationship between data in our database on existing Amazon dams. Carbon intensity (\( \text{C}_{\text{dam,CO}_2} \), kg CO2eq MWh^-1) is then calculated as:

\[ \text{C}_{\text{dam}} = \frac{\text{TE}_{\text{dam}}}{\text{EG}_{\text{dam}} + \text{C}_{\text{construction}}} \]  

where \( \text{C}_{\text{construction}} \) is a constant representing the carbon intensity associated with construction and infrastructure of hydropower dams (19 kg CO2eq MWh^-1) for a 100-year time horizon.

Uncertainty in estimated carbon intensities for proposed Amazon dams is largely influenced by variability in the GHG flux input data (i.e., \( F_{\text{CO}_2,\text{dam}} \) and \( F_{\text{CH}_4,\text{dam}} \)) in Eq. (1)). Thus, for each Amazon dam, we generated 10,000 carbon intensity predictions through the implementation of a bootstrapping procedure that randomly resampled with equal probability from the dataset of published CO2 and CH4 fluxes from tropical and subtropical reservoirs. Variation in calculated carbon intensity among dams is essentially driven by two parameters: installed capacity and flooded areas. Supplementary Fig. 4 shows examples of the bootstrapping output for two existing dams with contrasting power densities. Emissions results presented in the main text are based on mean and 95% confidence intervals for bootstrapped values. Our calculations incorporate the net change in GHG fluxes resulting from the transformation of a riverine landscape into a reservoir by dam construction. The most comprehensive review on GHG emissions from reservoirs, which we used to support our analysis, reported gross fluxes. To assess the net change in GHG fluxes resulting from the creation of a reservoir, emissions that would have existed under pre-impoundment conditions have to be discounted from the gross fluxes. Although conceptually simple, disentangling natural and anthropogenic reservoir emissions is a complex task with limited empirical support. A recent review suggested that it is reasonable to assume that practically all CH4 emissions from global reservoirs are new and therefore anthropogenic, whereas the majority of CO2 emissions (perhaps 75%) over a 100-year time horizon would take place even without the reservoir creation. In our analysis, we conservatively assumed that 75% of reservoir CO2 emissions and 10% of CH4 emissions reflect natural pre-impoundment emissions, and thus we incorporated these corrections in Eq. (1) (netCO2 and netCH4). For a particular reservoir, the percentage of CH4 emissions that can be attributed to reservoir creation depends in part on the preexisting environments that become inundated; floodplains and other wetlands would have higher CH4 emissions rates than non-wetland environments. We use the 10%
estimate in our analysis because preexisting land cover information for all of the existing and proposed reservoirs in the Amazon is not available. We ran sensitivity analyses to verify how much these assumptions affect our results (Supplementary Fig. 5). Emissions of nitrous oxide (N₂O) can also occur in reservoirs; however, this gas was not considered in our analysis because N₂O emissions generally represent < 5% of the total gross CO₂-equivalent emissions from impoundments14, and because Amazon soils have naturally high rates of N₂O emission, such that net increases in N₂O emissions associated with dams are expected to be relatively low15. Previous studies indicate that reservoir GHG emissions vary as a function of temperature18 and therefore latitude17, with low-latitude dams generally emitting more CO₂. Thus, we used flux information only from tropical and subtropical dams in the global reservoir emissions database to represent the latitudinal range of dam projects proposed in the Amazon19. Sensitivity analyses indicated that carbon intensities would not change substantially if fluxes from tropical dams only or dams from all climates (with most dams being located in northern temperate zones) were utilized instead of the subset that we adopted (Supplementary Fig. 6).

The increased rate of GHG emissions varies over the lifetime of a hydropower dam, with peak fluxes occurring in the first years after damming due to the decomposition of flooded biomass, followed by a protracted period of lower fluxes due to the conversion of soil organic carbon to continuous over inputs, and the aquatic primary production9,14,19. The reported GHG due to decomposition of soil organic matter, continuing river inputs, and new emissions from a hydropower project, we applied multiplier factors to the reported analyses to verify how much these assumptions affect our results (Supplementary 3).

The carbon intensity of existing or proposed hydropower dams and an edge represents a proposed or an existing dam. This abstract tree structure is used by our dynamic-programming algorithm for the sequence of the merging and pruning of Pareto-optimal solutions.

The dynamic-programming approach recursively computes the Pareto-optimal partial solutions from leaf nodes up to the root26,27. The key insight is that at a given node υ, we only need to keep the Pareto non-dominated partial solutions and we can therefore eliminate suboptimal (dominated) solutions. To increase incremental pruning, we convert the original tree into an equivalent binary tree. Given the tree with υ leaves, we first compute the 351 singleton portfolios with only one dam, 61,425 portfolios with two dams each and 351 singleton portfolios with only one dam, 61,425 portfolios with two dams each.

Carbon intensity of electricity sources. The International Energy Agency (IEA) releases an annual report on the status and trends of global energy (World Energy Outlook), which includes carbon intensities anticipated under a range of global energy development scenarios26,27. To place proposed hydropower dams in the Amazon in a global energy production context, we used benchmarks from the IEA 2040 Sustainable Development Scenario, which portrays a decarbonized global electricity sector to meet the United Nations 2030 Agenda for Sustainable Development goals26. The IEA report suggests that a decarbonized global electricity sector should emit about 80 kg CO₂eq MWh⁻¹. In that case we say that portfolio A dominates portfolio B since portfolio A has an installed capacity of 20,000 MW and carbon intensity of 90 kg CO₂eq MWh⁻¹, whereas portfolio B has an installed capacity of 18,000 MW and carbon intensity of 85 kg CO₂eq MWh⁻¹; in this scenario neither portfolio dominates the other. The Pareto frontier is then defined as the set of all portfolios of dams that are not dominated by any other portfolio.

The Pareto optimization code can be downloaded from Cornell University’s Institute for Computational Sustainability website (http://www.cs.cornell.edu/~gomes/silence/ downloads/hydro-pareto-tree-dp-2c/gomes-selman-et-al-dp-amazon-e-ghg naturecommunications-2019.zip).
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Author contributions
R.M.A., A.S.F., C.P.G., B.R.F., and S.K.H. conceived this study. R.M.A., S.A.S., and N.B. ran the carbon intensity analysis. C.P.G., Q.S., J.M.G.-S, X.W., and Y.X. designed and developed the computational framework for the Pareto optimization for this work. J.M.G.-S., Q.S., and G.P. implemented the algorithms for the Pareto optimization. Q.S. ran all the computations and experimental work for the Pareto optimization. R.G.-V., R.M.A., Q.S., and A.S.F. compiled and curated the hydropower dam dataset. R.M.A., Q.S., A.S.F., C.P.G., R.G.-V., B.R.F., S.K.H., N.B., S.A.S., H.A., M.M., and J.M.M. worked on the interpretation of the data. C.P.G. and Q.S. wrote the methods for the Pareto optimization. R.M.A. wrote the paper in close collaboration with A.S.F., B.R.F., and C.P.G., and with substantive revision by all authors.

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