1   **Streamflow response to forest management**

2   James W. Kirchner[1,2*], Wouter R. Berghuijs[1], Scott T. Allen[1,3], Markus Hrachowitz[4], Rolf Hut[4], and

3   Donna M. Rizzo[5]

4   [1]Dept. of Environmental Systems Science, ETH Zurich, Zurich, Switzerland

5   [2]Swiss Federal Research Institute WSL, Birmensdorf, Switzerland

6   [3]Dept. of Geology and Geophysics, University of Utah, Salt Lake City, UT, USA

7   [4]Dept. of Civil Engineering, Delft University of Technology, Delft, The Netherlands

8   [5]Dept. of Civil and Environmental Engineering, University of Vermont, Burlington, VT, USA

9   *e-mail: kirchner@ethz.ch

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11   Forests play a key role in the water cycle, so both planting and removing forests can affect

12   streamflow. In a recent Nature article[1], Evaristo and McDonnell used a gradient-boosted-tree model

13   to conclude that streamflow response to forest removal is predominantly controlled by the potential

14   water storage in the landscape, and that removing the world's forests would contribute an

15   additional 34,098 km^3 yr^{-1} to streamflow worldwide, nearly doubling global river flow. Here we

16   report several problems with Evaristo and McDonnell's[1] database, their model, and the

17   extrapolation of their results to continental and global scale. The main results of the paper[1] remain

18   unsubstantiated, because they rely on a database with multiple errors and a model that fails

19   validation tests.

20   **Database problems.** We spot-checked the database underlying Evaristo and McDonnell's analysis[1]

21   by comparing individual entries to the original cited references. Roughly half of these spot checks

22   revealed substantial errors in the calculated changes in water yields, or errors in the classification of

23   individual studies as forest planting vs. forest removal experiments. Here we describe four

24   examples. 1) The Valtorto catchment in Portugal is classified as a forest clearing experiment[1]

25   although the catchment was never forested, but rather covered by 50 cm tall heath[2]. The reported

26   post-clearing streamflow increase of 363.6 percent[1] is also inconsistent with Table 3 of the original

27   reference[2], which reports that average streamflow increased by 150 percent, from 1.0 to 2.5 m^3

28   day^{-1}. 2) The database reports that forest clearing at the Lemon catchment in Australia increased

29   streamflow by 631.8 percent[1], but from Table 1 of the original reference[3], we calculate that the

30   average pre- and post-clearing streamflows were 18.0 and 27.9 mm yr^{-1} respectively, implying that

31   streamflow increased by only 55 percent. 3) Brigalow catchments C2 and C3, which both appear

32   twice in the database, are classified as forest planting experiments[1] although neither was planted

33   with forest: C2 was planted with sorghum and wheat and C3 was planted with buffel grass for

34   pasture[4,5]. 4) Several forest conversion experiments, in which forests were cleared and replanted

35   with other vegetation (e.g., ref.'s 74, 114, 130, and 163 in ref. 1), are reported in the database as

36   showing, counterintuitively, large streamflow _increases_ due to forest planting[1]. However, the

37   reported changes in streamflow were calculated relative to intact forest control plots, not cleared

38   land, so they mostly reflect the effects of clearing the prior forest rather than the effects of planting.

39   We suspect that this mis-attribution of forest clearing effects to forest planting may underlie the

40   paper's surprising finding (see Fig. 2 of ref. 1 and associated discussion) that forest planting appears

41   to _increase_ streamflow by 100 percent or more at many sites, with the largest increases at sites with

42   the highest evapotranspiration rates, a pattern that should normally arise from forest clearing
43   instead.

44   **Model overfitting and validation failure.** Gradient-boosted trees are data-hungry, and although
45   Evaristo and McDonnell[1] compiled every paired watershed study that they could find, the resulting
46   databases of 161 forest clearing experiments and 90 forest planting experiments are much too small
47   to reliably estimate their seven-variable model. We checked the model codes that Evaristo and
48   McDonnell provided with their paper (see the code availability statement of ref. 1) and found that
49   the boosted tree algorithm fits 200 free parameters (not counting the dozens of additional free
50   parameters that define the tree's branch points), suggesting substantial overfitting. To test how this
51   overfitting might affect the model's predictions, we split the forest removal and planting databases
52   into training sets (80 percent of the data) and test sets (the remaining 20 percent of the data). To
53   balance the distributions of the variables between the training and test sets, we used stratified
54   random sampling; we also used un-stratified random sampling as a more stringent test. We then re-
55   ran the boosted-tree analysis, using the same data, the same platform (JMP, SAS Institute, Cary, NC,
56   USA), and the same algorithm options that Evaristo and McDonnell[1] used, for 300 of these random
57   splits of the data, both with and without "early stopping" (in which the fitting algorithm stops
58   whenever the next layer would reduce the R^2).

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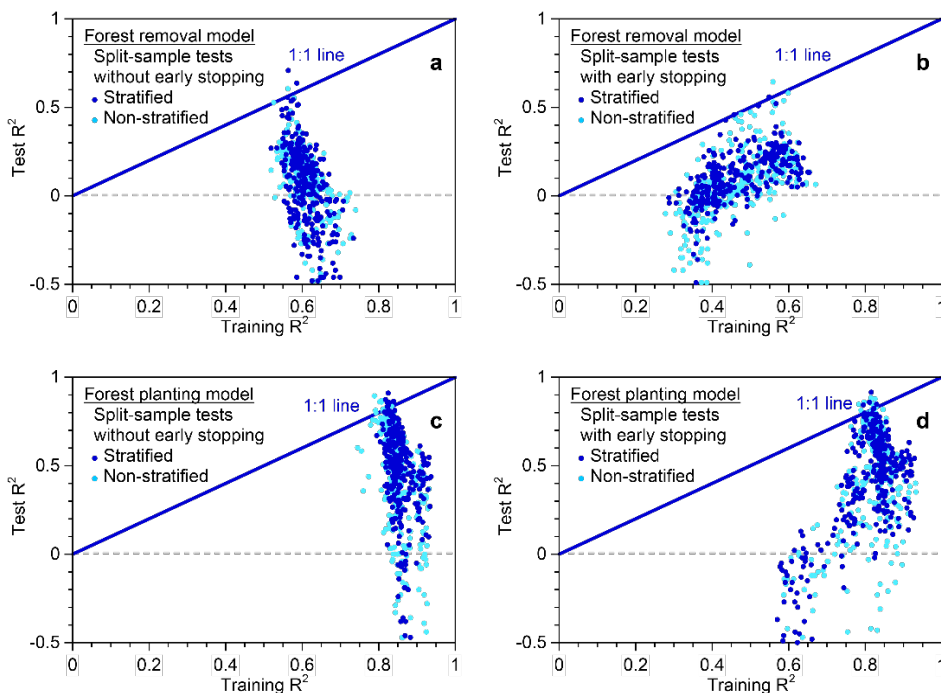
61   **Fig. 1. Split-sample validation tests of gradient-boosted-tree model fitted to forest**
62   **clearing (a, b) and forest planting (c, d) data.** The source data were randomly split into
63   300 training and test sets in 80/20 ratios, as described in the text. If the model were not
64   overfitted, the R^2 statistics obtained from the training and test sets would be similar to
65   one another, and thus the dots would lie close to the 1:1 lines. Instead, the test R^2
66   statistics are generally much smaller than the training R^2 values. Points with test R^2
67   values less than -0.5, which indicate that model predictions were much worse than
68   random guessing, are not shown.

69   The results in Fig. 1 show that the model fails these validation tests. If the model were not

70   overfitted, the fits to the test data (as measured by the test R^2 on the vertical axis) would be similar

71   to the fits to the training data (as measured by the training R^2 on the horizontal axis), and the dots

72   would lie close to the 1:1 line. Instead, many of the dots lie far below the 1:1 line, and many test R^2

73   values even lie below zero, indicating model predictions that are worse than random guessing.

74   Figure 1 thus shows that the model is overfitted and makes unreliable predictions (because it is too

75   flexible, and thus has been "fitted to the noise" in the training data). This result holds whether one

76   uses "early stopping" or not, and stratified and un-stratified validation tests yield broadly similar

77   results.

78   Although individual randomizations can yield test R^2 values that are similar to the training R^2 (or

79   even higher), one should not draw conclusions from such anomalies. Model performance is better

80   reflected in the medians of the training and test R^2 values across many randomization trials (Table

81   1). Table 1 confirms quantitatively what Fig. 1 shows visually; in each case, the median test R^2 is

82   much smaller than the median training R^2, and many test R^2 values are below zero.

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Model and split-sample test performed (80/20 split in all cases)	Median training R^2	Median test R^2	Fraction of test R^2<0
Forest removal model			
Stratified, with early stopping	0.449	0.108	31%
Stratified, without early stopping	0.605	0.096	36%
Unstratified, with early stopping	0.458	0.053	34%
Unstratified, without early stopping	0.608	0.057	40%
Forest planting model			
Stratified, with early stopping	0.827	0.455	13%
Stratified, without early stopping	0.852	0.486	10%
Unstratified, with early stopping	0.826	0.475	16%
Unstratified, without early stopping	0.844	0.474	17%

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85   **Table 1. Summary of split-sample validation test results**. Test results are shown for

86   boosted-tree model fitted to forest removal and forest planting data. "Fraction of test

87   R^2<0" indicates percentage of tests in which model predictions were worse than random

88   guessing.

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90   All of the paper's[1] main results are based on the boosted-tree model, so the validation failure

91   documented here invalidates the paper's conclusions. The other machine learning methods in the

92   paper have similar validation issues, but we will not explore them in detail because the paper's

93   conclusions do not depend on them.

94   **Exaggerated importance of potential storage.** The finding[1] that streamflow response to forest

95   removal was primarily controlled, not by climate, but by total potential water storage in the

96   landscape, was puzzling to us for two reasons. First, it was hard to imagine how total storage, much

97   of which may lie below the rooting zone of trees, could be the major control on the hydrological

98   effects of tree removal. Second, given that forest planting and forest removal both alter the same

99   variable (forest cover), but in opposite directions, it was hard to reconcile the paper's two main

findings[1]: that potential storage is the dominant control on streamflow response to forest clearing (but not planting), and that actual evapotranspiration (AET) is the dominant control on streamflow response to forest planting (but not clearing).

Closer examination reveals that the apparent importance of potential storage relies on one extreme data point (Lemon catchment, Australia), which has a potential storage of 15 meters, more than twice the next-highest value in the data set. If we remove this one data point, potential storage disappears as the most important factor (Table 2), and is replaced by potential evapotranspiration (PET). This one data point is so influential because Evaristo and McDonnell's analysis[1] uses an "independent uniform" variable importance profiler. This profiler is intended for use where the likely values of each variable will be uniformly distributed over the range of the data[6], which is inconsistent with the strongly skewed distributions of potential storage in Evaristo and McDonnell's paired watershed data set (Fig. 2a) and in their global catchment database (Fig. 2b). Potential storages exceeding 7.5 m comprise only 0.6% of Evaristo and McDonnell's paired watershed data set (light blue bars, Fig. 2a) and 6% of their global catchment database (light blue bars, Fig. 2b), but 50% of the distribution used to calculate the influence of potential storage, exaggerating potential storage's importance.
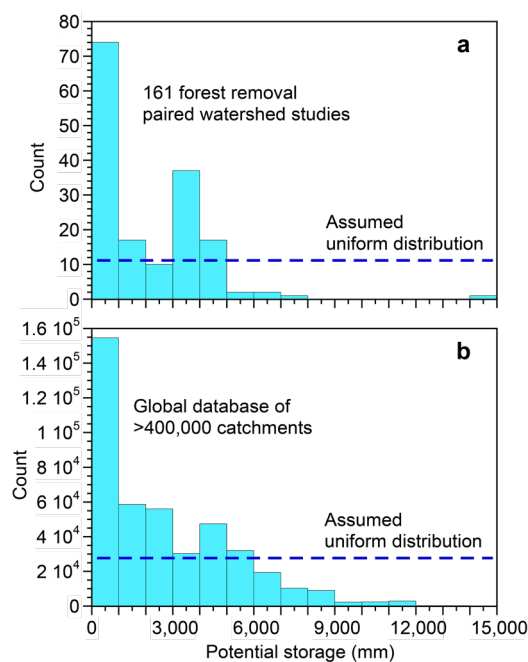
Fig. 2. Distributions of potential storage, compared to the uniform distribution used to estimate its influence in Evaristo and McDonnell's analysis[1].

Although Evaristo and McDonnell fully documented their choice of this "independent uniform" profiler[1], other choices, more consistent with the available data, lead to a different conclusion. For example, if we instead use a profiling method that takes account of the actual distributions of all of the variables ("independent resampled" profiling), PET becomes the most important variable, and potential storage drops to fourth place (Table 2). And if the profiling method also takes account of the correlations among the variables, in addition to their actual distributions ("dependent resampled" profiling), the most important variable is again PET, and potential storage drops to fifth

128 place out of seven variables (regardless of whether we include or exclude the Lemon catchment; see
129 Table 2).

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131 **Table 2. Relative variable importance using different profilers.**

Profiling method and treatment of Lemon catchment	Potential evapotran-spiration	Runoff coefficient	Drainage area	Potential storage	Actual evapotran-spiration	Root zone storage	Permea-bility
Independent uniform							
Lemon included	0.317 (2)	0.098 (3)	0.036 (5)	**0.508 (1)**	0.041 (4)	0.007 (6)	0.000 (7)
Lemon omitted	**0.500 (1)**	0.056 (4)	0.031 (5)	0.299 (2)	0.179 (3)	0.001 (6)	0.001 (6)
Independent resampled							
Lemon included	**0.642 (1)**	0.114 (3)	0.165 (2)	0.094 (4)	0.030 (5)	0.005 (6)	0.000 (7)
Lemon omitted	**0.710 (1)**	0.077 (4)	0.134 (2)	0.091 (3)	0.050 (5)	0.001 (6)	0.003 (7)
Dependent resampled							
Lemon included	**0.440 (1)**	0.189 (2)	0.171 (3)	0.137 (5)	0.109 (6)	0.155 (4)	0.095 (7)
Lemon omitted	**0.433 (1)**	0.180 (2)	0.174 (3)	0.129 (5)	0.102 (6)	0.161 (4)	0.098 (7)

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133 Relative importance scores for each of the seven variables in Evaristo and McDonnell's
134 forest removal model[1] are shown for three different profiling methods, and including
135 and excluding the Lemon catchment (see text). Ranks are shown in parentheses. The
136 most important variable in each case is highlighted in bold.

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139 **Exaggerated global streamflow implications.** To estimate the potential impact of forest clearing on
140 global streamflow (Table 1 of ref. 1), Evaristo and McDonnell first applied their boosted tree model
141 to a database of 442,319 catchments for which the required seven input variables are available
142 (whether or not they are actually forested). Evaristo and McDonnell then multiplied the median of
143 the modeled percentage change in streamflow for each continent's catchments, times the average
144 continental river flow (see Table 3). Because less than 30% of Earth's land area is forested[7],
145 however, the potential percentage increase in streamflow from forest clearing should not be applied
146 to the entire continental runoff; one cannot clear forests from the 70% of Earth's land surface where
147 no forests exist. Evaristo and McDonnell's calculation[1] implicitly assumes that Earth's entire
148 landmass is forested, and leads to unrealistic results. For example, under Evaristo and McDonnell's
149 median scenario[1], their Table 1 implies that total post-clearing runoff in Asia would be 95% of total
150 Asian precipitation[8] (32,140 km^3 yr^{-1}), a runoff ratio that is rarely observed even in urban areas
151 (Table 3). For Australia and Oceania, the results in Evaristo and McDonnell's[1] Table 1 violate
152 conservation of mass, with total post-clearing runoff (1,970+5,412=7,382 km^3 yr^{-1}) exceeding total
153 precipitation[8] (6,405 km^3 yr^{-1}).

154 Distributed over the roughly 40 million km^2 of the Earth's surface that is actually forested[7], Evaristo
155 and McDonnell's claimed global streamflow increase[1] of 34,098 km^3 yr^{-1} implies an average of 850
156 mm yr^{-1} more streamflow from cleared forest lands. This value exceeds the streamflow increases
157 that were measured in every one of the 95 paired watershed studies reviewed by Stednick[9], and
158 exceeds their average by a factor of five.

Table 3. Modeled effects of forest cover change on continental runoff.

Region	Total river runoff[1]	Change in runoff in response to forest-cover change[1] (km³ yr⁻¹)		Total river runoff after removal[2]	Total precipitation[3]	Change in runoff in response to forest-cover change (%)[4]		Median water yield in complete catchment data set (%)[5]	
	(km³ yr⁻¹)	Planting	Removal	(km³ yr⁻¹)	(km³ yr⁻¹)	Planting	Removal	Planting	Removal
Africa	4,320	-605(1,944)	8,986(5,616)	13,306	20,780	-14.0(45.0)	208.0(130.0)	-14(45)	208(130)
Asia	14,550	-1,979(5,835)	16,062(25,783)	30,612	32,140	-13.6(40.1)	110.4(177.2)	-14(40)	110(177)
Australia and Oceania	1,970	-412(725)	5,412(4,962)	7,382	6,405	-20.9(36.8)	274.7(251.9)	-21(36)	275(252)
Europe	3,240	-875(1,102)	813(1,426)	4,053	7,165	-27.0(34.0)	25.1(44.0)	-27(34)	25(44)
North and Central America	6,200	-806(2,034)	918(2,102)	7,118	13,910	-13.0(32.8)	14.8(33.9)	-13(33)	15(34)
South America	10,420	0(3,751)	1,908(17,559)	12,328	28,355	0.0(36.0)	18.3(168.5)	0(36)	18(168)
Totals	40,700	-4,676	34,098	74,799	109,755				

Values with parentheses are medians (and interquartile ranges). [1]From Table 1 of ref. 1.
[2]Sum of total river runoff and median change due to removal. [3]Total precipitation from
ref. 8, which is also the original source of the total river runoff values. [4]Median and IQR
of runoff changes, as percentage of total river runoff. [5]Median and IQR of water yield
predictions (each rounded to the nearest percent in the published database) for Evaristo
and McDonnell's 442,319 "complete" catchments. These agree within roundoff error
with the percentages calculated by dividing the change in runoff by the total runoff for
each continent. This agreement demonstrates that the changes in runoff shown in Table
1 of ref. 1 were calculated by multiplying the median (and IQR) of the percentage water
yield predictions by the total river runoff, rather than the runoff from forested areas.

Back-of-the-envelope calculations suggest different conclusions. Globally, evapotranspiration from
forests is roughly 250 mm yr⁻¹ greater than from croplands or grasslands[10], and multiplying this
difference by the 40 million km² of global forests[7] yields a rough estimate of 10,000 km³ yr⁻¹, less
than one-third of Evaristo and McDonnell's[1] result. Even this may be an overestimate, because the
lower evapotranspiration rates of grasslands partly reflect the fact that they often occur in drier
climates; thus the difference between forest and grassland evapotranspiration may exaggerate the
effects of converting forests to grasslands.

Concluding remarks. Evaristo and McDonnell are valued colleagues of ours, and we greatly
appreciate their transparency in making their data and codes available, without which the issues
described here would have been much harder to diagnose. We agree with them that streamflow
response to forest management is an important issue that deserves a comprehensive analysis,
including subsurface catchment characteristics as potential explanatory variables.

Readers should also keep in mind that this is not a purely academic exercise. How much, and under
what conditions, forests should be cleared is an important policy question with wide-ranging
consequences for economies, societies, and ecosystems. In that regard, we are concerned that the
conclusion that "forest removal can lead to increases in streamflow that are around 3.4 times
greater than the mean annual runoff of the Amazon River"[1] is overstated and could be
misinterpreted. The Amazon flows continuously, but the streamflow benefits of forest clearing are
transient, typically lasting only a few years, or at most decades, after felling[11]. One must also keep in
mind that the water transpired by vegetation is an important source of precipitation farther

192 downwind, estimated to account for roughly 40% of continental precipitation[10]. Thus, sustained
193 large-scale clearing of forests would predictably lead to precipitation decreases and drying of
194 continental interiors, although the precise magnitude of this effect remains difficult to constrain.

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196 **Data availability statement.** All of the data analyzed here are available as described in the data
197 availability and code availability statements of ref. 1, or from the cited references.

198 **Author contributions statement.** All authors discussed the issues raised here, and contributed to
199 the writing. J.W.K. analyzed the data and led the writing effort.

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203 **References**

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205 1.   Evaristo, J. & McDonnell, J. J. Global analysis of streamflow response to forest management.
206   *Nature* **570**, 455-461 (2019).
207 2.   Stoof, C. R. et al. Hydrological response of a small catchment burned by experimental fire.
208   *Hydrology and Earth System Sciences* **16**, 267-285 (2012).
209 3.   Ruprecht, J. K. & Schofield, N. J. Effects of partial deforestation on hydrology and salinity in
210   high salt storage landscapes. I. Extensive block clearing. *Journal of Hydrology* **129**, 19-38
211   (1991).
212 4.   Lawrence, P. A. & Thorburn, P. J. (eds.) *Changes in hydrology, soil fertility, and productivity of*
213   *brigalow catchments following clearing* (Project Report RQR89002, Department of Primary
214   Industries, Brisbane, 1989).
215 5.   Thornton, C. M., Cowie, B. A., Freebairn, D. M. & Playford, C. L. The Brigalow catchment
216   study: II. Clearing brigalow (Acacia harpophylla) for cropping or pasture increases runoff.
217   *Australian Journal of Soil Research* **45**, 496-511 (2007).
218 6.   SAS Institute Inc. *JMP 14 Profilers* (SAS Institute Inc., Cary, NC, 2018).
219 7.   FAO. *Global Forest Resource Assessment 2015* (Food and Agriculture Organization of the
220   United Nations, Rome, 2016).
221 8.   L'vovich, M. I. & White, G. F. in *The Earth as Transformed by Human Action* (eds. Turner, B. L.
222   et al.) 235-252 (Cambridge University Press, Cambridge, 1990).
223 9.   Stednick, J. D. Monitoring the effects of timber harvest on annual water yield. *Journal of*
224   *Hydrology* **176**, 79-95 (1996).
225 10.   Ellison, D., Futter, M. N. & Bishop, K. On the forest cover-water yield debate: from demand-
226   to supply-side thinking. *Global Change Biology* **18**, 806-820 (2012).
227 11.   Andreassian, V. Waters and forests: from historical controversy to scientific debate. *Journal*
228   *of Hydrology* **291**, 1-27 (2004).