ARTICLE

Global analysis of streamflow response to forest management

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Predicting the responses of streamflow to changes in forest management is fundamental to the sustainable regulation of water resources. However, studies of changes in forest cover have yielded unclear and largely unpredictable results. Here we compile a comprehensive and spatially distributed database of forest–management studies worldwide, to assess the factors that control streamflow response to forest planting and removal. We introduce a vegetation–to–bedrock model that includes seven key landscape factors in order to explain the impacts of forest removal and planting on water yield. We show that the amount of water stored in a landscape is the most important factor in predicting streamflow response to forest removal, whereas the loss of water through evaporation and transpiration is the most important factor in predicting streamflow response to forest planting. Our findings affect model parameterizations in climate change mitigation schemes (involving, for example, afforestation or deforestation) in different geologic and climate regions around the world, and inform practices for the sustainable management of water resources.

The response of streamflow to forest management is quantified by landscape experiments called paired watershed studies (PWS), in which one watershed serves as a reference, whereas the adjacent watersheds are treated with various forest-management approaches (for example, forest harvesting, conversion, afforestation, and so on). PWS originated in the United States[1] and have been the standard approach for quantifying the effects of forest management on water yield, which is defined as the annual streamflow from the watershed outlet and is a key measure of the sustainability of the surface water supply[2]. Because forests provide ecosystem services such as water provisioning and purification[3], an increase or decrease in forest cover may heighten the water-security risks for approximately four billion people who rely on forested headwater catchments for their water supply[4].

But PWS findings have been highly equivocal[2] and have been able to show only the local consequences of planting and removal on streamflow. We still lack clear guidance for generalizing predictions of how forest manipulation affects streamflow across diverse climate, geology, vegetation and topographic settings. Indeed, our present PWS understanding[5–8] shows wide scatter, suggesting general increases in water yield in response to the removal of forest, and conversely decreases in the response of water yield to planting, but with many examples that show opposite or unobservable effects of forest-cover management. This knowledge gap counts as one of many barriers to developing policy and achieving UN Sustainable Development Goals (SDGs) targets 6.6, 15.1, 15.2 and 15.4 (on water resources and forest-management sustainability[9,10]). Our lack of predictive power undermines forest-management strategies in both public and private sectors[11,12], and across the developed and developing world.

Here, we take a holistic view of forested headwaters—using a comprehensive, spatially distributed and up-to-date database on PWS—to get to grips with the controls of forest removal and forest planting on catchment water yield. We assemble a PWS database for 502 catchments, tabulated as 251 treatment–control catchment pairs, representing globally distributed locations. We compile data on the response of water yield into four intervention schemes (see Methods): afforestation/forestation, regrowth, conversion (planting) and deforestation

(removal). To identify plausible controls on water yield, we go beyond previous syntheses of water-yield response—which have been restricted to a few presumptive controls such as climate[5,7], percentage change in forest cover[5,6] and catchment area[8]—and adopt a vegetation-to-bedrock perspective[13–17]. This perspective includes factors that extend from the top of the vegetation canopy through to the soil and down to fresh bedrock and groundwater. We explore the effect of these aboveground and belowground factors and then rank their relative importance in the variability of catchment water yield response to planting and removal.

We quantify these vegetation-to-bedrock factors by using collocated spatial datasets on runoff coefficient (the ratio of long-term streamflow to precipitation[18]), potential evapotranspiration[19] (PET), permeability and porosity[20], plant-available (rooting-zone) water-storage capacity[21], depth to bedrock[22] and biome classification. We calculate actual evapotranspiration (AET) as the difference between mean annual precipitation and long-term streamflow[23]. We also derive a parameter called 'potential storage' as the product of depth to bedrock and deeper subsoil porosity. We consider the relationship of these seven factors to the direction and magnitude of water-yield response. We implement multiple models from a suite of linear, neural and recursive partitioning techniques, and then calculate model-independent indices that rank the importance of the explanatory factors on the basis of the model that best predicts water-yield response (see Methods). Finally, we apply the model predictions to more than 440,000 catchments worldwide[24], using a bottom-up (catchment-level) approach in estimating the response of water yield to change in forest cover. We report results at spatial resolutions that convey socio-economic, ecologic and water resources management importance[25].

Figure 1a shows the locations represented in the PWS database and their corresponding mean annual streamflow, spanning 3,132 years of cumulative streamflow records. Figure 1b shows that intervention schemes involving forest planting and removal have resulted in disparate effects on the direction and magnitude of water yields. The effects (quoted as mean ± 1 standard deviation (s.d.)) of deforestation (Fig. 1c), conversion (Fig. 1d), regrowth (Fig. 1e) and afforestation/

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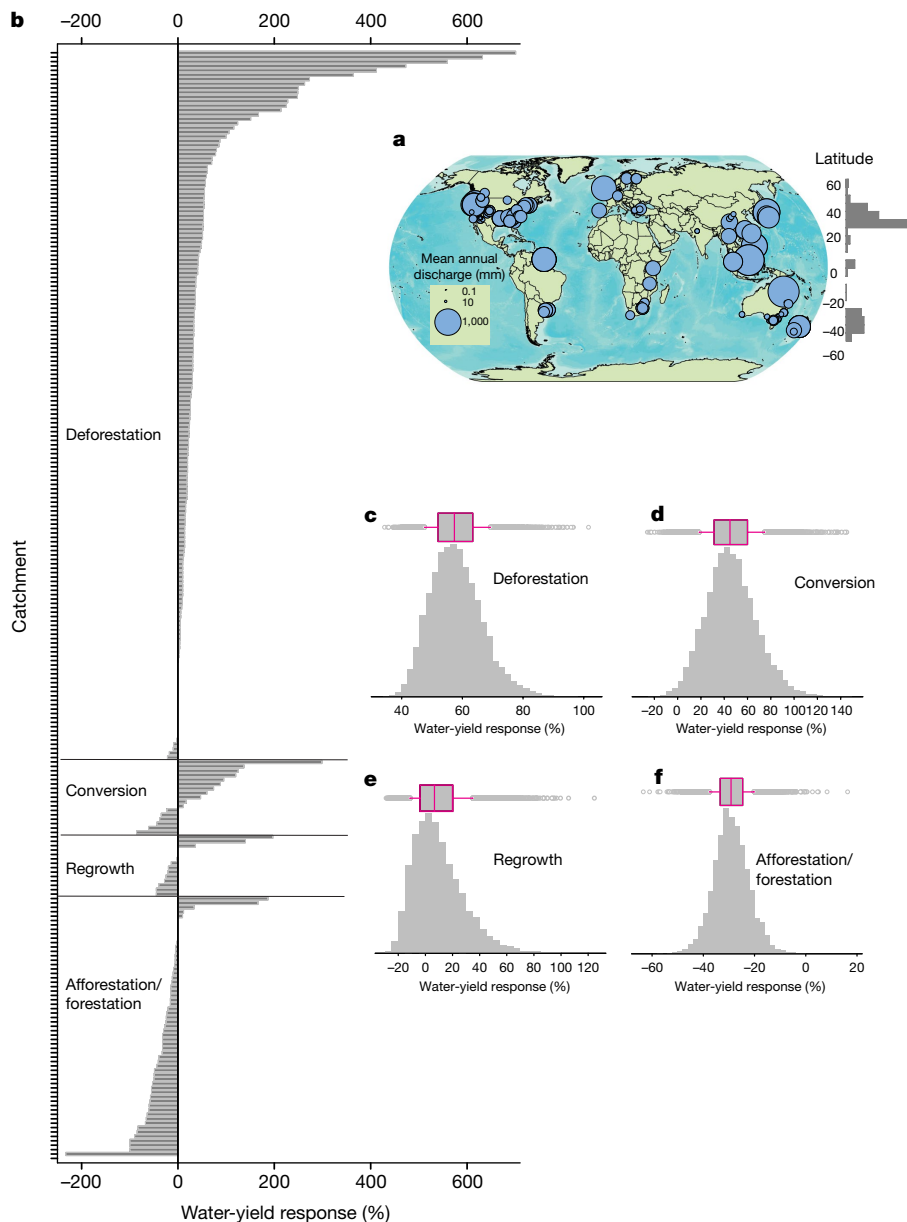
Fig. 1 | Global paired watershed studies. a, Study sites ($n = 251$) represented by the source papers used here. The bubble sizes represent relative mean annual streamflow; the histogram shows the latitudinal distribution of study densities. **b,** Summary of water-yield response, grouped by the type of intervention in forest cover (deforestation, $n = 161$; conversion, $n = 17$; regrowth, $n = 14$; afforestation/forestation, $n = 59$). **c–f,** Histograms and box plots showing mean responses of water yield to different changes in forest cover, approximated via Bayesian bootstrapping ($n = 10{,}000$)[26]. The boxes show the extent of the 25th and 75th percentiles; the whiskers show the extent of outliers.

forestation (Fig. 1f) on water yields are $58 \pm 8.6\%$, $46 \pm 22\%$, $9.6 \pm 18\%$ and $-29 \pm 7.1\%$, respectively (see a previously published study[26] for the statistical approach used).

Storage determines response to deforestation

Our first finding focuses on the effect of forest removal on catchment water yield. The underlying datasets in Fig. 2 show that some studies with 100% forest removal show minimal water-yield response, whereas other watersheds with less than 20% forest removal show a substantial response. Our model suggests that potential storage (effectively, the amount of water that can be held between the soil surface and the unweathered bedrock), and to some degree PET and AET, determines much of the unexplained variance in runoff response to forest removal (Fig. 2a; overall model fit $R^2 = 0.557$). These three factors constitute 93% importance (64%, 26% and 3%, respectively) to the model. This suggests that variation in potential storage results in highest variability in water-yield response, making potential storage the most important

factor relative to the model. Analysis of model sensitivity shows that removal schemes (for example, deforestation and thinning) are more likely to enhance water yield, particularly in areas where potential storage is high (for example, thick, high-porosity soils; Fig. 2c, dark grey histogram). By contrast, only modest increases in annual water yield are likely when removal schemes are implemented in areas where potential storage is low (for example, shallow, low-porosity soils; Fig. 2c, light grey histogram).

Vegetation determines response to forestation

Our second finding is that AET is the most important factor in predicting the response of runoff to planting intervention schemes (Fig. 2d; overall model fit $R^2 = 0.846$). Model-sensitivity analysis shows that planting schemes (for example, afforestation, conversion and regrowth) are more likely to result in generally undesirable outcomes of reduced water yield in settings in which AET is relatively low, for example, in drier regions or in grasslands/shrublands[27] (Fig. 2f, light grey
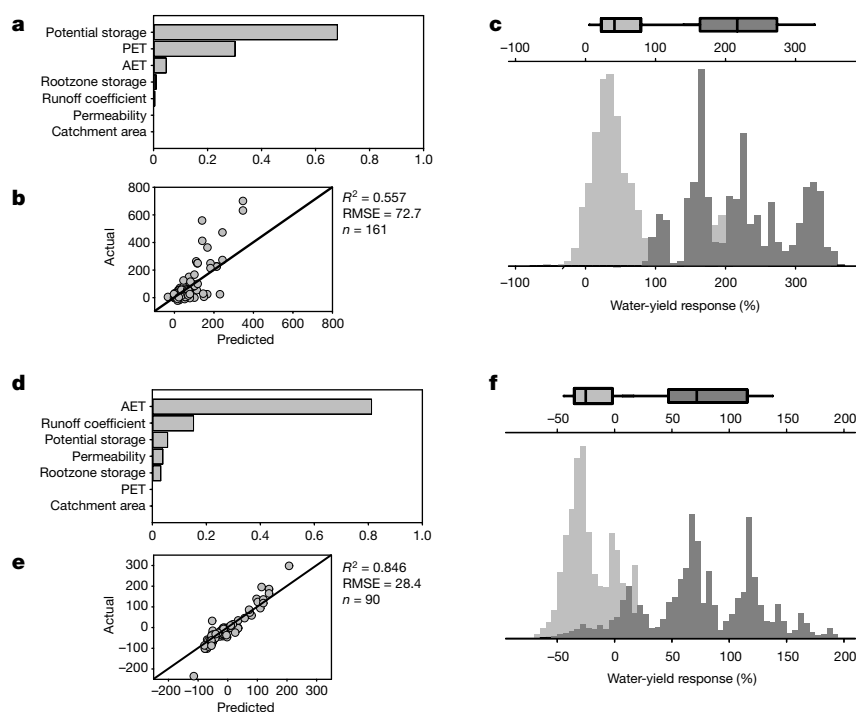
Fig. 2 | Controls on water-yield response. a, d, Model-independent ranked importance indices for factors affecting water-yield response in removal (**a**) and planting (**d**) schemes. **b, e**, Model predictions versus actual water-yield response in removal (**b**) and planting (**e**) schemes. **c, f**, Model simulation results showing distributions of water-yield response to removal (**c**) and planting (**f**) schemes, as a function of potential storage and AET, respectively. Histograms and box plots represent the distribution of simulation results at the lower (light grey) and upper (dark grey) limits of the range for each factor (see Methods, 'Sensitivity and uncertainty analysis'). The boxes show the extent of the 25th and 75th percentiles; whiskers show the extent of outliers. RMSE, root mean squared error.

histogram). But enhanced water yield change is likely when planting schemes are implemented in settings in which AET is relatively high, for example, in wetter regions or in previously forested areas (Fig. 2f, dark grey histogram).

Vegetation–to–bedrock perspective

Our working hypothesis to explain these findings is that geology and climate together modulate the balance of water partitioned for streamflow and transpiration, and that these geologic and climatic factors express themselves differently for planting and removal. Figure 3a, b shows a simple conceptual model to explain the response of streamflow to forest-removal schemes, in which the magnitude of the annual streamflow response is controlled predominantly by the size of the potential storage. Our data show that potential storage varies greatly—from 4 mm to 15,000 mm across the 502 PWS catchments—and that these potential storage reservoir differences, and to some degree PET and AET, are what mediate much of the hitherto unexplained variance in Fig. 1. This recognition of the importance of potential storage is consistent with a body of recent research that points to a different way of considering streamflow as a consequence of storage release[2,14–17,28–31]. Studies of belowground storage[32] in forested landscapes have highlighted its essential control on both streamflow and transpiration locally. Case studies have shown that root-zone moisture-storage capacities have been highly affected by forest conversion[33]. But so far potential storage has received minimal attention in PWS, and our synthesis suggests that this key variable[13–17] could explain much about the impacts of forest-cover removal on streamflow. Moreover, these results suggest that if potential storage is much higher than AET, then an annual time step is less than ideal for forcing the closure of water balance and for evaluating the integrated hydrologic response, given that the streamflow could be years to decades old[28].

Notwithstanding, the climatic (not the geologic) theory that underpins these findings is well established[34]. Often referred to as the 'Budyko Curve', the theory holds that the fraction of precipitation (P) attributable to transpiration and evaporation (AET) (the evaporative index) can be predicted by a watershed's aridity (PET/P) (the dryness index). Figure 4 shows a summary of streamflow response to removal with respect to the evaporative and dryness indices of the world's 13 biomes in our database. That the biomes plot relatively close to the theoretical prediction suggests that climatic factors matter to the fraction of precipitation that leaves a watershed via AET and, by extension, to what is left as streamflow (Fig. 4a): there is less streamflow in cases in which AET/P is high (dry sites), and more streamflow in cases in which AET/P is low (wet sites). The scatter around the prediction, however, indicates that the steady-state assumption of the Budyko model (that is, that there are no changes in storage) is not universal, hence the need to account for factors beyond the simple Budyko framework[31]. Our analysis shows that energy-limited regions (with a dryness index of less than 1) tend to result in less water-yield response to forest removal ($83 \pm 0.2\%$; Fig. 4b) than in water-limited regions (with a dryness index of greater than 1; $149 \pm 0.3\%$; Fig. 4c). This corresponds to less potential storage in wet areas ($2,527 \pm 5$ mm storage; Fig. 4d) than in dry areas ($4,086 \pm 14$ mm; Fig. 4e). These patterns are consistent with our vegetation-to-bedrock model showing the importance of potential storage in water-yield response to forest-cover removal.

We note, however, that our vegetation-to-bedrock model on streamflow response to forest-cover removal could account for only 60% of the overall variance. The model, as with the other statistical models used (see Methods), tends to underestimate higher water-yield response in 6 out of 161 catchments (Fig. 2b). Remarkably, the range of potential storage in these six catchments is higher than in the rest (155 out of 161) of the deforestation catchments, with an interquartile range (IQR) of 8,119 mm compared with 3,004 mm. Although these results demonstrate the importance of potential storage in streamflow response to deforestation, no statistical model could sufficiently predict streamflow response in these 6 catchments. This suggests that applying the
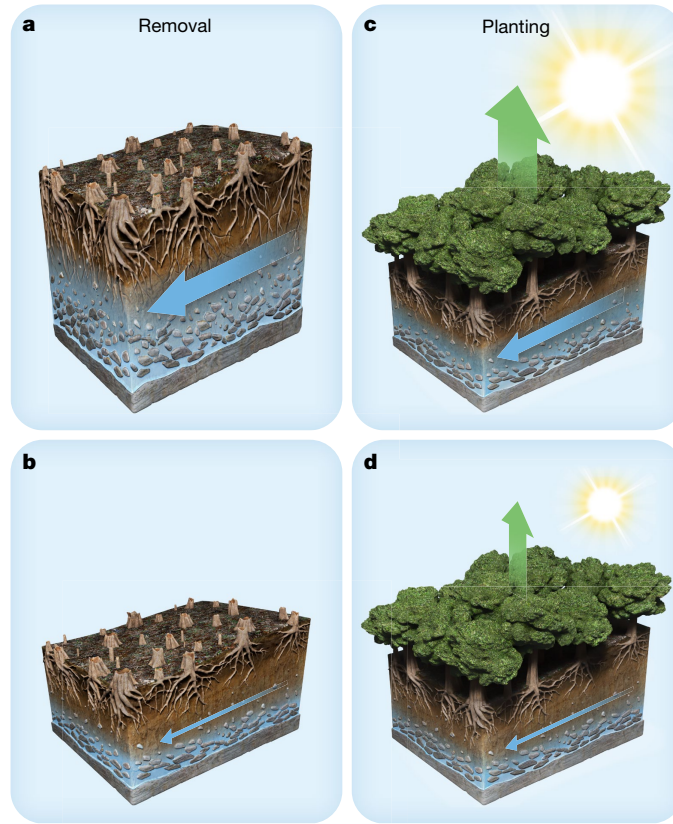
Fig. 3 | A geoclimate conceptual model for streamflow response to forest management. a, **b**, In forest-removal schemes, the relative magnitude of change of the streamflow response is controlled by the size of the subsurface potential water storage. **c**, **d**, In forest-planting schemes, the magnitude of the streamflow response is controlled mainly by water-vapour loss through evaporation and transpiration. Blue and green arrows represent streamflow and evapotranspiration, respectively. The size of the arrows represents the relative magnitude of change of these components. The relative size of the Sun denotes differences in AET. Illustrations courtesy of Melissa Logies 2019.
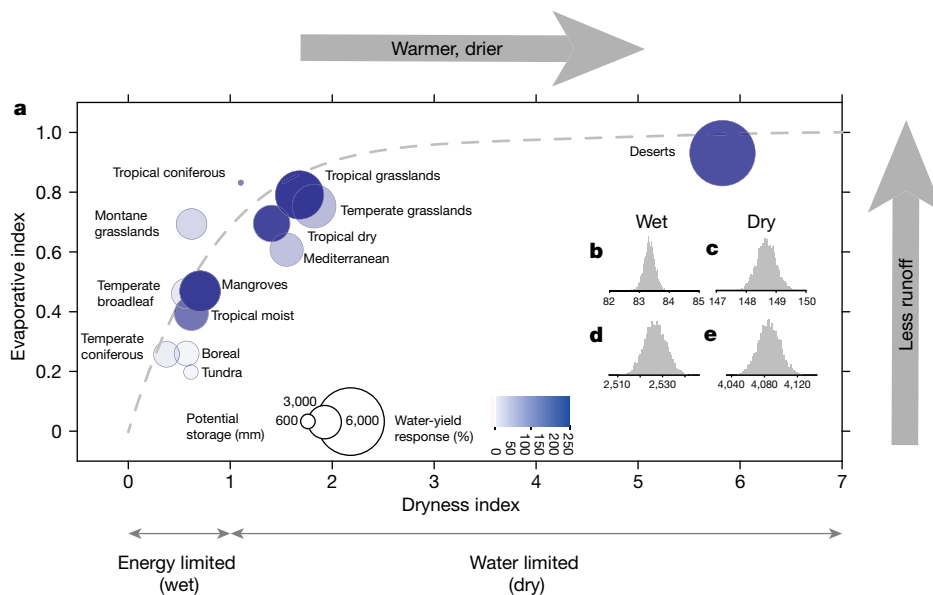
Fig. 4 | Framework for energy–water balance in the response of streamflow to forest removal. a, Evaporative index (AET/P) versus dryness index (PET/P) for catchments grouped per biome: boreal ($n = 26,640$), deserts ($n = 24,056$), mangroves ($n = 21,945$), Mediterranean ($n = 23,920$), montane grasslands ($n = 2,122$), temperate broadleaf ($n = 133,932$), temperate coniferous ($n = 51,631$), temperate grasslands ($n = 7,193$), tropical coniferous ($n = 575$), tropical dry ($n = 9,539$), tropical grasslands ($n = 22,644$), tropical moist ($n = 109,582$) and tundra ($n = 3,587$). The dashed curve is the Budyko[34] model prediction; the size of the bubbles represents the relative amount of potential storage (in mm); and the heat colour intensity represents the streamflow response to forest removal (as a percentage). **b**, **c**, Histograms showing the streamflow response of catchments classified as energy limited (wet; dryness index less than 1) and water limited (dry; dryness index greater than 1). **d**, **e**, Histograms showing the potential storage of catchments as classified in **b**, **c**. The histograms of streamflow response and potential storage were generated via Bayesian bootstrapping ($n = 5,000$)[26].

Table 1 | Effects of changes in forest cover on continental runoff

Region	Total river runoff (km³ yr⁻¹)	Change in runoff in response to forest-cover change (km³ yr⁻¹)	
		Planting	Removal
Africa	4,320	−605 (1,944)	8,986 (5,616)
Asia	14,550	−1,979 (5,835)	16,062 (25,783)
Australia and Oceania	1,970	−412 (725)	5,412 (4,962)
Europe	3,240	−875 (1,102)	813 (1,426)
North and Central America	6,200	−806 (2,034)	918 (2,102)
South America	10,420	0 (3,751)	1,908 (17,559)
Totals	40,700	−4,676	34,098

Total river runoff estimates have been published previously[36]. Values are medians (and IQRs). Positive and negative values are increases and decreases, respectively, with respective to total river runoff.

model predictions globally may underestimate the actual response of streamflow to deforestation, probably in water-limited settings in which potential storage is high.

For forest-planting schemes, the magnitude of streamflow response is controlled mainly by AET (Fig. 3c, d). Although afforestation is known to result in streamflow decreases[8,27] (Fig. 1f), other planting schemes, particularly conversion and regrowth (Fig. 1d, e), can result in stream-flow increases. Indeed, water yield is enhanced when planting schemes are implemented in settings in which AET is higher (Fig. 3c; see the model sensitivity in Fig. 2f) than in places where AET is lower (Fig. 3d). While perhaps surprising initially, Fig. 2d shows that the model-independent indices for planting include the explanatory factors of runoff coefficient and potential storage in the top three ranking. Our conceptual model is buttressed by these additional factors in which

areas with higher runoff coefficients, and therefore excess streamflow, can result in streamflow increases in areas with high AET, explaining much of the unexplained variance in runoff response to forest planting (Fig. 1d–f). Our simple conceptual model helps to disentangle these geoclimate effects. As in a previously published study[35], our results highlight the need to recognize explicitly geologic as well as climatic controls on forest management.

## Implications and discussion

The importance of our findings to water resources is illustrated in our summary of 440,000 catchments in Table 1. These tabulations of our model predictions show that forest removal can lead to increases in runoff that are around 3.4 times greater than the mean annual runoff of the Amazon River[36]. This translates to 20,757 km³ yr⁻¹—about six times more than the global storage capacity of dams used actively in the regulation of river runoff[36]. Looked at another way, this is equivalent to about 1.2 times the size of the surface water pool of Brazil, Russia, India, China and the United States (BRIC + US)[37], which together comprises 40% of global annual runoff. Globally, planting schemes can result in reductions in runoff of 15% (median; IQR 37%). This is equivalent to roughly 38% of the BRIC + US surface water pool, or approximately the mean annual runoff of the Amazon River. Across continents (Table 1), reductions in annual runoff because of planting schemes are the largest in Europe (median reduction −27%, or about 875 km³ yr⁻¹) and the smallest in South America, the only continent where planting schemes may lead to a slight increase, rather than a decrease, in annual runoff (median reduction 9 ± 41%, or about 919 ± 4,240 km³ yr⁻¹).

At the biome level, Fig. 5 shows the response of water yield to planting (Fig. 5a) and removal (Fig. 5b), delineated according to biomes
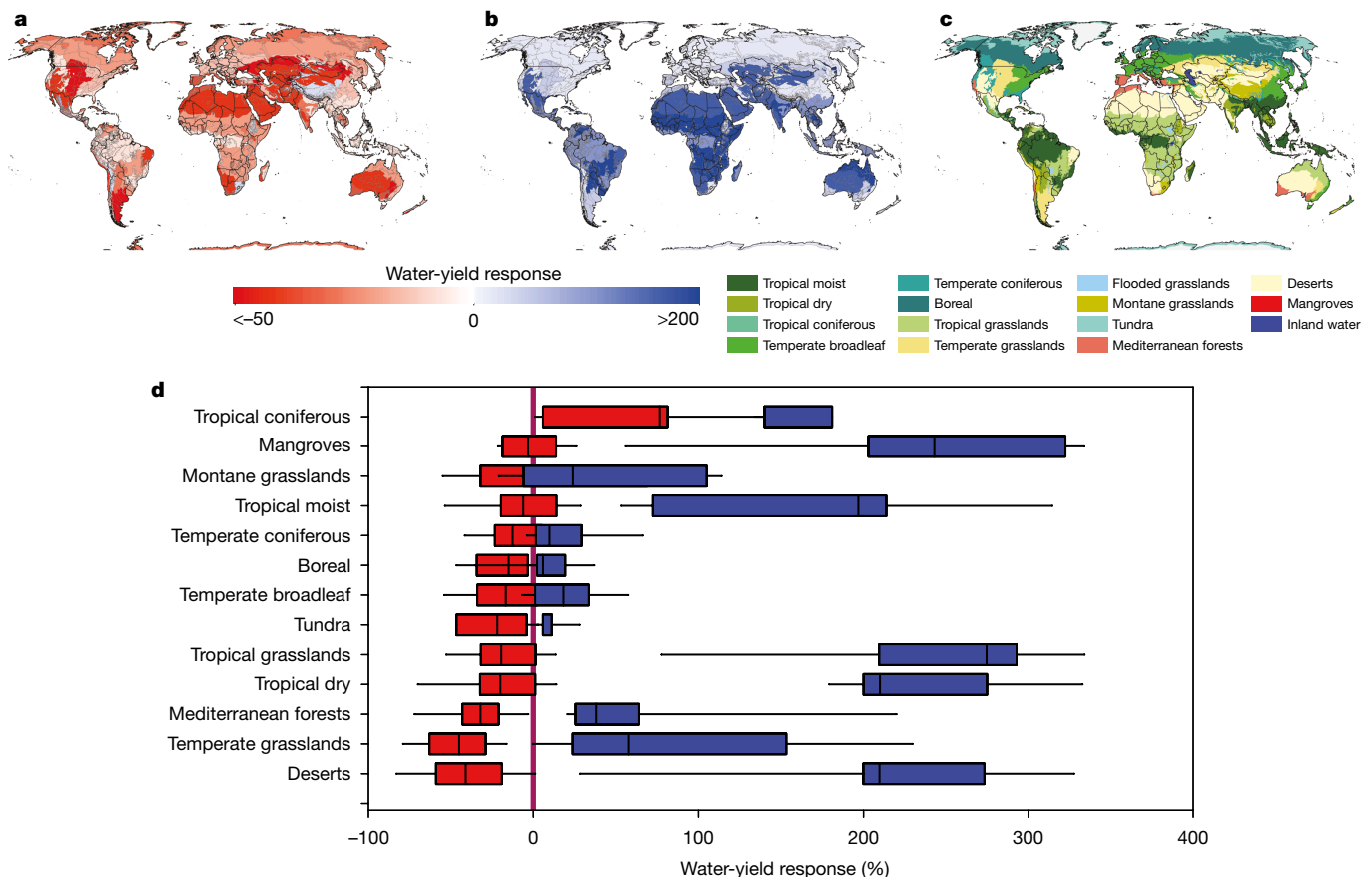
Fig. 5 | Biome-level responses of water yield to forestation and deforestation. a, b, Maps showing the effects of planting (**a**) and removal (**b**). **c,** Corresponding ecoregions. **a–c,** Shapefiles were sourced from The Nature Conservancy, http://www.nature.org. **d,** Box plots of water-yield

response associated with planting (red) and removal (blue), grouped by ecoregion, delineated by catchment sizes of 93 km² or less. The boxes show the extent of the 25th and 75th percentiles; whiskers show the extent of outliers.
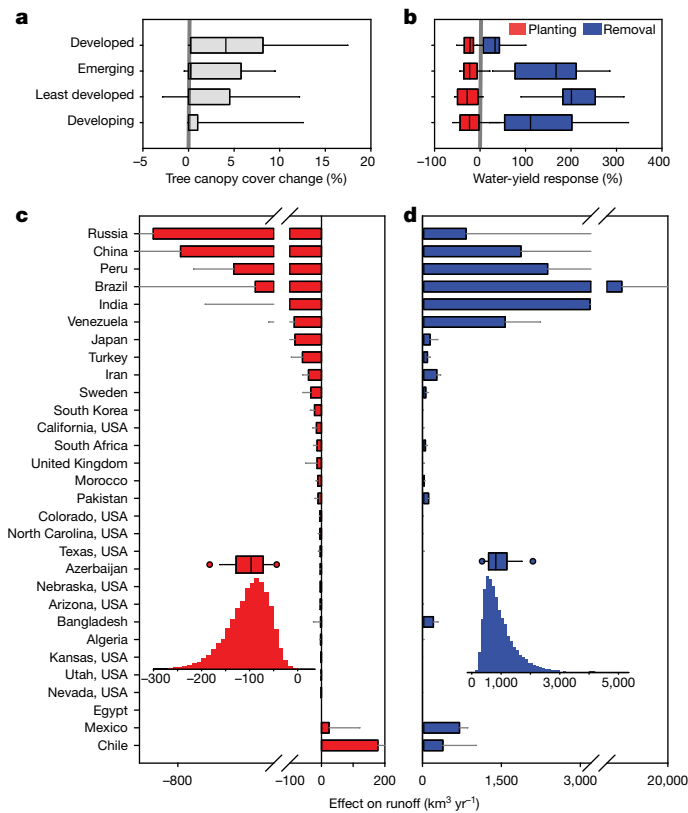
Fig. 6 | Changes in tree canopy cover and effects on runoff. a, Tree canopy cover change (1982–2016)[39] for countries represented in our database, grouped according to economic classification (see Methods). **b**, Box plots of water-yield response associated with removal and planting schemes, grouped according to economic classification. The boxes show the 25th and 75th percentiles; whiskers show the extent of the outliers. **c, d**, Rates of planting (**c**) and removal (**d**) in 21 countries and 9 US states classified as 'water stressed'[25]. Columns and error bars represent mean ± 1 s.d. The inset histograms are bootstrapped estimates ($n = 20,000$) of the effects of planting and removal in water-stressed states. The extents of the box plots show the 25th and 75th percentiles; whiskers show the extents of outliers. Outlier points represent the 5th and 95th percentiles.

(Fig. 5c). Although planting results generally in reductions in water yield (Fig. 5d), some catchments in tropical coniferous forests (notably in Mexico ($n = 446$) and in El Salvador ($n = 13$)) and montane grassland biomes (notably in New Zealand ($n = 767$)) tend to result in modest increases in water yield. Such exceptions to broader trends suggest that planting schemes in these catchments may well result in a net increase in runoff. Again, vegetation-to-bedrock factors are a useful way of understanding why these differences are expressed. Biome-level patterns associated with removal, however, are more straightforward than with planting schemes (Fig. 5d). Percentage increases in annual runoff owing to removal are smallest in boreal forests (median 6%, IQR 17%) and largest in desert (210%, 74%) and tropical grassland (275%, 83%) biomes.

The implementation of our model to globally distributed catchments, however, carries the caveat that the magnitude of change in land cover is implicit in the PWS data used by our machine-learning ensemble method (see Methods). Thus, we make a prudent assumption that the magnitude of land-cover change and water-yield response are correlated, albeit in complex, highly nonlinear and nuanced ways[6,38]. We explore the conceptual utility of this assumption by using actual data on global land-cover change[39] from 1982 to 2016. Figure 6a shows that tree canopy cover, with respect to a country's economic classification, decreases in developed, emerging, least-developed and developing countries (IQRs 7.9%, 5.8%, 4.5% and 0.9%, respectively).

Indeed, the minimum tree-cover change in developing and least-developed countries was −36% and −14%, respectively, compared to −0.3% and −1.7% in developed and emerging economies, respectively. Meanwhile, the magnitude and spread (mean ± 1 s.d.) of runoff response to removal schemes vary greatly and are larger in least-developed (208 ± 75%), emerging (160 ± 86%) and developing (131 ± 98%) economies than in the developed world (41 ± 58%) (Fig. 6b, blue box plots). This suggests that the impacts of removal in regions with more-limited infrastructure (using the United Nations' economic classification as proxy) may be greater than in relatively affluent economies. By contrast, the magnitude and range of runoff response to planting schemes are comparable across economic groups (Fig. 6b, red box plots). This suggests that countries that have infrastructure in place for capturing and storing water may be least vulnerable to possible water-supply shortages associated with planting schemes, which could be accentuated during drought years. These patterns are consistent with the conceptual underpinnings of the relationship between forest-cover trends and economic development[40].

When we apply our vegetation-to-bedrock model framework to 21 countries and 9 US states that have been classified as 'water stressed'[25], we can see that, in 28 of these regions, planting schemes may exacerbate problems of water-supply sustainability by further reducing streamflow (median reduction in runoff 97 km³ yr⁻¹, IQR 57 km³ yr⁻¹; Fig. 6c and inset; the exceptions are Mexico and Chile). That planting schemes may reduce the availability of water for downstream users is widely recognized[8], and its importance in water-resources management is institutionalized. South Africa's National Water Act, for example, requires the licensing of 'streamflow reduction activities', such as afforestation, in the country's bid to regulate land-use activities that reduce water supply for downstream users[41]. By contrast, forest removal (for example, forest harvesting or thinning) might offer some relief to all 30 water-stressed regions (Fig. 6d) by increasing streamflow (median 820 km³ yr⁻¹, IQR 628 km³ yr⁻¹; Fig. 6d, inset). Of the nine US water-stressed states illustrated, Arizona, California and Texas could make the most gains in terms of streamflow at 10 km³ yr⁻¹, 12 km³ yr⁻¹ and 14 km³ yr⁻¹, respectively. Nonetheless, our model may not capture the uniqueness of how forest removal affects streamflow at some sites. In a Mediterranean climate, for example, the seasonal timing of streamflow is a more important metric than annual streamflow for water provisioning. Furthermore, if forest removal increases peak flows (the time when the river reaches its highest flows) but not low flows, then this may aggravate water-supply issues, especially in places that have limited infrastructure for capturing runoff. Thus, although programmatic forest thinning or reductions in forest cover might alleviate declining runoff and augment water supply for people and ecosystems, catchment-specific nuances take primacy. Nonetheless, the global-in-scale insights derived from our model underscore a resource and management importance that highlights the role of a vegetation-to-bedrock continuum in the sustainability of water resources[42,43].

Goals 6 and 15 of the UN's SDGs—which focus on the sustainability of water resources and forest management—could be impeded by the highly equivocal outcomes of PWS and by uncertainty regarding the effects of forest management on streamflow[2]. Our work shows that: first, forest-removal schemes increase water yield most markedly in areas with substantial potential storage; second, forest-planting schemes reduce water yield most acutely in places that are already facing water-scarcity issues; and third, biome-level controls may explain some of the nuances associated with streamflow response, particularly to planting schemes. Our improved understanding of what drives variability in water yield in response to changes in forest cover is important practically for predicting water supply, but perhaps most importantly for recalibrating the cost–benefit matrix of climate change mitigation schemes (for example, planting and removal) in different geoclimate regions around the world.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41586-019-1306-0.

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METHODS

Data compilation and treatment. The PWS approach involves comparing the streamflow response of two similar catchments before and after exposing one catchment to an intervention scheme ('treatment') while leaving the other untreated as a reference ('control'). We built a comprehensive and up-to-date PWS database[44] by conducting a comprehensive search of the published literature on the topic (Extended Data Fig. 1). Because we were interested in understanding the effects of land-cover interventions on annual water-yield (that is, streamflow) response, we included only PWS (hereafter 'source papers'[45–174]) that expressly examined and reported annual streamflow. To address the disparate reporting metrics of water-yield effects (hereafter 'effects'), we reported the magnitude and direction of effects as percentage water yield. In cases in which effects were reported as amount of change in streamflow response, we calculated the percentage change in streamflow amount relative to the reference catchment. The study sites represent 10 of 14 terrestrial biomes (delineated by the Nature Conservancy, http://www.nature.org): boreal forests ($n = 3$), deserts ($n = 33$), Mediterranean forests ($n = 16$), montane grasslands ($n = 11$), temperate broadleaf ($n = 116$), temperate conifer ($n = 35$), temperate grasslands ($n = 2$), tropical dry ($n = 3$), tropical grasslands ($n = 12$) and tropical moist ($n = 20$). These biomes represent the following numbers of years of cumulative streamflow records (that is, lengths of time for which PWS were performed): boreal forests, 26 years; deserts, 264 years; Mediterranean forests, 97 years; montane grasslands, 182 years; temperate broadleaf, 1,511 years; temperate conifer, 689 years; temperate grasslands, 32 years; tropical dry, 30 years; tropical grasslands, 121 years; and tropical moist, 180 years.

For each type of treatment intervention, we used the exact term or qualitative description used in the source paper (Extended Data Fig. 1), for example, deforestation ($n = 161$), conversion ($n = 17$), regrowth ($n = 14$) and afforestation/forestation ($n = 59$). We also further classified the four intervention types into two groups: planting and removal. The former included afforestation/forestation, conversion and regrowth intervention types ($n = 90$); the latter included deforestation and thinning intervention types ($n = 161$).

The database comprises a median annual streamflow of 340 mm and a range of 2,903 mm (Fig. 1a), representing 3,132 years of cumulative streamflow records (median 10 years, IQR 13 years). The sites are divided approximately equally between energy-limited sites (PET/P < 1; 124 out of 251 sites) and water-limited sites (PET/P > 1; 127 out of 251) (Extended Data Fig. 2, x axis). The density of studies, however, is higher in the former than in the latter (kernel density plots, Extended Data Fig. 2, x axis). This suggests that our knowledge of water-yield response to land-cover change is skewed in favour of energy-limited systems. Notwithstanding, removal studies tend to capture a wider extent of water-limited settings than planting studies. The density of removal studies is also more uniformly distributed in both high and low evaporative index (AET/P) settings than is the case for planting studies (kernel density plots, Extended Data Fig. 2, y axis).

We extracted the geographic coordinates for each study site as reported in the source paper. When not provided in the source paper, we obtained the geographic coordinates from other sources—for example, Google Earth, catchment-monitoring websites, and other published manuscripts that matched the description of the study site described in the source paper. We used best efforts to ensure that geographic coordinates fell within the boundaries of the study site, using either the centroid when boundary coordinates could be obtained, or the stream gauge location were provided. Whereas earlier paired watershed syntheses focused on water-yield changes as a function of climate[5,7], percentage change in forest cover[5,6] or catchment area[8], we assessed the possible controls on water-yield response by taking a holistic view of factors that sufficiently represent the vegetation-to-bedrock continuum— climatic, hydrologic, edaphic, geologic and biotic. We achieved this by retrieving collocated spatial datasets on runoff coefficient (the ratio of long-term runoff or streamflow to precipitation[18]), long-term runoff[18], PET[19], deeper subsoil permeability and porosity[20], plant-available rooting-zone water-storage capacity[21], depth to bedrock[22] and biome classification (delineated by the Nature Conservancy, http://www.nature.org). We calculated AET as the difference between mean annual precipitation and runoff[23]. We derived a parameter called 'potential storage' as the product of depth to bedrock (L) and porosity. Data on depth to bedrock[22] were derived from soil profile observations from more than 130,000 locations and borehole logs from about 1.6 million locations worldwide, combined to map the global depth to bedrock for land surface modelling at a spatial resolution of 250 m. A substantial advance in the mapping of depth to bedrock globally is presented in a previous study[22], compared with other studies that estimated depth to bedrock at coarse resolutions and limited accuracy, usually limited to within just 2 m of depth[175–178]. Data on porosity[20] were derived from a high-resolution global lithology map that discriminates between fine-grained and coarse-grained sediments. A substantial advance in mapping porosity globally is presented in a previously published study[16], with a resolution that is more than a hundredfold increase over previous work[178].

Overall, we considered seven factors that could possibly explain the direction and magnitude of water-yield response, analysed by broad intervention (planting and removal) schemes.

Statistical modelling. We implemented numerous models and compared the performance of competing models to identify one that best predicts water-yield response[179]. Three linear models (penalized generalized regression, standard least squares and partial least squares), two recursive partitioning models (bootstrap forest and boosted trees) and a machine-learning algorithm (neural network) are described in detail below. Notwithstanding the long history of PWS in understanding the effects of various land-cover treatments on water yield, dating back to the Wagon Wheel Gap study[1] of 1911, and the many synthesis efforts since Bosch and Hewlett's review[7], we know of no paired watershed synthesis to date that has explicitly examined the full suite of controls—climatic, hydrologic, edaphic, geologic and biotic—considered here. The state-of-knowledge heretofore implies that no a priori set of models could be invoked in hypothesis testing and modelling that properly ranks the relative importance of possible controls. After identifying the statistical model that best predicts water-yield response (see the section on 'Model selection and inference' below), we addressed the latter issue using a multimodel inference framework that ranks the relative importance of predictor variables[180].

Penalized generalized regression. We used generalized regression to achieve two objectives: to select variables for model reduction and to address issues of multi-collinearity. We used an adaptive version of the elastic net technique[181] to penalize the size of model coefficients, thereby building variable selection in the modelling approach. The technique penalizes variables in the model that have an actual effect on water-yield response, resulting in estimates that are biased and reducing variance in the prediction and overall error. We implemented the model by transforming water-yield response to approximate a normal distribution, constructing model effects with main effects and two-way interactions (that is, factorial up to two degrees), and setting AICc (corrected Akaike's information criteria[182]) as the validation method and an elastic net (α) of 0.9.

Standard least squares. We used standard least squares to construct linear models for water-yield-response data using the least squares. We implemented the model by transforming water-yield response to approximate a normal distribution, constructing model effects with main effects and two-way interactions (that is, factorial up to two degrees). In contrast to penalized generalized regression, there is no penalty in this estimation method.

Partial least squares. We made the reasonable assumption that the seven factors (that is, explanatory variables) identified as possible controls on water-yield response are highly dimensional. Partial least squares addresses high-dimensional data as well as multicollinearity issues, the latter being a relatively more important issue in planting (PET versus AET, PET versus plant-available rooting-zone water-storage capacity, potential storage versus AET: correlation coefficients ranged between −0.3148 and 0.4715) than in removal schemes. We constructed model effects with main effects and two-way interactions (factorial up to two degrees), and then centred and scaled the factors and water-yield response to have a mean of 0 and standard deviation of 1. This meant that the factors and response were placed on an equal footing relative to their variation—that is, a change of one standard deviation in one factor resulted in an approximately equivalent change of one standard deviation in another factor. We also standardized the model effects so that all factors that are involved in an interaction or polynomial term are standardized before inclusion in the model[183]. Finally, we used a nonlinear iterative partial least-squares fitting algorithm (NIPALS[184,185]), and set KFold = 7 as the validation method. This KFold validation method randomly divides the original data into seven subsets, using each of the seven sets to validate the model fit on the rest of the data[186].

Bootstrap forest. We used a bootstrap forest algorithm to randomly generate bootstrap samples with replacement of the data, using the created datasets to make a 'forest' of decision trees. We fit the individual decision tree using recursive partitioning by selecting a random set of predictors for each split. We set the number of trees to 100, minimum splits per tree to 10, and maximum splits per tree to 2,000. The overall prediction was the average predicted response values over all decision trees[186].

Boosted tree. We used a gradient-boosted tree algorithm to generate an additive decision-tree model based on decision trees that were constructed in layers. A first tree was built, followed by a second (which was built on the scaled residuals of the first), followed by a third (which was built on the scaled residuals of the second), and so on. Finally, the trees were combined to generate a final set of 'if–then' statement rules. Prediction was improved through the logic of generating subsequent trees on the errors of earlier models, thereby increasing (or boosting) the importance of misclassified observations. Each layer was fit using recursive fitting. In contrast to bootstrap forest, fitting stopped at a specified number of splits (here set at three). We set the learning rate to 0.1, which slowed model convergence but also resulted in a smaller tendency to overfit the data. Overall prediction for

an observation was the sum of the predicted residuals for that observation over all the layers[186].

Neural network. We used a fully connected machine-learning algorithm (neural network) to predict water-yield response as a flexible function of the seven factors. A neural network is a function of a set of derived inputs called hidden nodes, which are nonlinear functions of the original inputs. An activation function, which is a transformation of a linear combination of the seven factors, is applied at the hidden nodes. Using 20% of the data as a validation set, we set three nodes for a hyperbolic tangent activation function.

Model selection and inference. We compared the predictive ability of the different models using the following measures of fit: R^2 statistic, root average squared error (RASE) and average absolute error (AAE)[179]. Extended Data Figure 3 summarizes the results of the multimodel comparison. In both planting (Extended Data Fig. 3a) and removal (Extended Data Fig. 3b) schemes, gradient-boosted tree models gave the best predictive ability. We then used the respective gradient-boosted tree models to gauge the relative importance of the predictor variables (that is, factors). This was achieved by calculating indices that measured the importance of factors in a manner that was independent of the model type and fitting method. The best-fitted gradient-boosted tree model was only used in calculating the predicted values. This model-independent inference method was predicated on the knowledge that the variability in the predicted response is based on a range of variation for each factor. That is, if variation in the factor resulted in high variability in the response, then that effect was important relative to the model[187].

Following a previously published study[187], suppose that $x_1, x_2, \ldots, x_n$ are the factors in the model and f is the function that represents the gradient-boosted tree model, then $y = f(x_1, x_2, \ldots, x_n)$. The expected value of y, $E(y)$, is estimated by integrating y with respect to the joint distribution of $x_1, x_2, \ldots, x_n$. The variance of y, $\mathrm{Var}(y)$, is estimated by integrating $(y - E(y))^2$ with respect to the joint distribution of $x_1, x_2, \ldots, x_n$. The impact of a factor x_j on y is described by $\mathrm{Var}(E(y|x_j))$, which measures the variation, over the distribution of x_j, in the mean of y when x_j is fixed. We then calculated importance indices (Fig. 2a, d) by assuming that the likely values of the factors were uniformly spread over the range represented here. Given that our study is, to our knowledge, the most up-to-date synthesis of PWS, we consider this assumption to be acceptable. This was achieved by generating Monte Carlo samples, drawn from a uniform distribution that was defined by the minimum and maximum observed values.

Sensitivity and uncertainty analysis. To test the sensitivity of the gradient-boosted tree model to changes in the factors (ranked by importance index), we simulated the distribution of water-yield response as a function of the random variation in the factors and model noise. That is, we simulated how the distribution of water-yield response changed when the location (mean) and variability (spread) of the factors changed. We achieved this by generating random numbers for each factor using the Mersenne–Twister technique[188] uniformly between 0 and 1, resulting in an approximately even distribution. The three most important factors in each intervention scheme (potential storage, PET and AET in removal, Fig. 2a; AET, runoff coefficient and potential storage in planting, Fig. 2d), constituting 93% and 84% importance to the model, respectively, were then simulated, specifying 5,000 as the number of runs. We then used the simulation results to examine the distributions of water-yield response at the lower and upper limits of the range for each factor. Figure 2c, f illustrates the distributions of the most important factors—potential storage for removal and AET for planting. The lower and upper values of potential storage were 47.5 mm and 14,973.2 mm, respectively. The lower and upper values of AET were 145.7 mm and 2,234.9 mm, respectively. This enabled us to derive robust estimates of the distributions of water-yield response, bounded by the range of possible values of the most important factors. To quantify the uncertainties in the original source data, we performed a Bayesian bootstrap analysis[26] ($n = 10,000$). The method treated sampling probabilities as unknown parameters, with the posterior distribution derived using a non-informative prior. Probability estimates were obtained from the posterior distribution, which were then used to construct the bootstrap weights. The outputs from bootstrapping were reported as bias-corrected 95% confidence intervals (Extended Data Table 1), which we then used to report mean, lower and upper 95% bias-corrected percentile intervals[189].

Model implementation and spatial modelling. Following model selection and sensitivity analysis, we applied the gradient-boosted-tree prediction formula to globally distributed catchments ($n = 2,219,782$)[24,44]. We adopted a conservative approach, whereby we considered only catchments for which data for all seven factors were available ($n = 442,319$; Extended Data Figs. 4, 5). The implementation of the model to 442,319 catchments globally carries the caveat that the magnitude of change in land cover is implicit in the PWS data on which the machine-learning ensemble method was used. The seven vegetation-to-bedrock factors used in the model expressly did not include the proportion of the catchment that has been treated (for example, the percentage area removed or planted). This was because the correlation between treatment area and water-yield response, in the context of PWS, is known to be weak ($R^2 = 0.17$)[6]. That is, some studies with 100% forest

removal showed minimal water-yield response, whereas other watersheds with less than 20% forest removal showed a substantial response. We considered this prior knowledge a compelling argument against including treatment area as a predictor in our model.

We also raise the caveat that the bottom-up (catchment-level) implementation of the model to catchments globally does not include the magnitude of land-cover change as a predictor. It is possible that our spatial model may underestimate or overestimate the likely water-yield response, depending on the magnitude and direction of effects of changes in land cover on water yield. Outside the context of PWS literature, however, a prudent assumption can be made that the magnitude of land-cover change and water-yield response may be correlated, albeit in complex, highly nonlinear and nuanced ways[6,38]. We explored the conceptual utility of this assumption by using actual data on land-cover change[39] from 1982 to 2016, which show that, globally, tree cover has increased by 7.1% relative to the 1982 level. We used the data from this previous study[39] to match the catchments in our dataset. We also categorized the catchments into either energy limited (dryness index less than 1) or water limited (dryness index greater than 1; Fig. 4). To derive meaningful information from the wide range of water-yield response to forest-cover removal (for example, Figs. 1b, 2c), given a wide range of potential storage across catchments, we calculated the mean statistic of water-yield response to removal (Fig. 4b, c) and corresponding potential storage (Fig. 4d, e). We made the estimation of the corresponding mean statistic robust by performing Bayesian bootstrapping ($n = 5,000$)[26].

We then supplemented water-yield predictions in these catchments with corresponding categorical descriptors: countries and economic groups[190]; surface water pool size (km³ yr⁻¹)[37]; biome classification (delineated by the Nature Conservancy, http://www.nature.org); and states and countries classified as 'water stressed'[25]. This approach enabled us to report results at spatial resolutions that convey the importance of socioeconomic factors, ecologic factors and water-resources management (Figs. 4, 5).

Mechanism. Our geoclimate working hypothesis (Fig. 3) is that belowground potential storage—and how trees and streams drain that storage—is central to explaining why we see a global pattern of, first, forest removal causing larger increases in flow in catchments with greater storage; and second, forest planting causing decreases in flow but opposite effects in catchments in which AET is relatively higher. This explanation is consistent with the global data to which we have access. But we acknowledge that, beyond the factors explored in this analysis, there are other factors that could be at work in terms of further explaining the effects of forest management on water yield[191]. The interactions of canopy, root processes and flow pathways at different scales can affect hydrologic connections and behaviour and drive the variability of responses observed in managed watersheds[192]. Furthermore, studies have shown that ecosystems can 'dynamically design' their root systems to cope between droughts[193], with some species tapping rock moisture in weathered rock beneath the soil profile[29]. Others have also shown that the impacts of forest change within regions vary with climate, species and time after a forest disturbance[194,195]. These factors may limit the time frame of hydrologic changes, and may shift patterns from increases to decreases. The control watershed may also introduce nuances given its dynamic and evolving nature. In snow-dominated areas, snow and radiation responses have been shown to vary widely in space. So, too, is there variability in water storage intercepted by the canopy, which has a role in water-yield response. Although these additional factors could be important, we do not have data to examine them across the many catchments represented here.

Of the factors that we have identified as possible controls on water yield, potential storage is the most important new predictor, specifically in schemes that involve the removal of forest cover (for example, deforestation or thinning). Studies looking at the age of stream water also suggest that subsurface storage in forested watersheds can be large and variable, with water leaving that storage and forming streamflow on time scales from months to decades—hinting at considerable reservoirs of stored water in soil, weathered rock and glacial deposits that PWS often ignore. Recent stable-isotope analysis[196] and remotely sensed data[197] have shown too that trees can use belowground storage reservoirs that are seemingly disconnected to streamflow. Moreover, the water used by trees can be decades old[198], well beyond the time scale of the PWS annual water balance calculation. The ability of deep-rooted trees to access stored water has fundamental implications for the sensitivity of streamflow to forest management. However, relatively little is known about how a forest's access to these different water storages evolves following disturbance. Other possible factors can include the types of vegetation, their rooting and water-uptake dynamics, and the leaf area that return after forest harvest[199]. Our work has not afforded the opportunity to examine these factors individually in any statistically meaningful way.

Data availability

The datasets generated during and/or analysed here are available in the Figshare repository[44] (https://doi.org/10.6084/m9.figshare.7770035).

Code availability

Codes used (available in C) for statistical modelling are available from https://github.com/jevaristo/pws.

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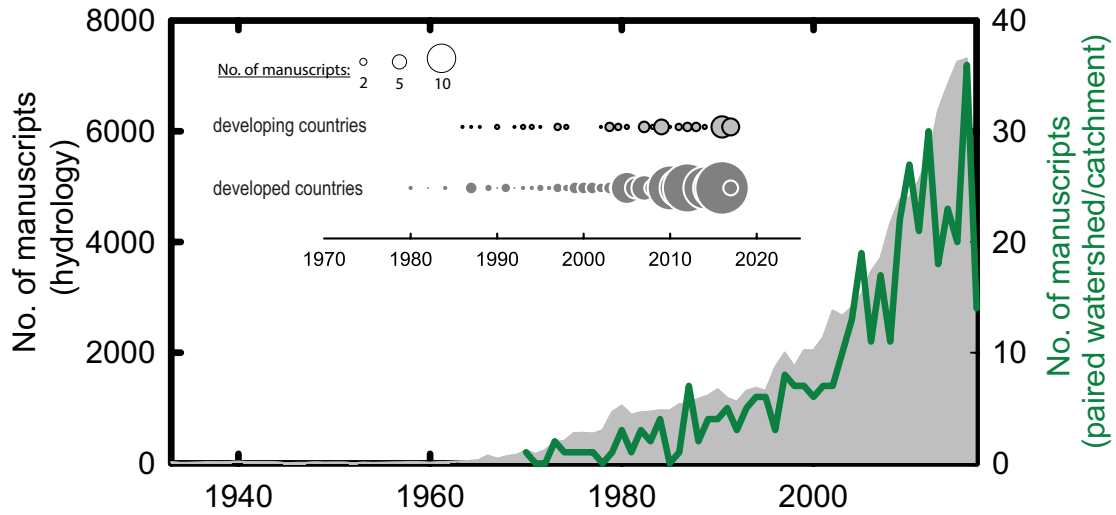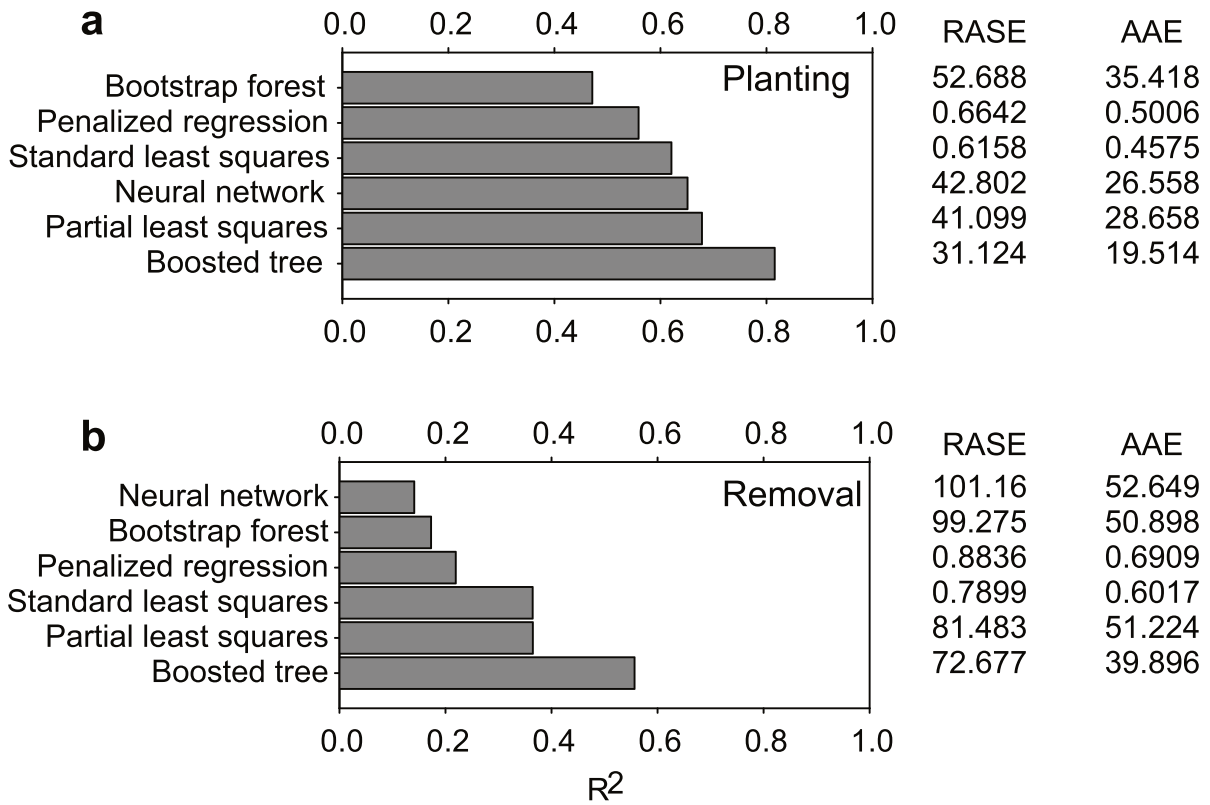
Extended Data Fig. 1 | Global database of paired watershed studies. Numbers of published manuscripts from 1933 to 2017 that match our Scopus database queries in the title, abstract or keyword. We identified a manuscript as a 'hydrology' paper (filled area) if it carried the tag 'hydrolog*' as a catch-all keyword for terms such as 'hydrology', 'hydrological', and so on. We identified a manuscript as a 'paired watershed' or 'paired catchment' study (dark green line) if it carried either of these phrases. The inset shows numbers of manuscripts (sizes of bubbles) according to a country's United Nations World Economic Situation and Prospects (WESP) classification[189].
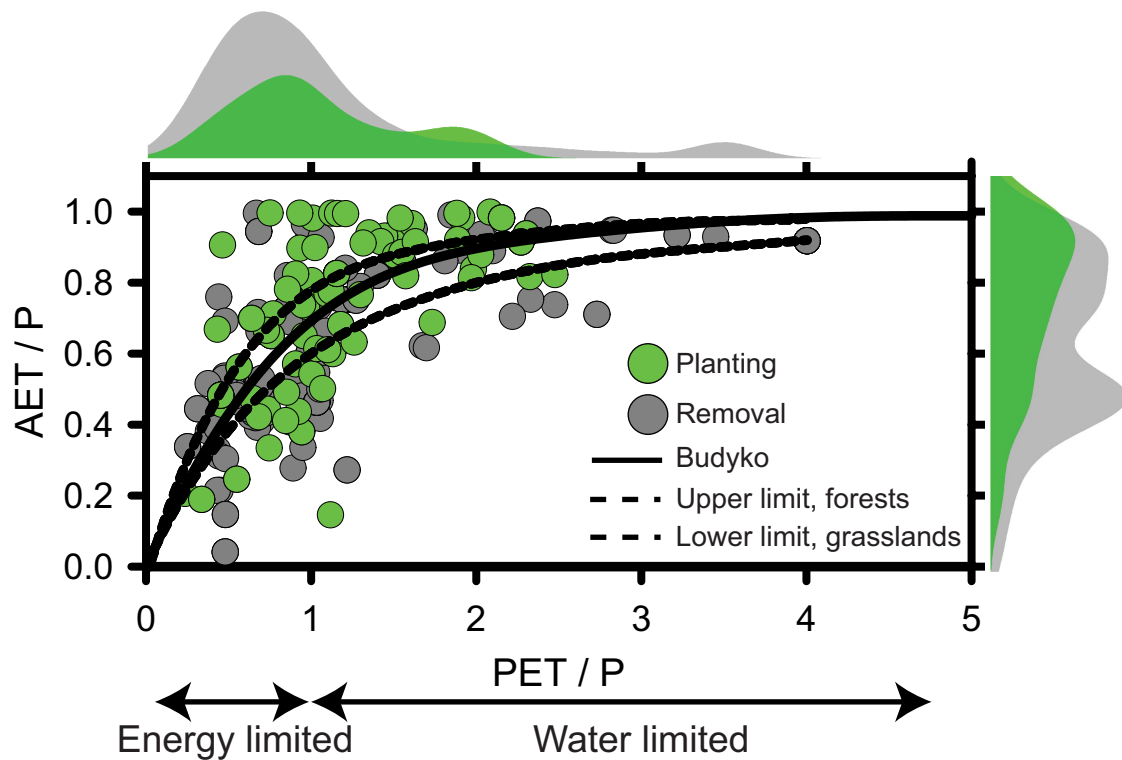
Extended Data Fig. 2 | Budyko plot of catchments in the PWS database. A Budyko plot of study sites within each intervention scheme (planting or removal), with dryness index (PET/P; *x* axis) plotted against evaporative index (AET/P; *y* axis). Also shown are kernel density plots of intervention schemes (top and right) . The solid curve is the Budyko prediction; dashed lines represent upper (forests) and lower (grasslands) limits according to equation (10) in previously published study[200].

a

	RASE	AAE
Bootstrap forest	52.688	35.418
Penalized regression	0.6642	0.5006
Standard least squares	0.6158	0.4575
Neural network	42.802	26.558
Partial least squares	41.099	28.658
Boosted tree	31.124	19.514

b

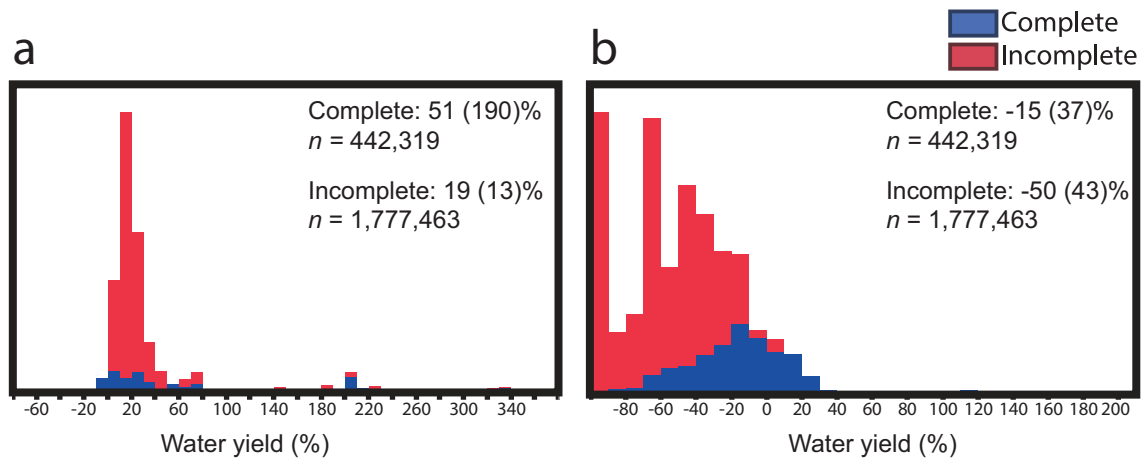|	RASE	AAE
Neural network	101.16	52.649
Bootstrap forest	99.275	50.898
Penalized regression	0.8836	0.6909
Standard least squares	0.7899	0.6017
Partial least squares	81.483	51.224
Boosted tree	72.677	39.896

Extended Data Fig. 3 | Model comparison. a, **b**, Comparison of modelling for planting (**a**) and removal (**b**) intervention schemes. Also shown are the model-fit statistics, R^2, RASE and AAE.
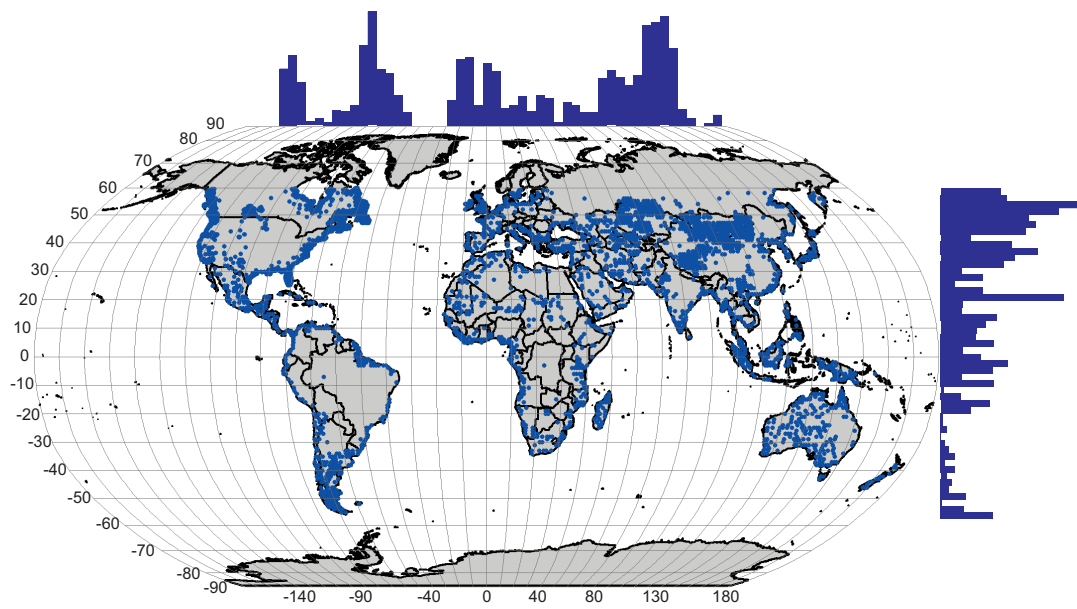
Extended Data Fig. 4 | Catchments. Locations of catchments ($n = 442{,}319$) for which data for all seven factors are available and in which the gradient-boosted-tree predictions are implemented. Histograms show distributions of catchments along latitude and longitude.

a

Complete: 51 (190)%
n = 442,319

Incomplete: 19 (13)%
n = 1,777,463

Water yield (%)

b

Complete
Incomplete

Complete: -15 (37)%
n = 442,319

Incomplete: -50 (43)%
n = 1,777,463

Water yield (%)

Extended Data Fig. 5 | Modelling catchments with complete and incomplete data. a, b, Histograms showing model output for removal (**a**) and planting (**b**) schemes. Complete (blue) and incomplete (red) refer to catchments in which all seven vegetation-to-bedrock factors are available ($n = 442,319$; complete) or for which one or more factors are not available ($n = 1,777,463$; incomplete). Values are median and interquartile range (in brackets).

Extended Data Table 1 | Uncertainty estimates for water-yield responses

Removal			
Biome	Mean	Lower 95%	Upper 95%
Boreal	15	6	26
Deserts	96	58	167
Mediterranean forests	190	68	405
Temperate broadleaf	35	26	51
Temperate coniferous	25	19	35
Tropical grasslands	162	17	393
Tropical moist	85	47	157
Planting			
Biome	Mean	Lower 95%	Upper 95%
Deserts	-26	-76	-7
Mediterranean forests	-59	-77	-51
Montane grasslands	-51	-115	-21
Temperate broadleaf	-28	-38	-20
Temperate coniferous	-13	-16	-9
Temperate grasslands	11	-24	47
Tropical dry	-61	-84	-41
Tropical grasslands	59	17	94
Tropical moist	94	32	163

These estimates were derived via bootstrapping ($n = 10,000$) using the PWS source data (see Methods). The lower 95% and upper 95% columns show the bias-corrected percentile intervals of the lower and upper end points, respectively, of the 95% confidence limits.