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Global prevalence of non-perennial rivers and streams

Main text

Mathis Loïc Messenger^{1,2}, Bernhard Lehner¹, Charlotte Cockburn^{1,3}, Nicolas Lamouroux²,
Hervé Pella², Ton Snelder⁴, Klement Tockner⁵, Tim Trautmann⁶, Caitlin Watt^{1,7}, Thibault
Datry²

¹ Department of Geography, McGill University, 805 Sherbrooke Street West, Montreal, Quebec H3A
0B9, Canada

² RiverLY Research Unit, National Institute for Agricultural and Environmental Research (INRAE), 5
rue de la Doua, CS 20244, 69625 Villeurbanne Cedex, France

³ Current affiliation: Department of Earth Science, Dartmouth College, Hanover, NH 03755, United
States

⁴ Unit 13, 212 Antigua Street, Christchurch 8023, New Zealand

⁵ Senckenberg Society for Nature Research and Faculty of Biological Sciences, Goethe University
Frankfurt, Frankfurt am Main, Germany

⁶ Institute of Physical Geography, Goethe University Frankfurt, Frankfurt am Main, Germany

⁷ Current affiliation: Lethbridge Research and Development Centre, Agriculture and Agri-Food
Canada, 5403 1st Avenue South, Lethbridge, Alberta T1J 4B1, Canada

Corresponding authors: Mathis Loïc Messenger (mathis.messenger@mail.mcgill.ca), Bernhard Lehner
(bernhard.lehner@mcgill.ca), Thibault Datry (thibault.datry@inrae.fr)

24 **Summary**

25 Flowing waters play a unique role in supporting global biodiversity, biogeochemical cycles,
26 and human societies¹⁻⁵. While the importance of permanent watercourses is well recognized,
27 the prevalence, value and fate of non-perennial rivers and streams that periodically cease to
28 flow tend to be overlooked, if not ignored⁶⁻⁸. This oversight contributes to the degradation of
29 the main source of water and livelihood for millions of people⁵. Here we predict that water
30 ceases to flow for at least one day per year along 51-60% of the world's rivers by length,
31 demonstrating that non-perennial rivers and streams are the rule rather than the exception on
32 Earth. Leveraging global information on the hydrology, climate, geology, and surrounding
33 land cover of the Earth's river network, we show that non-perennial rivers occur within all
34 climates and biomes, and on every continent. Our findings challenge the assumptions
35 underpinning foundational river concepts across scientific disciplines⁹. To understand and
36 adequately manage the world's flowing waters, their biodiversity and functional integrity, a
37 paradigm shift is needed towards a new conceptual model of rivers that includes flow
38 intermittence. By mapping the distribution of non-perennial rivers and streams, we provide a
39 stepping-stone towards addressing this grand challenge in freshwater science.

40

41 **Main**

42 Virtually every river network on Earth includes channels that periodically cease to flow.
43 From Himalayan snow-fed creeks to occasionally water-filled Saharan wadis, river flow
44 cessation is naturally prevalent worldwide. Yet the global extent of intermittent rivers and
45 ephemeral streams (IRES) is largely unknown. IRES vary widely in size and flow duration,
46 encompassing all non-perennial watercourses — from large, rarely intermittent rivers with
47 nearly continuous channel flow to mostly dry streams that only flow after intense rainfall (see
48 **Extended Data Table 1** for additional definitions and IRES terminology). IRES are pivotal
49 components of the landscape, significantly contributing to the biodiversity^{1,2}, biogeochemical
50 processes and functional integrity of fluvial systems^{3,4}. Many formerly perennial rivers and
51 streams have become intermittent in the past 50 years due to water abstractions, climate
52 change, and land use transitions, including sections of iconic rivers such as the Nile, Indus,
53 Yellow, and Colorado^{10,11}. Given continued global change, an increasingly large proportion
54 of the global river network is expected to seasonally cease to flow over the coming
55 decades^{12,13}.

56 Despite their prevalence, IRES are frequently mismanaged due to a lack of recognition⁶,
57 or altogether excluded from management actions and conservation laws⁷. As a result, non-
58 perennial rivers and streams are being degraded at an alarming rate⁶. Recent attempts to
59 further remove IRES from environmental legislation and national water governance systems
60 (e.g., in the United States⁸), if implemented, would worsen their already inadequate
61 protection. The long-standing neglect of IRES is partly the result of their continued omission
62 from scientific research. Most freshwater science has focused on the functioning and
63 conservation of perennial water bodies; and only recently has riverine flow cessation become
64 a substantial subject of study^{1,9,10}. Consequently, science-based methods for managing these
65 unique ecosystems, such as biomonitoring tools and protocols, are still limited or absent^{5,14}.

66 Management frameworks also need to be adapted to conserve environmental flows in IRES¹⁵
67 — i.e., the quantity, timing, and quality of freshwater flows necessary to sustain aquatic
68 ecosystems and their associated benefits¹⁶. But perhaps the most important gap until now was
69 our inability to quantify and map IRES worldwide. Accurate mapping of non-perennial rivers
70 and streams would provide crucial baseline information to determine and monitor their role in
71 biogeochemical and water cycles and in supporting global biological diversity³.

72 Streamflow monitoring data for IRES are scant, spatially biased, and of uneven quality¹⁷.
73 Indeed, most streamflow gauging stations are installed on large, perennial rivers worldwide¹⁷.
74 The dearth of primary data has triggered the development of alternative methods to map
75 IRES, including citizen science or expert field observations of streamflow state, *in-situ* sensor
76 networks, and remote sensing^{18–20}. However, these efforts only provide information at local
77 scales and suffer from several limitations (e.g., remote sensing of smaller rivers can be
78 obstructed by overhanging riparian vegetation and cloud cover²⁰). Model-based
79 classifications of river types, either IRES-focused (e.g., in mainland France²¹, the north-
80 western U.S.²², eastern Australia²³) or general (e.g., Australia²⁴, California²⁵), have also
81 provided important baseline estimates of the spatial distribution of IRES from the catchment
82 to the national scale. However, a rigorous estimation of the global prevalence and distribution
83 of IRES is still lacking.

84 In this study, we developed a statistical Random Forest (RF) model (see *Methods* for
85 details) to produce the first reach-scale estimate of the distribution of IRES for the 23.3
86 million kilometres of mapped rivers and streams across the globe whose long-term average
87 naturalised discharge exceeds $0.1 \text{ m}^3 \text{ s}^{-1}$, and then extrapolated our IRES estimates to the
88 nearly 64 million km of rivers and streams with an average discharge higher than $0.01 \text{ m}^3 \text{ s}^{-1}$.
89 For this purpose, we linked quality-checked observed streamflow data from 5,615 gauging
90 stations (on 4,428 perennial and 1,187 non-perennial reaches) with 113 candidate

91 environmental predictors available globally (**Extended Data Table 2**). Predictors included
92 variables describing climate, physiography, land cover, soil, geology, and groundwater as
93 well as estimates of long-term naturalised (i.e., without anthropogenic water use in the form
94 of abstractions or impoundments) mean monthly and mean annual flow (MAF), derived from
95 a global hydrological model (WaterGAP 2.2²⁶). Following model training and validation, we
96 predicted the probability of flow intermittence for all river reaches in the RiverATLAS
97 database²⁷, a digital representation of the global river network at high spatial resolution.

98 **Prevalence and distribution of IRES**

99 We predict that water ceases to flow for at least one day per year, on interannual
100 average, along 41% of the mapped global river network length, i.e., all rivers and streams
101 with $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$ (**Fig. 1, Table 1**). However, any estimate of the percentage of IRES
102 reaches in a river system, whether for a small catchment or for the globe, is inherently
103 dependent on cartographic scale. Although many dryland rivers exhibit downstream
104 decreases in discharge due to channel evaporation and transmission losses²⁸, river flow tends
105 to become more permanent with increasing drainage area and distance from the headwaters in
106 a basin²⁹, which is well reflected in the predictions of our model. Because of the dendritic
107 nature of river networks, small headwater streams, which are more prone to intermittence,
108 make up a greater proportion of the total stream length than larger downstream rivers³⁰.
109 Consequently, the percentage of the river network length that is non-perennial increases with
110 decreasing size of the smallest mapped stream. To account for this distribution, we made a
111 first-order approximation of the prevalence of intermittence in small streams by extrapolating
112 our estimate to streams with $0.01 \text{ m}^3 \text{ s}^{-1} \leq MAF < 0.1 \text{ m}^3 \text{ s}^{-1}$ (see *Methods* for details).
113 Including this size class, we estimate that 60% of all rivers and streams globally are IRES;
114 and we found a lower bound of this estimate at 51% after applying an alternative, more

115 conservative extrapolation approach. This demonstrates, for the very first time, that IRES
116 represent the world's most widespread type of rivers.

117 For river flow to occur, water from rainfall, snowmelt, or releases from existing
118 storage (e.g., lakes, reservoirs, groundwater) must exceed losses from infiltration and
119 evapotranspiration³¹. Climatic variables, in particular climate-induced aridity, were therefore
120 the leading predictors of river flow cessation and the occurrence of IRES (**Fig. 2**). Our model
121 indicates that where evaporation rates significantly exceed precipitation for at least part of the
122 year, as expressed by a low aridity index (ratio of mean annual precipitation to mean annual
123 potential evapotranspiration), river networks comprise large proportions of IRES. In
124 extremely hot and xeric environments, which cover nearly a tenth of the global landmass and
125 encompass most of India, northern Australia and the Sahel region of Africa (see **Extended**
126 **Data Fig. 1a** for the global typology of bioclimates³²), 95% of the river and stream network
127 length is prone to flow cessation ($MAF \geq 0.01 \text{ m}^3 \text{ s}^{-1}$; **Table 1**). In these environments, we
128 find that even the main stem of major rivers, such as the Niger or Godavari, can dry out.

129 Outside of arid regions, flow in river networks is primarily controlled by catchment
130 processes influenced by interacting climate and basin conditions^{1,29}. In cold climates, for
131 instance, a combination of scarce precipitation, its storage as snow during winter months, and
132 completely freezing streams³³ can lead to high prevalence of flow intermittence. In humid
133 and temperate regions, IRES are concentrated in the upper end of channel networks where
134 small drainage areas and steep slopes lead to rapid delivery of water to and through the river
135 channel, causing a lack of buffering from variations in precipitation³⁴. Therefore, even in the
136 wettest climates (e.g., extremely hot and moist; **Extended Data Fig. 1a**), up to 35% of
137 headwater streams are non-perennial (**Table 1**). In lowland and large basins, temporary
138 storage and subsequent attenuated release from groundwater, lakes, and wetlands, as well as

139 the averaging of local hydrologic variability across a larger drainage area lead to more
140 balanced, steady, and thus perennial flow²⁹.

141 Our study is the first empirically grounded effort to specifically quantify the
142 prevalence of flow intermittence of rivers and streams globally, and to show that IRES occur
143 across all climates and biomes, and on every continent (**Fig. 1, Table 1**). Previous
144 assessments reported from 29% to 36% of the global length of rivers to be non-
145 perennial^{28,36,37}, with inferred and extrapolated estimates exceeding 50%^{10,38}. However, these
146 estimates were either generalised hypotheses (e.g., based on the global distribution of
147 drylands²⁸), geographically constrained (i.e., south of 60°N³⁶⁻³⁸), or research by-products
148 within larger projects (e.g., using a regional extrapolation to remove IRES from estimates of
149 the global CO₂ emissions of inland waters³⁸), rather than dedicated global IRES
150 quantification efforts, and are therefore not directly comparable to our predictions. The FAO
151 AQUAMAPS³⁶ and GRIN³⁷ global river networks, for instance, assume that streamflow
152 cessation only occurs in arid and semi-arid areas. See Supplementary Information *Section I*
153 for a review of how previous estimates relate to our predictions, including a map of
154 AQUAMAPS and GRIN estimates.

155 Our study improves on these previous estimates because it represents diverse
156 hydrometeorological processes beyond aridity at the river reach scale (rather than at the basin
157 scale³⁸) by leveraging extensive, high-resolution global data on the hydrology, climate,
158 physiography, geology, and surrounding land cover of the world's river network.
159 Furthermore, no global estimate prior to this study has used global empirical streamflow data
160 for training and validation, which allowed our model to make fine-grained predictions of the
161 intermittence class of rivers across all climates.

162 **Model performance and uncertainties**

163 Performance analysis showed that our RF model could predict the binary flow
164 intermittence class of streamflow gauging stations with high confidence. Cross-validation
165 yielded an overall classification accuracy (the percentage of correctly classified gauges),
166 ranging from 90% to 92% (depending on cross-validation method), and indicated that model
167 predictions were unbiased globally — i.e., adequately reflecting the proportion of IRES
168 gauges in the training dataset. In general, sparsely gauged basins exhibit lower accuracy and
169 higher bias (**Fig. 3**; e.g., in Africa and the Arctic). Boundary areas between climate zones
170 (i.e., from mainly non-perennial regions to mainly perennial regions) are also characterized
171 by higher misclassification rates (**Extended Data Fig. 2**). See **Fig. 3** as well as **Extended**
172 **Data Table 3** for cross-validation results.

173 Our model is based on an inclusive definition of IRES as those rivers and streams that
174 cease to flow at least one day per year on average. To test the sensitivity of our results to the
175 specific threshold of cessation length, we adapted our model and found that 44-53% of the
176 global river network cease to flow at least one month per year (lower-bound and main
177 estimate, respectively, with $MAF \geq 0.01 \text{ m}^3 \text{ s}^{-1}$; see *Methods*; **Extended Data Fig. 1b-c**).

178 Comparisons with national hydrographic datasets that include information on flow
179 intermittence show that our model predicts a substantially higher prevalence of IRES in the
180 contiguous U.S. than mapped in the country's atlas (by 31 percentage points), but coincides
181 well with the patterns and extents depicted in the Australian, Argentinian, and Brazilian
182 atlases, and with model-generated maps³⁹ in mainland France (**Extended Data Figs. 3-5**).
183 The divergence observed in the U.S. (and to a limited extent in Australia) largely stems from
184 the thresholds used to define IRES — when applying a minimum of one zero-flow month per
185 year, our predictions more closely concur with the comparison dataset (**Extended Data Figs.**
186 **3 and 5**).

187 At an even more local scale, comparing our model predictions against datasets of
188 ground observation points of flow cessation for the U.S. Pacific Northwest and mainland
189 France reveals particular challenges in predicting flow intermittence for small rivers and
190 streams (median MAF $\approx 0.5 \text{ m}^3 \text{ s}^{-1}$, **Extended Data Fig. 6**). Our model only achieved a
191 balanced accuracy of 0.59 for mainland France ($n = 2,297$) and of 0.47 for the U.S. Pacific
192 Northwest ($n = 3,725$), both under- and overestimating reported IRES, respectively. We
193 hypothesize that heavy water abstractions for domestic and agricultural use are the main
194 reason for the greater contemporary prevalence of intermittence observed in France⁴⁰ (from
195 2012 to 2019) than predicted by our model, which aims to depict the natural distribution of
196 IRES. In the U.S. Pacific Northwest, a lower frequency of observations per site may have led
197 to an underestimation of the prevalence of IRES in the comparison dataset, since the
198 probability of observing a no-flow event increases with the number of observations. In
199 addition, the mountainous landscape of the region is characterized by complex, local
200 hydrological processes associated with snow and groundwater dynamics that our model can
201 only superficially represent²².

202 Despite the increasing uncertainties at national and local scales, the global validation
203 findings demonstrate that our overall statistics and large-scale representation of the spatial
204 distribution of IRES are robust. However, we advise caution in using our model outputs to
205 interpret fine-scale variations in intermittence for small spatial units or for small rivers and
206 streams. The quality of our model results is constrained by the resolution of the river network
207 and associated hydro-environmental predictor variables (250-1,000 m grid cells for most
208 predictors²⁷). Accurate, fine-scale data on catchment soil types and lithology (e.g., karst
209 areas), riverbed sediments, and groundwater dynamics would be needed to capture variation
210 in the processes influencing flow intermittence at the sub-catchment and reach scales²⁹.
211 Groundwater–surface water interaction in particular is an enduring challenge in global

212 hydrological modelling⁴¹ and represents a key process that is only partly represented in our
213 analysis. Also, potential local biases in training data (e.g., IRES being inconsistently
214 represented in streamflow gauging networks) introduce uncertainties. For instance, model
215 predictions in the south-eastern U.S. may overestimate the prevalence of IRES due to the
216 relative scarcity of gauging stations for model training on small, perennial watercourses in
217 that region. Similarly, the general under- and misrepresentation of small watercourses and
218 arid regions in the global hydrometric network¹⁷ causes substantial difficulty in consistently
219 predicting the prevalence of IRES across the gamut of river types worldwide. Global
220 hydrological models are known to overestimate flow in arid climates²⁸, further complicating
221 IRES mapping in these regions.

222 Finally, our model's ability to predict the natural prevalence of flow intermittence is
223 affected by the impact of human activities on most gauged basins. Our study aims to depict
224 the natural distribution of non-perennial watercourses by excluding those gauging stations
225 from model training that were affected by flow regulation and/or whose flow intermittence
226 class changed over the discharge record (see *Methods*). We also used naturalised estimates of
227 discharge as predictor variables, which exclude anthropogenic water use in the form of
228 abstractions or flow regulation. Nevertheless, disentangling the potential effects of
229 contemporary land use, impoundments and human water abstractions on flow intermittence
230 remains a research frontier⁴². We expect that continued improvements in global hydro-
231 environmental datasets and hydrological models, combined with greater access to national
232 hydrometric datasets, will be key to improve future IRES mapping efforts.

233 **Understanding and managing IRES dynamics**

234 Our global map of IRES may become a crucial tool for understanding and managing these
235 long-undervalued ecosystems. High-resolution predictions of flow intermittence for all river
236 reaches with $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$ can support spatially explicit studies down to the national

237 scale, while our first-order extrapolation of the total prevalence of non-perennial rivers and
238 streams by region and river basin can offer additional insights into the role of IRES at
239 continental and global scales. Our results also provide an important baseline for the
240 assessment of future changes in flow intermittence in river networks. Quantifying the
241 variability of flow cessation in space and time is required to better understand the impact of
242 climate change, water abstraction and flow regulation; IRES are not only becoming
243 increasingly common but the flow regime of existing IRES can shift e.g., from intermittent to
244 ephemeral, whereas others will turn perennial⁴³.

245 In this study we identified *whether* and *where* rivers and streams cease to flow, but further
246 quantification of the spatiotemporal dynamics of flow occurrence across stream networks
247 worldwide is required to determine *when* and for *how long*. Knowledge of the natural
248 frequency, duration, and timing of flow cessation, the primary determinants of the
249 functioning of IRES^{2,3}, forms the basis of flow alteration analyses that can inform strategies
250 to mitigate the impacts of future changes¹⁵. In particular, tools for assessing environmental
251 flows globally are needed to appraise freshwater planetary boundaries⁴⁴ and to define
252 quantitative targets for the 2030 UN Sustainable Development Goals⁴⁵. Yet current tools
253 exclude arid and semi-arid regions⁴⁶, which are dominated by IRES and where alternative
254 sources of water are scarce⁵.

255 **Rethinking the significance of IRES**

256 Our findings call for a paradigm shift in river science and management. The
257 foundational concepts of river hydrology, ecology, and biogeochemistry have been developed
258 from and for perennial waterways, and as a result, have all traditionally assumed year-round
259 surface channel flow⁹. Here we show that this assumption is invalid for most rivers on Earth,
260 which bolsters previous appeals for bringing together aquatic and terrestrial disciplines into
261 river science^{5,10}.

262 Multiple conceptual models rely on the assumption that river discharge increases
263 monotonically downstream from the headwaters to the mouth — e.g., the River Continuum
264 Concept⁴⁷, a theoretical pillar of river ecology. Moreover, current models define hydrological
265 connectivity within river networks in binary terms, as either free-flowing or perpetually
266 fragmented by barriers such as waterfalls and dams⁴⁸, but we show that *temporary*
267 fragmentation by seasonal drying⁴⁹ is a widespread phenomenon on Earth. In hydrology, the
268 parameterization and calibration of predictive models of runoff and discharge are usually
269 based on average or peak flows (e.g., for flood forecasting) rather than being calibrated to
270 simulate low-flow quantities and timing, including flow cessation events, thus failing to
271 reliably predict intermittence²⁰. Up to date, global estimates of biodiversity have also
272 overlooked IRES, which provide unique habitats for aquatic and terrestrial species^{5,10}.
273 Finally, recent research shows that omitting the role of non-perennial inland waters in carbon
274 models may result in underestimating CO₂ emissions from inland waters by ~10%⁴; similar
275 biases might undermine other global biogeochemical estimates, notably with respect to
276 nitrogen cycling.

277 IRES have always been integral to human societies, whether culturally or as a source
278 of food and water⁵. We estimate that for 52% of the world's population in 2020, the nearest
279 river or stream is non-perennial (see *Methods*). The relationship between the seasonal
280 hydrology of IRES and the ecosystems services they provide to society is a pressing area of
281 research, particularly in regions where climate change is disrupting the water pulses to which
282 people's livelihoods are tuned⁵⁰. In many languages, multiple words exist to designate IRES
283 and their mark on the landscape, highlighting the long history of inter-dependence between
284 humans and seasonal freshwater systems⁵. However, the spiritual and cultural values that
285 IRES provide, often to indigenous people (e.g., in Australia or in sub-Saharan Africa), remain
286 to be acknowledged⁵.

287 The past decade has witnessed several efforts to highlight both the values and ongoing
288 degradation of IRES^{6,8}, yet current tools and policies still fall short of ensuring their
289 biomonitoring and conservation^{14,15}. A recognition of the prevalence and ecological
290 significance of IRES by the scientific community may trigger efforts to adequately manage
291 them and halt current attempts to exclude them from protective legislation⁸. As a stepping-
292 stone, our new dataset intends to provide a baseline for identifying gaps in hydrological and
293 biological monitoring efforts, to inform global biogeochemical upscaling and riverine species
294 distribution models, and to decipher the links between hydrological patterns and culture-
295 language. It can assist in discerning the role of IRES in the Earth system to safeguard the
296 integrity of river networks and the well-being of those who directly rely on these ecosystems
297 for their livelihood and culture.
298

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410 **Tables**

411 **Table 1. Global prevalence of IRES across climate zones and streamflow size classes.**

412

Climate zone ¹	Prevalence of intermittence (% of network length) by streamflow size class (m ³ s ⁻¹)							Total intermittence % length	Total stream length ² 10 ³ km
	extrapolated ³			mapped					
	[10 ⁻² ,10 ⁻¹)	[10 ⁻¹ ,1)	[1,10)	[10,10 ²)	[10 ² ,10 ³)	[10 ³ ,10 ⁴)	≥ 10 ⁴		
Extremely hot and arid	100	100	100	98	49	0	-	99 (98)	1032 (249)
Hot and arid	100	100	100	97	46	0	-	99 (98)	990 (238)
Arctic 1	100	92	71	100	-	-	-	96 (92)	11 (6)
Warm temperate and xeric	99	96	89	59	11	0	0	96 (89)	1351 (444)
Extremely cold and wet 2	100	93	69	34	0	-	-	96 (87)	766 (243)
Extremely hot and xeric	99	90	95	90	45	0	0	95 (89)	4551 (1,605)
Arctic 2	100	89	18	8	-	-	-	92 (82)	98 (41)
Cool temperate and xeric	94	81	70	37	2	0	-	87 (72)	1709 (552)
Extremely cold and mesic	96	70	45	34	26	22	0	83 (61)	8083 (3,051)
Extremely cold and wet 1	92	59	10	1	0	-	-	72 (50)	227 (109)
Cold and mesic	90	47	26	6	3	0	0	70 (37)	8189 (3,084)
Warm temperate and mesic	84	45	35	16	1	0	0	63 (39)	3582 (1,646)
Hot and dry	77	47	36	23	7	0	0	62 (41)	4054 (1,683)
Cool temperate and dry	65	46	34	11	0	0	0	57 (39)	4087 (1,325)
Hot and mesic	77	30	24	23	5	0	0	54 (27)	4452 (2,023)
Extremely hot and moist	35	18	20	21	4	0	0	30 (18)	19117 (6,002)
Cool temperate and moist	52	18	10	0	0	0	-	29 (13)	1164 (691)
Cold and wet	34	1	0	0	0	0	-	14 (1)	493 (299)
World	70	47	35	26	9	1	0	60 (41)	63,956 (23,291)

413

414 ¹ Global Environmental Stratification (GENS)³², see **Extended Data Fig. 1a**.

² Excluding sections of river reaches contained within a lake.

³ Extrapolated statistics based on the main estimate (as opposed to the lower-bound estimate, see *Methods* for details).

415 **Figure legends**

416 **Figure 1. Global distribution of non-perennial rivers and streams. [Alternative title:** 417 **Non-perennial rivers and streams occur in all climates, biomes, and continents.]**

419 Intermittence is defined as flow cessation for at least one day per year on average. The median probability
420 threshold of 0.5 was used to determine the binary flow intermittence class for each reach in RiverATLAS²⁷.

421 Mapping software: ArcMapTM (ESRI).

422 **Figure 2. Climate-induced aridity and hydrologic variables are the main predictors of** 423 **global flow intermittence.**

426 The two sets of ranked predictor variables represent results from a split random forest model trained on **a**,
427 gauges with a mean annual naturalised flow $< 10 \text{ m}^3 \text{ s}^{-1}$ and **b**, gauges with a mean annual naturalised flow ≥ 1
428 $\text{m}^3 \text{ s}^{-1}$. See *Methods – Machine learning models* for details on model structure and implementation. Rectangular
429 bars show the balanced accuracy-weighted average of Actual Impurity Reduction³⁵ (AIR) across non-spatial
430 cross-validation folds and repetitions. The longer the bar (i.e., the higher the AIR), the more important the
431 variable in predicting flow intermittence. Error brackets show \pm one weighted standard deviation of AIR. After
432 the variables' names, the first abbreviation denotes each variable's spatial extent: *p* (derived at the pour point of
433 the river reach), *c* (derived within the local catchment that drains directly into the reach), or *u* (derived within
434 the total drainage area upstream of the reach pour point). The second abbreviation denotes each variable's
435 dimension: yr (annual average), mn (annual minimum), mx (annual maximum), or mj (spatial majority). See
436 *Methods* and **Extended Data Table 2** for data sources of variables.

437 **Figure 3. Flow intermittence classification accuracy decreases and prediction bias** 438 **increases in river basins with fewer streamflow gauging stations.**

440 Maps of **a**, classification accuracy, **b**, prediction bias, and **c**, number of streamflow gauging stations per river
441 basin based on 40-fold spatial cross-validation. See Supplementary Information **Fig. S3** for the distribution of
442 cross-validation folds. River basins correspond to BasinATLAS²⁷ level 3 subdivisions with an average surface
443 area of $4.6 \times 10^5 \text{ km}^2$. Mapping software: ArcMapTM (ESRI).

445 **Methods**

446 See **Extended Data Fig. 7** for a summary of the data and methods used in this study.

447 **Data**

448 *Global underpinning hydrography*

449 We predicted the distribution of IRES for river reaches in the global RiverATLAS
450 database²⁷. RiverATLAS is a widely-used representation of the global river network built on
451 the hydrographic database HydroSHEDS^{51,52}. Rivers are delineated based on drainage
452 direction and flow accumulation maps derived from elevation data at a pixel resolution of 3
453 arc-seconds (~90 m at the equator) and subsequently upscaled to 15 arc-seconds (~500 m at
454 the equator). In this study, we only included river reaches with a modelled MAF $\geq 0.1 \text{ m}^3 \text{ s}^{-1}$
455 and excluded i) smaller streams (due to increasing uncertainties in their geospatial location
456 and flow estimates derived from global datasets and models; see also *Hydro-environmental*
457 *predictor variables* below); and ii) sections of river reaches within lakes (identified based on
458 HydroLAKES polygons⁵³). We define a ‘river reach’ as a cartographic — rather than a
459 functional — unit, represented by the smallest spatial element of our global river network,
460 that is, a line segment between two neighbouring confluences. We made predictions for
461 6,198,485 individual river reaches with an average length of 3.8 km, totalling 23.3 million
462 kilometres of river network.

463 *Reference intermittence data for model training and cross-validation*

464 Two streamflow gauging station repositories were used as the source of training and
465 cross-validation data for the split Random Forest (RF) model (**Extended Data Fig. 7b-8**) —
466 the World Meteorological Organization Global Runoff Data Centre (GRDC)⁵⁴ database ($n \approx$
467 10,000) and a complementary subset of the Global Streamflow Indices and Metadata archive
468 (GSIM, $n \approx 31,000$), a compilation of twelve free-to-access national and international
469 streamflow gauging station databases⁵⁵. Whereas the GRDC offers daily river discharge

470 values for most stations, GSIM only contains time series summary indices computed at the
471 yearly, seasonal and monthly resolution (calculated from daily records whose open-access
472 release is restricted for some of the compiled data sources)⁵⁶. Therefore, we used the GRDC
473 database as the core of our training/testing set and complemented it with a subset of
474 streamflow gauging stations from GSIM. A GSIM station was included only if i) it was not
475 already part of the GRDC database, ii) it included auxiliary information on the drainage area
476 of the monitored reach (for reliably associating it to RiverATLAS), iii) it had a drainage area
477 $< 100 \text{ km}^2$ or else (i.e., for gauges with drainage area $\geq 100 \text{ km}^2$) it was located either iv) on
478 an IRES or v) in a river basin which did not already contain a GRDC station (assessed based
479 on level 5 sub-basins of the global BasinATLAS database⁵¹, average sub-basin area = $2.9 \times$
480 10^4 km^2). We applied the described GSIM selection criteria to balance the relative amount of
481 non-perennial vs. perennial records, and the spatial distribution of stations in the model
482 training dataset.

483 Each station in the combined dataset was geographically associated with a reach in the
484 RiverATLAS stream network and every discharge time series was quality-checked through
485 statistical and manual outlier detection (see Supplementary Information *Section II - Selection*
486 *and pre-processing of gauging station and discharge data* for details on these procedures).
487 Non-perennial gauging stations were only included in the dataset if they were free of
488 anomalous zero-flow values (e.g., from instrument malfunction, gauge freezing, tidal flow
489 reversal¹⁷). We also excluded stations whose streamflow was potentially dominated by
490 reservoir outflow regulation (i.e., with a degree of regulation $> 50\%$ ^{27,57}) or whose discharge
491 time series exhibited an alteration (see online research compendium at
492 <https://messamat.github.io/globalIRmap/> for an interactive visualization of processing
493 information for every gauging station) as flow regulating structures may change the flow
494 class of a river either from perennial to non-perennial or vice-versa depending on their mode

495 and rules of operation^{58,59}. We further narrowed our selection by adding only gauging stations
496 with a streamflow time series spanning at least 10 years — excluding years with more than
497 20 days of missing records for the calculation of this criterion and in subsequent analysis.
498 Finally, we classified stations as non-perennial if their recorded discharge dropped to zero at
499 least one day per year on average over the years of record, and as perennial otherwise.
500 Stations with at least one zero-flow day per year on average (i.e., non-perennial) but without
501 a zero-flow day during 20 consecutive valid years of data (those with ≤ 20 missing days),
502 anywhere in their record, were deemed either to have experienced a shift in flow
503 intermittence class (regardless of the direction of the shift) or to have ceased to flow due to
504 exceptional conditions of drought and were also excluded. Based on these selection criteria,
505 the training dataset contained data for 4,428 perennial river reaches and for 1,187 non-
506 perennial reaches, with 41 and 34 years of daily streamflow data on average, respectively,
507 across all continents (except Antarctica) (**Extended Data Fig. 8**).

508 The threshold used to define flow intermittence varies among studies, ranging from a
509 single zero-flow day across the entire streamflow record^{21,60} to at least five days per year on
510 average⁶¹. Because zero-flow values in streamflow gauging records may be erroneous¹⁷, other
511 studies have used a flow percentile threshold value (e.g., $Q_{99} < 0.0283 \text{ m}^3 \text{ s}^{-1}$ in the U.S.
512 Pacific Northwest²²). To test the sensitivity of altering our criterion (one zero-flow day per
513 year on average) on the resulting number of non-perennial stations, we changed the threshold
514 to one zero-flow month (30 consecutive or non-consecutive days) per year, which yielded a
515 dataset with 4,735 perennial stations and 880 non-perennial stations, respectively. Given the
516 substantial difference between these thresholds, we also produced model estimates for the
517 latter definition (**Extended Data Fig. 1b-c**).

518 Although our training dataset of gauging stations encompasses a wide range of river types
519 found on Earth, it is inherently limited by the global availability of hydrometric data

520 **(Extended Data Fig. 8)**. Most notably, rivers with $\text{MAF} > 500 \text{ m}^3 \text{ s}^{-1}$ are over-represented
521 whereas those with $\text{MAF} < 50 \text{ m}^3 \text{ s}^{-1}$ are under-represented. In addition, few stations monitor
522 rivers in extreme climates, whether cold or hot, dry or wet (e.g., classes 1-4 and 16-18 for
523 extremely cold and extremely hot climates, respectively; **Extended Data Fig. 1a** shows the
524 extent of each climate stratum³²). Other significantly under-represented river types include
525 those with annual average snow cover extent $> 75\%$ in their upstream drainage area and
526 rivers with a shallow groundwater table or with $> 90\%$ of karst outcrops across their upstream
527 drainage area.

528 *Hydro-environmental predictor variables*

529 The primary source of predictor variables was the global RiverATLAS database,
530 version 1.0, which is a subset of the broader HydroATLAS product²⁷. RiverATLAS provides
531 hydro-environmental information for all rivers of the world, both within their contributing
532 local reach catchment and across the entire upstream drainage area of every reach (**Extended**
533 **Data Table 2**). This information was derived by aggregating and reformatting original data
534 from well-established global digital maps, and by accumulating them along the drainage
535 network from headwaters to ocean outlets²⁷.

536 RiverATLAS also includes estimates of long-term (1971-2000) naturalised (i.e.,
537 without anthropogenic water use in the form of abstractions or impoundments) mean monthly
538 and mean annual flow (MAF). These discharge estimates are derived through a geospatial
539 downscaling procedure⁵¹ based on the 0.5 degree resolution runoff and discharge layers
540 provided by the global WaterGAP model (version 2.2 as of 2014²⁶). A validation of the
541 downscaled discharge estimates against observations at the 2,131 GRDC gauging stations
542 used in this study with ≥ 20 years of streamflow data from 1971 to 2000, representing rivers
543 with MAF between 0.006 and $180,000 \text{ m}^3 \text{ s}^{-1}$, confirmed good overall correlations for MAF
544 (log-log least-square regression, $R^2 = 0.96$, with a symmetric mean absolute percentage error

545 sMAPE of 30%; see Supplementary Information **Table S1** for all validation results). The
546 sMAPE increased from 5% for rivers with $MAF \geq 1000 \text{ m}^3 \text{ s}^{-1}$ to 20% for $10 \text{ m}^3 \text{ s}^{-1} \leq MAF$
547 $< 1000 \text{ m}^3 \text{ s}^{-1}$, and to 52% for $MAF < 10 \text{ m}^3 \text{ s}^{-1}$. Minimum monthly discharge was also found
548 to be an effective proxy for Q90 ($R^2=0.84$).

549 We complemented the RiverATLAS v1.0 data with three additional sets of variables.
550 The first set of variables describes the inter-annual open surface water dynamics as
551 determined by remote sensing imagery from 1999 to 2019⁶². In the original dataset, each 30-
552 meter resolution pixel which has been covered by water sometime during this time period
553 was assigned one of seven “interannual dynamic classes” (e.g., permanent water, stable
554 seasonal, high frequency changes) based on a time series analysis of the annual percent of
555 open water in the pixel. We computed the percent coverage of each of these interannual
556 dynamic classes relative to the total area of surface water within the contributing local
557 catchment and across the entire upstream drainage area of every river reach.

558 Second, we replaced the soil and climate characteristics in RiverATLAS v1.0 with
559 updated datasets. Specifically, we computed the average texture of the top 100 cm of soil
560 based on SoilGrids250m version 2⁶³. We also updated the climate variables with WorldClim
561 version 2⁶⁴ (adding all bioclimatic variables to the existing set of variables) as well as the
562 Global Aridity Index and Global Reference Evapotranspiration (Global-PET) datasets version
563 2⁶⁵. Finally, we updated the Climate Moisture Index (CMI), computed from the annual
564 precipitation and potential evapotranspiration datasets provided by the WorldClim v2 and
565 Global-PET v2 databases, respectively.

566 We derived a third set of variables by combining multiple variables already included
567 in the model through algebraic operations. These metrics included the runoff coefficient (i.e.,
568 ratio of MAF and mean annual precipitation), specific discharge (i.e., MAF per unit drainage
569 area), and various temporal (e.g., minimum annual/maximum annual discharge) and spatial

570 (e.g., mean elevation in local reach catchment/mean elevation in upstream drainage area)
571 ratios.

572 The application of all described procedures yielded a total of 113 candidate predictor
573 variables to be used in our statistical model development (**Extended Data Table 2**).

574 **Machine learning models**

575 We developed and used a split RF machine learning model to predict the flow
576 intermittence class, as a probability response, of all river reaches globally, with 1 denoting a
577 100% predicted probability of being an IRES. RF models have already been successfully
578 used to predict the distribution of IRES in Australia and France^{21,66} and they have been
579 shown to achieve high performance when compared to other approaches, including other
580 machine learning models, logistic regression, and single decision trees^{67,68}. Below, we briefly
581 describe the model development and validation procedure conducted for our split RF model;
582 see Supplementary Information *Section III - Random forest implementation* for additional
583 information.

584 Our final predictions are based on the probability RF algorithm developed by Malley
585 and colleagues⁶⁹, a derivative of the standard RF algorithm for making probabilistic
586 predictions of class membership, as included in the *ranger* R package⁷⁰. This algorithm was
587 selected following a comparison^{71,72} of several probability RF variants (namely, Conditional
588 Inference Forest^{73,74} and a newly developed regression RF algorithm using MAXimally
589 selected rank STATistics⁷⁵). To address known biases in RF models from class imbalance in
590 the training data (more perennial than non-perennial gauging stations on large rivers)^{22,76}, we
591 implemented random oversampling of non-perennial gauging stations⁷⁷.

592 For our split model approach, we trained and cross-validated two probability RF sub-
593 models with slightly overlapping ranges in river size, one trained to predict the streamflow
594 intermittence probability of small-to-medium rivers with $MAF < 10 \text{ m}^3 \text{ s}^{-1}$ and the other for

595 medium-to-large rivers with $MAF \geq 1 \text{ m}^3 \text{ s}^{-1}$. Within the overlapping range of 1-10 $\text{m}^3 \text{ s}^{-1}$
596 MAF , the average probability was calculated to avoid abrupt transitions at a singular size
597 threshold. This split approach performed better than a single model and was motivated by the
598 distinct class imbalance in training gauging stations between large rivers (4.87:1 perennial to
599 non-perennial ratio) versus small rivers (1.98:1 perennial to non-perennial ratio). With a
600 single model, the use of a common oversampling factor for both size classes underpredicted
601 the prevalence of IRES in large rivers (see **Extended Data Table 3**).

602 **Model development and diagnostics**

603 To optimize the predictive performance of the two sub-models, avoid overfitting, and
604 obtain unbiased estimates of statistical uncertainty, we implemented a nested resampling
605 framework for hyperparameter tuning and cross-validation⁷⁸, first for comparison across RF
606 algorithm variants, and then for comparing model performance with and without predictor
607 variable selection (see Supplementary Information *Section IV - Model development and*
608 *diagnostics: technical documentation* for a full description of the tuning and cross-validation
609 procedure^{79,80}). Tuning was performed for 2-3 hyperparameters (depending on the RF
610 algorithm) through random search with a termination criterion of 100 iterations. The inner
611 (hyperparameter tuning) loop was composed of a 4-fold cross-validation and the outer loop
612 (for predictive performance assessment) involved a twice-repeated 3-fold cross-validation.
613 Cross-validation strategies usually involve 2-10 folds⁷⁹, with a lower number of folds (as
614 chosen here) yielding a more stringent evaluation of performance (i.e., a relatively
615 pessimistic evaluation bias). The outer cross-validation procedure was repeated twice and the
616 results were averaged to reduce the variance caused by randomly splitting the data into few
617 folds⁷⁸. A spatial cross-validation procedure based on k -means spatial clustering ($k=40$, see
618 Supplementary Information **Fig. S3** for the distribution of clusters) was also used in the outer
619 resampling loop to avoid overoptimistic error estimates that arise in cases of significant

620 spatial autocorrelation⁸¹⁻⁸⁴. We chose to implement 40 spatial folds to strike a balance
621 between two extremes. Fewer folds would risk evaluating the predictive ability of the model
622 across areas so large that they may represent unique hydro-climatic conditions outside of the
623 model's training set (for a given fold), therefore underestimating the model's performance.
624 More folds would have inflated our estimate of model accuracy by relying on training sets
625 too similar to the testing sets and would have made the computational requirements of cross-
626 validation even greater.

627 All algorithms were compared using the same inner and outer sets of training and
628 testing partitions. Hyperparameters were tuned to optimize the Balanced class ACCuracy
629 (BACC) metric⁸⁵, which is equivalent to the raw accuracy (or one minus the misclassification
630 rate) but with each sample weighted according to the inverse prevalence of its true class
631 (large river model: 4.87 and 1.00 weights for the non-perennial and perennial classes,
632 respectively; small river model: 1.98 and 1.00 for the non-perennial and perennial classes,
633 respectively). To assess predictor variable importance, weighted averages of Actual Impurity
634 Reduction (AIR, an unbiased version of Gini impurity³⁵) and the associated p -values
635 (determined via 100 permutations, following ref⁸⁶) were computed for each outer resampling
636 cross-validation fold and repetition, using the BACC of each resampling instance as weight.

637 Prior to final model training and evaluation, only predictors with a variable importance p -
638 value < 0.05 were retained, so that 92 and 82 variables were retained in the final small-river
639 and large-river models, respectively. Variable selection was implemented to both increase
640 model performance^{87,88} and decrease model training time.

641 In addition to the BACC and the variable importance, several additional diagnostics were
642 examined to determine the performance and characteristics of the RF model as follows:

- 643 (i) We assessed the classification accuracy (percentage of correctly classified
644 gauges), the sensitivity (percentage of correctly classified IRES reaches, also

645 known as true positive rate or recall), specificity (percentage of correctly
646 classified perennial reaches, also known as true negative rate or selectivity), and
647 precision (percentage of reaches predicted to be IRES that are actually IRES) of
648 the model for each streamflow size class (**Extended Data Table 3**), based on
649 spatial and non-spatial cross-validations.

650 (ii) We examined the geographic, hydrological, and environmental distributions of the
651 intermittence prediction residuals (IPR) for each reference stream gauging station
652 (**Extended Data Fig. 2**):

653 $IPR = \text{predicted intermittence probability} - \text{observed intermittence class}$ (Equation 1),
654 with observed intermittence class $IR = \{0: \text{perennial}, 1: \text{non-perennial}\}$. If $|IPR| \leq$
655 0.5, the binary intermittence class of the reach associated with the gauging station
656 was accurately predicted, with $|IPR|$ values closer to 0.5 indicating greater
657 uncertainty. If $IPR > 0.5$, the reach was predicted to be non-perennial when it was
658 perennial. If $IPR < -0.5$, the reach was predicted to be perennial when it was non-
659 perennial. We also examined the distribution of classification accuracy and bias
660 (**Fig. 3**), as well as residual spatial autocorrelation (see Supplementary
661 Information *Section IV.d*), by river basin.

662 (iii) Partial dependence plots were generated for the 27 most important predictors
663 using the *edarf* package⁸⁹ (see Supplementary Information **Fig. S5**). These plots
664 display estimates of the marginal relationship between each predictor variable and
665 the model's predictions by holding the rest of the predictors at their respective
666 mean values⁹⁰.

667 **Assessing the global prevalence of IRES**

668 After training the two final probability RF sub-models, the constructed prediction
669 rules were used to estimate the probability of intermittence for each river reach included in

670 the global river network (i.e., with $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$). All reaches with a resulting probability
671 ≥ 0.5 were classified to be non-perennial (and perennial otherwise). This threshold was
672 chosen following an analysis of model performance sensitivity to probability thresholds
673 ranging from 0.25 to 0.75 for each RF sub-model which showed a balanced model
674 performance at 0.5 (see Supplementary Information *Section IV.e*). When adjusting the
675 probability threshold between 0.45 and 0.55, the RF-predicted (i.e., non-extrapolated) global
676 prevalence of IRES varied from 36% to 48% (compared to 41% with a 0.5 threshold).

677 We then used the binary intermittence class predictions to compute the global
678 prevalence of IRES by country, continent, climate zone, terrestrial biome, and major
679 freshwater habitat type (**Table 1** and **Supplementary Data**). Although gauging stations on
680 reaches with $MAF < 0.1 \text{ m}^3 \text{ s}^{-1}$ were included in the training dataset, we did not produce RF
681 predictions of the probability of flow intermittence for individual reaches below this
682 discharge threshold for two reasons. First, there existed only 59 gauges with $MAF < 0.1 \text{ m}^3 \text{ s}^{-1}$
683 and at least 10 valid years of data (including only 13 on perennial reaches), which was
684 insufficient to confidently train a model and assess its uncertainty for this discharge size
685 class. Second, there exists a discontinuity in RiverATLAS below $0.1 \text{ m}^3 \text{ s}^{-1}$ whereby only
686 those reaches with a drainage area $\geq 10 \text{ km}^2$ are included²⁷, leading to a varying discharge
687 cut-off depending on a region's aridity. Bounding our RF predictions to $0.1 \text{ m}^3 \text{ s}^{-1}$ enabled us
688 to establish a robust estimate of the prevalence of flow intermittence in a range of discharge
689 size classes which we then used for an extrapolation to smaller streams (see Methods section
690 *Extrapolating the global prevalence of IRES to smaller streams*).

691 **Estimating human population near IRES**

692 To estimate the percentage of the global population living near an IRES, we first
693 aggregated 2020 population count data from WorldPop⁹¹. We used constrained, rather than
694 unconstrained, top-down WorldPop population estimates to avoid erroneous allocation of

695 population to all land cells⁹¹. Population count estimates were aggregated from 3 arc-second
696 (~90 m at the equator) to 15 arc-second pixels (~500 m, i.e., the resolution of the
697 hydrographic data underpinning the RiverATLAS river network). We associated the
698 population within each larger pixel to the river reach in RiverATLAS (with $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$
699 ¹) that was nearest to that pixel. Finally, we summed the population across all pixels in the
700 world that were associated with a reach predicted to be non-perennial by our model.

701 **Extrapolating the global prevalence of IRES to smaller streams**

702 To create a first-order approximation of the global prevalence of IRES including even
703 smaller streams, we extrapolated our model estimates to the next smaller streamflow size
704 class range of $[0.01, 0.1) \text{ m}^3 \text{ s}^{-1}$. While streams of this size class are rarely monitored or
705 mapped globally, they are ecologically and environmentally critical⁹². For instance, at least
706 64% of rivers and streams in the U.S. (by length) show a $MAF < 0.1 \text{ m}^3 \text{ s}^{-1}$, and 25% show a
707 $MAF < 0.01 \text{ m}^3 \text{ s}^{-1}$ (according to the U.S. National Hydrographic Dataset, NHDPlus at
708 medium resolution). We limited our extrapolation to one order of magnitude (i.e., we did not
709 include even smaller streams, with $MAF < 0.01 \text{ m}^3 \text{ s}^{-1}$, that still can form stream channels) as
710 we expect uncertainties to continuously increase when moving further outside the range of
711 our trained and tested RF model.

712 The prevalence of IRES for this stream size class was independently extrapolated for
713 a total of 465 spatial sub-units representing all occurring intersections of 62 river basin
714 regions (BasinATLAS²⁷ level 2 subdivisions, average surface area $2.2 \times 10^6 \text{ km}^2$) and 18
715 climate zones (Global Environmental Stratification³²). For each basin-climate sub-unit, we
716 first extrapolated the empirical cumulative distribution of total stream length (of all reaches
717 with $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$) down to $0.01 \text{ m}^3 \text{ s}^{-1}$ MAF using a Generalised Additive Model⁹³
718 (GAM). We excluded reaches larger than the 95th percentile of MAF (i.e., the largest rivers)
719 within the sub-unit from model fitting to avoid common discontinuities at the high end of the

720 empirical distribution that can affect the low end of the power law-like trendline (see
721 Supplementary Information **Fig. S8a&c**).

722 Second, we extrapolated the prevalence of flow intermittence (in percentage of stream
723 length) down to $0.01 \text{ m}^3 \text{ s}^{-1}$ MAF. In this case, we fitted a GAM for beta-distributed data —
724 i.e., with a (0, 1) range — to the prevalence of intermittence in each logarithmic MAF size
725 bin of the sub-unit. MAF logarithmic size bins ($\text{m}^3 \text{ s}^{-1}$) were defined as $[10^i, 10^{i+0.1})$ for every
726 i in $\{-1, -0.9, -0.8, \dots, 5.3\}$ for model fitting, and every i in $\{-2, -1.9, \dots, -1.1\}$ for model
727 extrapolation. See Supplementary Information **Fig. S8b&d** for illustrative examples of this
728 approach. GAMs were used to conduct both extrapolations because this non-parametric, non-
729 linear approach does not require assumptions to be made regarding what distribution (e.g., a
730 power-law⁹⁴) the empirical cumulative distributions should follow. This is justifiable because
731 the aim of the analysis was to make a pragmatic first-order approximation of IRES
732 prevalence rather than to demonstrate the existence (or not) of a specific distribution.

733 Following the fitting of all GAM models, the length of IRES in each linear MAF size
734 class between $0.01 \text{ m}^3 \text{ s}^{-1}$ and $0.1 \text{ m}^3 \text{ s}^{-1}$ was computed as the product of the extrapolated
735 length of streams and the prevalence of intermittence in that size class. Finally, the total
736 length of IRES in the extrapolated size classes was combined with the predictions from the
737 split RF model to estimate the global prevalence of IRES as a percentage of the total global
738 length of rivers and streams with $\text{MAF} \geq 0.01 \text{ m}^3 \text{ s}^{-1}$.

739 We also produced an additional estimate with the assumption that, for each basin-
740 climate sub-unit, the prevalence of IRES in streams with $0.01 \leq \text{MAF} < 0.1 \text{ m}^3 \text{ s}^{-1}$ was equal
741 to the prevalence of IRES in streams with $0.1 \leq \text{MAF} < 0.2 \text{ m}^3 \text{ s}^{-1}$. Even with this
742 conservative assumption, we estimate that 51% of all global rivers and streams with $\text{MAF} \geq$
743 $0.01 \text{ m}^3 \text{ s}^{-1}$ are IRES. In contrast to the RF models, which estimate the probability of flow
744 intermittence at the scale of individual river reaches, the GAM-based extrapolation provides

745 aggregate estimates of IRES prevalence for basin-climate sub-units, which are best suited for
746 global accounting studies.

747 **Model comparisons**

748 *Comparisons with reported intermittence prevalence at national scales*

749 The most common source of information on the prevalence of flow intermittence across
750 large regions are national hydrographic datasets, derived mainly from paper topographic
751 maps in which non-perennial watercourses are usually depicted by dashed lines. We
752 compared our model estimates of the percentage of stream length that is non-perennial with
753 this type of hydrographic data for four countries covering a wide range of environmental,
754 geological, and climatic conditions: the contiguous U.S., Australia, Brazil, and Argentina
755 (**Extended Data Figs. 3-4**; for data sources see **Extended Data Fig. 7b**). In addition, we
756 compared our results in mainland France with predictions of a national model (ref²¹).

757 It should be noted that we do not consider these comparisons to be an accuracy
758 assessment of our model outputs due to the inherent yet unknown uncertainties in the national
759 hydrographic datasets. While the national maps represent the most comprehensive records of
760 presumed intermittence, most are characterized by high levels of inconsistency among
761 regions and cartographers, even for a fixed map scale (e.g., 1:24,000), in both stream density
762 and flow intermittence assessment^{95,96}. For instance, streamflow intermittence classifications
763 contained in the U.S. National Hydrography Datasets (NHDPlus, which was used in this
764 study), based on one-time field surveys typically conducted in the mid- to late-1900s, have
765 been shown to exhibit misclassification rates as high as 50% compared to independent field
766 surveys^{95,96}. Hafen and colleagues report Only an 80-81% agreement between ground-based
767 streamflow field observations from the U.S. Pacific Northwest and the NHDPlus
768 classifications has been reported (ref⁹⁷). In the Brazilian dataset and the NHDPlus,
769 neighbouring topographic map sheets differ in whether flow intermittence was mapped,

770 leading to artefactual hard edges between regions in terms of the prevalence of
771 intermittence⁹⁸ (e.g., **Extended Data Fig. 4**). Despite these limitations, map-based national
772 hydrographic datasets remain the reference used by most government agencies and
773 institutions in determining the extent and flow intermittence of river networks, and thus
774 provide a useful benchmark for comparing the output of our model.

775 A custom processing workflow was developed to format each of the four national river
776 network datasets to ensure comparability with our model predictions. This involved filtering
777 each source dataset to keep only river and stream channels (e.g., excluding lake shorelines
778 and marine coastlines), excluding reaches in the source data that do not correspond with the
779 streamflow threshold applied for the mapped rivers in this study ($MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$), and
780 excluding artificial channels (e.g., canals and ditches). For a full description of the formatting
781 workflow, see Supplementary Information *Section VI.a*. Following this formatting process,
782 we compared the percentage of river network length that was categorized as IRES in each of
783 the source datasets to our model results for the same region (**Extended Data Fig. 5**). We
784 could not perform this quantitative comparison for Brazil and Argentina because there was no
785 measure of river size in these datasets. Lastly, we visually assessed whether spatial patterns
786 of intermittence were similar between the source datasets and our model results. Aside from
787 Argentina, we were unable to compare our predictions to hydrographic maps in countries
788 where sparse hydrometric networks result in higher modelling uncertainties, due to the
789 unavailability of hydrographic data in these regions.

790 *Comparisons with local on-the-ground visual observations*

791 Datasets of on-the-ground visual observations of flow presence or absence (flow
792 state) by trained individuals provide some of the most reliable records of flow intermittence
793 ^{22,99,100}. We compared our predictions of intermittence to datasets of this type for two regions:
794 the U.S. Pacific Northwest and mainland France (**Extended Data Fig. 6**; see Supplementary

795 Information *Section VI.b* for additional details). We did not use these observations directly
796 for the training of the RF sub-models as we could not apply the same criterion to define
797 ‘intermittence’ as for gauging stations (i.e., at least one day per year of flow cessation, on
798 average, across the entire record) and their inclusion would have represented a strong
799 regional bias. These datasets instead enabled an independent comparison of the model
800 predictions for smaller rivers and streams (here mostly $< 1 \text{ m}^3 \text{ s}^{-1}$), which are poorly
801 represented in the global hydrometric network.

802 For the U.S. Pacific Northwest, we used 5,372 observations across 3,725 reaches
803 (3,547 perennial, 178 non-perennial) from a larger dataset of 24,316 stream observations¹⁰¹
804 that occurred from July 1st to October 1st, between 1977 and 2016. The source dataset is a
805 compilation of 11 smaller datasets from independent projects that include aquatic species
806 habitat surveys, wet/dry stream channel mapping, beneficial use reconnaissance surveys, or
807 were collected specifically for the PROSPER intermittent river mapping project^{22,101}.
808 Streamflow observations included one-time surveys and repeat surveys extending over
809 several years, as well as discrete locations or continuous sections of a stream channel reach.
810 Based on the approach used by Jaeger et al.²², we considered that a river section was
811 perennial only if all observations (July 1st - October 1st) reported the presence of water.
812 Despite this strict criterion, this dataset may underestimate the prevalence of intermittence
813 since most sites were only observed 1-3 times and the probability that flow cessation is
814 observed at a given reach increased with the number of observations (logistic regression, $n =$
815 9,850, $p\text{-value} < 0.001$, see Supplementary Information *Section VI.b* for details).

816 For France, we used 124,112 observations across 2,297 reaches (878 perennial, 1,419
817 non-perennial) from a larger set of ca. 3,300 sites uniformly distributed across France from
818 the national river drying observatory (ONDE) network¹⁰². The ONDE network provides a
819 stable set of sites on river and stream reaches of Strahler orders under five which, since 2012,

820 have been inspected by agency employees from the French Office for Biodiversity (OFB) at
821 least monthly between May and September. We considered an observation to reflect flow
822 intermittence if it was classified as either “with no visible flow” or “dried out” (as opposed to
823 “with visible flow”). In case of multiple observations on one reach, we considered the reach
824 to be non-perennial if a single observation of flow cessation existed.

825 All flow state observations were linked to the RiverATLAS stream network through
826 custom semi-automated procedures designed for each dataset, using the proximity between
827 the point observations and the reach locations in RiverATLAS, as well as associated
828 information from local river network datasets and ancillary attribute data provided for each
829 location (e.g., drainage area, site name; see Supplementary Information *Section VI.b* for
830 details). Following data formatting and harmonization, we assessed the degree of agreement
831 at the river reach level between the binary intermittence class predicted by our model and that
832 reported by the two datasets of visual observations.

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981

982 **Data availability**

983 The global river network dataset and the associated attribute information for every river
984 reach—that is, the hydro-environmental attributes, predicted probability of intermittence and
985 associated binary class—as well as the main results of the study are available at
986 <https://figshare.com/s/a60b0c16b93738f2bbc0T> [*will be replaced with DOI upon final*
987 *acceptance of the manuscript*]. The dataset can be used together with the published source
988 code (see ‘Code availability’) to recalculate the main study results with updated data and
989 parameters. The streamflow time series from the Global Runoff Data Centre are available in
990 summarized format. The daily records are not available in the data repository owing to
991 licensing issues but are freely available upon written request through
992 https://www.bafg.de/GRDC/EN/Home/homepage_node.html. Original data that supported
993 the study are freely available and their sources are summarized in **Extended Data Fig. 7b**.
994

995 **Code availability**

996 The source code and results of this research are available under the GNU General Public
997 License v3.0 at <https://messamat.github.io/globalIRmap/>.
998

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1009

1010 **Author contributions**

1011 CRediT (Contributor Roles Taxonomy): conceptualization - TD, BL, KT, MLM;
1012 Methodology - MLM, BL, TS, CC, NL; data curation - MLM, BL, CC, CW, TS, HP;
1013 software, validation, visualization - MLM; formal analysis - MLM, CC; writing original draft
1014 - MLM, TD, BL; writing review and editing - all authors; project administration and
1015 supervision - MLM, BL, TD; funding acquisition - BL, TD, MLM.
1016

1017 **Competing interests**

1018 The authors declare no competing interests.
1019

1020 **Additional information**

1021 Correspondence and requests for materials should be addressed to Mathis L. Messenger
1022 (mathis.messenger@mail.mcgill.ca).

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Extended Data legends

Extended Data Table 1 | Definitions of commonly used terms for non-perennial rivers and streams.

Extended Data Table 2 | Hydro-environmental characteristics used as candidate predictor variables in the split random forest model. Spatial representations refer to: p (derived at the pour point of the river reach), c (derived within the local catchment that drains directly into the reach), or u (derived within the total drainage area upstream of reach pour point). See ref²⁷ for a full description of the methodology to calculate the variables.

Extended Data Fig. 1 | Global prevalence of IRES with at least one zero-flow month per year on average. **a**, Distribution of global climate zones used in this study. Data provided by Global Environmental Stratification (GENS³²). **b**, Predicted probability of river flow intermittence, defined as at least one zero-flow month (30 days) per year on average, across the global river and stream network²⁷. The median probability threshold of 0.5 was used to determine the binary flow intermittence class for each reach. **c**, Global prevalence of IRES with at least one zero-flow month (30 days) per year on average, across climate zones and streamflow size classes (based on long-term average naturalised discharge). Note that in regions with sparse training data, the model results can differ substantially from the results shown in Table 1, as the underlying random forest and extrapolation models were developed independently. No stations were available in the Arctic (1 & 2), and few stations were available in Extremely cold and wet (1 & 2) and in Extremely hot and arid climates (together representing 3% of global river and stream length). Rows are sorted in the same order as in Table 1, and the same footnotes as in Table 1 apply. Mapping software: ArcMapTM (ESRI).

Extended Data Fig. 2 | Distribution of cross-validation results. **a**, Maps of spatially cross-validated predictive accuracy of flow intermittence for streamflow gauging stations. See Supplementary Information **Fig. S3** for the distribution of spatial cross-validation folds and details on the cross-validation procedure. The classification errors shown here are not necessarily present in the final predictions but illustrate the ability of the model to predict the flow intermittence class for each region if that region was excluded from the training set. For instance, it shows that the model would be unable to predict the presence of IRES in western France and northern Spain (inset *ii*, dark red dots), or in western India (inset *iii*) without training stations in these regions. **b-e**, Intermittence prediction residuals vs. gauging station characteristics and environmental variables. The mean intermittence prediction residual (IPR) is the difference between the average predicted probability of flow intermittence (across 3 cross-validation folds and 2 repetitions) and the observed flow intermittence of the gauging station (1 = non-perennial, 0 = perennial). Overall, prediction errors and uncertainties decrease with an increase in the number of recorded years by gauging stations as well as the drainage area and the degree of flow intermittence (average annual number of zero-flow days and flow cessation events) of the corresponding reaches. Mapping software: ArcMapTM (ESRI).

Extended Data Table 3 | Performance summary of binary flow intermittence class predictions. Tables show summary results for the split model approach based on **a**, a twice-repeated 3-fold non-spatial cross-validation (CV) and **b**, a once-repeated 40-fold spatial CV, as well as for comparison **c**, a single (non-split) model approach based on a twice-repeated 3-fold non-spatial CV. The color coding mirrors Extended Data Fig. 2 with light colors slightly

1074 darkened for readability. The split model approach involves training two random forest sub-
1075 models with slightly overlapping MAF ranges, one trained to predict the streamflow
1076 intermittence probability of small-to-medium rivers with $MAF < 10 \text{ m}^3 \text{ s}^{-1}$ and the other for
1077 medium-to-large rivers with $MAF \geq 1 \text{ m}^3 \text{ s}^{-1}$. Within the overlapping range of $1\text{-}10 \text{ m}^3 \text{ s}^{-1}$
1078 MAF, the average probability was calculated to avoid abrupt transitions at a singular size
1079 threshold. Gauging stations monitoring streams with a mean annual naturalised discharge $<$
1080 $0.1 \text{ m}^3 \text{ s}^{-1}$ were included in model training and testing (shown in grey font); however, no
1081 model predictions were made below this discharge threshold. Sensitivity is the proportion of
1082 non-perennial reaches correctly classified as non-perennial. Specificity is the proportion of
1083 perennial reaches correctly classified as perennial. Precision is the proportion of reaches
1084 classified as non-perennial that are truly non-perennial. See Supplementary Information **Fig.**
1085 **S3** and *Section IV.b* for the distribution of spatial cross-validation folds and details on the
1086 cross-validation procedure.

1087

1088 **Extended Data Fig. 3 | Comparing global predictions to national maps of IRES in the**
1089 **U.S. and Australia.** Comparison of **a**, the U.S. National Hydrographic Dataset (NHDPlus,
1090 medium resolution) and **d**, the Australian hydrological geospatial fabric, with our model
1091 predictions based on two thresholds of flow intermittence, either **b**, **e**, ≥ 1 zero-flow day per
1092 year or **c**, **f**, ≥ 1 zero-flow month (30 days) per year, on average. Only rivers and streams with
1093 $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$ are shown for the U.S. (**a-c**) and with drainage area $\geq 10 \text{ km}^2$ for Australia
1094 (**d-f**). The U.S. reference dataset portrays 19-22% of the length of rivers and streams as non-
1095 perennial, depending on whether reaches without flow intermittence status are assumed to be
1096 perennial or removed; our estimates range from 51% (≥ 1 zero-flow day per year) to 36% (\geq
1097 1 zero-flow month per year). We hypothesize that the remaining gap in IRES prevalence is
1098 attributable to a tendency of our model to overpredict intermittence across the eastern U.S
1099 and an under-accounting of intermittence in medium to large rivers by the national dataset.
1100 The Australian reference dataset portrays 91% of the length of rivers and streams as non-
1101 perennial; our estimates range from 95% (≥ 1 zero-flow day per year) to 92% (≥ 1 zero-flow
1102 month per year). See Extended Data Fig. 7b for data sources. Mapping software: ArcMapTM
1103 (ESRI).

1104

1105 **Extended Data Fig. 4 | Comparing global predictions to national maps of IRES in**
1106 **Brazil, Argentina, and France.** Comparison of **a**, the continuous cartographic base of Brazil
1107 (BC250), **d**, the Argentinian hydrographic network, and **g**, model predictions from Snelder et
1108 al. (2013), with our model predictions based on two thresholds of flow intermittence, either **b**,
1109 **e**, **h**, ≥ 1 zero-flow day per year or **c**, **f**, ≥ 1 zero-flow month (30 days) per year, on average.
1110 In **a** and **d**, only first-order streams (determined through network analysis) are visually
1111 differentiated (finer, semi-transparent lines) due to the lack of watercourse size attribute in
1112 the Brazilian and Argentinian datasets. In **b-c**, **e-f**, and **g-h**, only rivers and streams with
1113 $MAF \geq 0.1 \text{ m}^3 \text{ s}^{-1}$ are shown. Snelder et al. predict that 17% of the length of rivers and
1114 streams in France are non-perennial. We predict that 14% are non-perennial. This slight
1115 divergence may be partly driven by the difference in definition of flow intermittence: Snelder
1116 et al. classified stations with ≥ 1 zero-flow day in the streamflow record as IRES whereas we
1117 used a threshold of 1 zero-flow day per year across the streamflow record. See Extended Data
1118 Fig. 7b for data sources. Mapping software: ArcMapTM (ESRI).

1119

1120 **Extended Data Fig. 5 | Quantitative comparison between the predicted prevalence of**
1121 **flow intermittence and national estimates.** Comparisons were conducted for France (**a-b**),
1122 the U.S. (**c-d**), and Australia (**e-f**), based on two thresholds of flow intermittence, either (**a**, **c**,

1123 **e**) ≥ 1 zero-flow day per year or (**b, d, f**) ≥ 1 zero-flow month (30 days) per year, on average.
1124 Bars for mapped rivers and streams with $MAF < 0.1 \text{ m}^3 \text{ s}^{-1}$ (for France and the U.S.) are
1125 greyed-out as they were not included in the calculation of summary statistics. Inset graphs in
1126 **b, d, f** show comparisons of total river network length (log-transformed y-axis), which in
1127 case of discrepancies can explain some of the differences in the predicted prevalence of
1128 intermittence.

1129

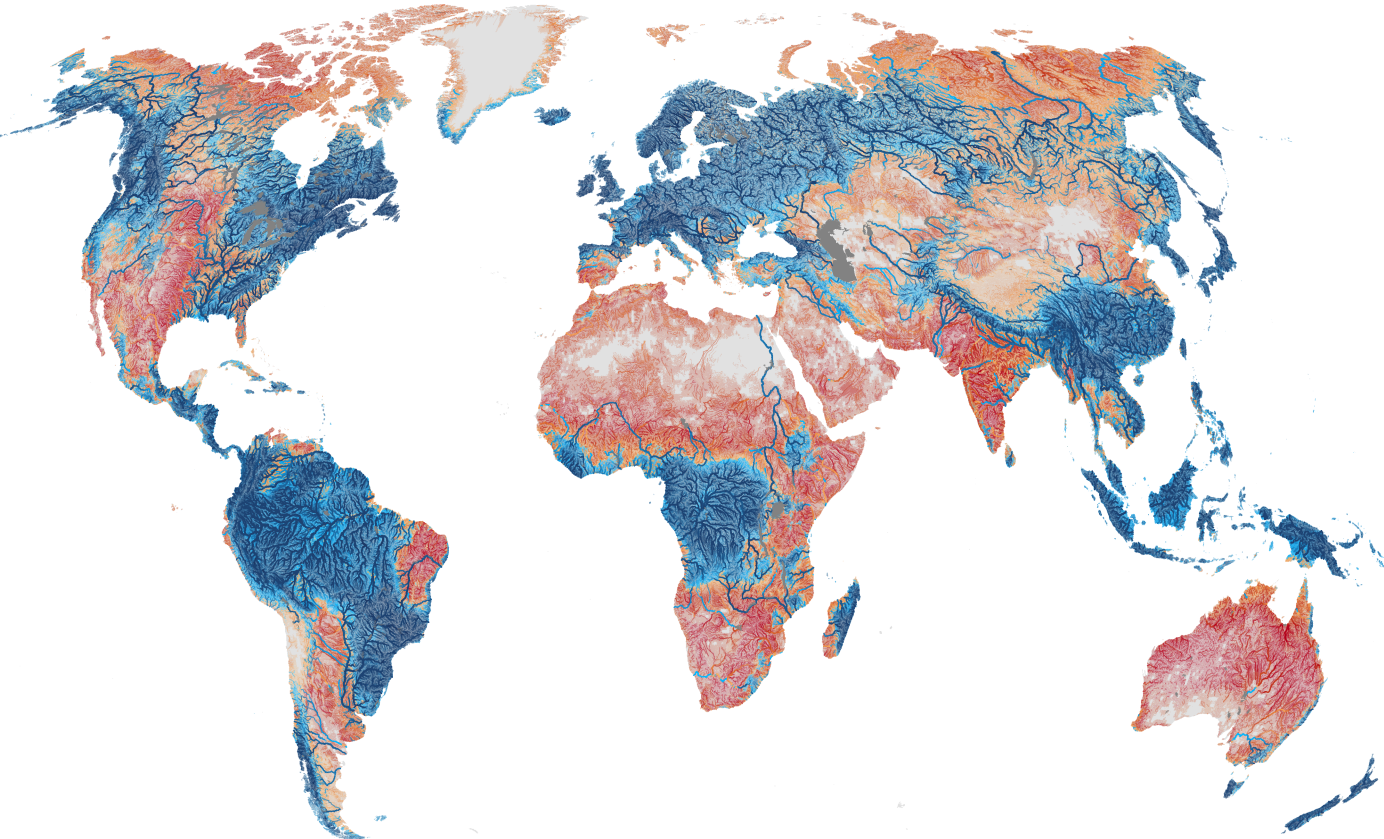
1130 **Extended Data Fig. 6 | Comparing global predictions to on-the-ground observations of**
1131 **flow cessation.** Maps show individual RiverATLAS reaches and their predictive accuracy for
1132 **a**, France and **b**, the U.S. Pacific Northwest. Maps are drawn at identical cartographic scales.
1133 France (n=2,297): balanced accuracy=0.59, classification accuracy=51%, sensitivity=24%,
1134 specificity=94%. U.S. Pacific Northwest (n=3,725): balanced accuracy=0.47, classification
1135 accuracy=80%, sensitivity=10%, specificity=83%. See Extended Data Fig. 7b for data
1136 sources. Mapping software: ArcMapTM (ESRI).

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1138 **Extended Data Fig. 7 | Overview of study design and main data sources.** **a**, Diagram of
1139 modelling workflow and **b**, main data sources used in model development, predictions,
1140 diagnostics, and comparisons.

1141

1142 **Extended Data Fig. 8 | Spatial and environmental distribution of streamflow gauging**
1143 **stations used in model training and cross-validation.** Gauging stations (n = 5,615) were
1144 deemed **a**, perennial if their streamflow record included less than one zero-flow day per year,
1145 on average, across their record, or **b**, non-perennial if they included at least one zero-flow day
1146 per year, on average, and at least one zero-flow day in every 20-year moving window across
1147 their record. Stations fulfilling neither condition a nor b were excluded. Darker points
1148 symbolize longer streamflow records. Only gauging stations with streamflow time series
1149 spanning at least 10 years were included in this analysis, excluding years with more than 20
1150 missing days. **c-p.** Distribution of values for 14 hydro-environmental variables across the
1151 streamflow gauging stations used for model training/testing (purple, n = 5,615) and across all
1152 reaches of the global river network (blue, n = 23.3×10^6). The distribution plots show
1153 empirical probability density functions (i.e., the area under each density function is equal to
1154 one) for all variables, aside from Climate Zones (**g**) for which the relative frequency
1155 distribution is shown. All variables were averaged across the total drainage area upstream of
1156 the reach pour point associated with each gauging station or river reach, respectively. See
1157 Extended Data Table 2 for a description of the variables and Extended Data Fig. 1a for a
1158 description of the climate zones. No stations were available for climate zones Arctic 1 and
1159 Arctic 2. Mapping software: R statistical software (R Core Team).



Mean annual discharge
(line width and transparency)

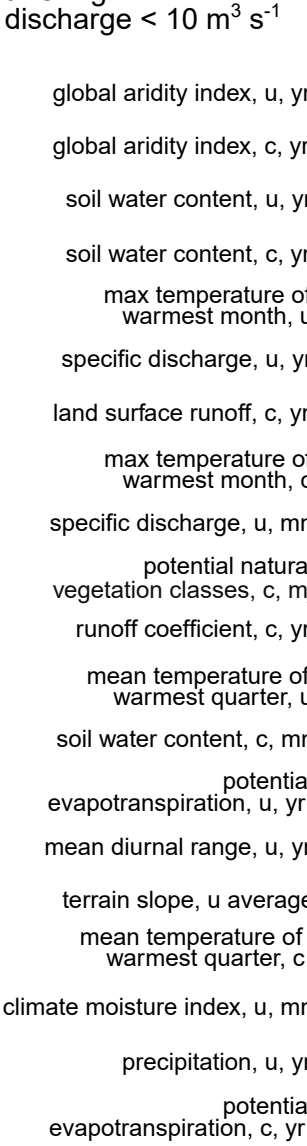
10^{-1} 1 10^1 10^2 10^3 10^4 $\text{m}^3 \text{s}^{-1}$

Probability of flow intermittence

Non-perennial █ █ █ Perennial
1 0.75 0.5 0.25 0

█ Lake or reservoir
█ No flow

a. Gauges with mean annual discharge <math> < 10 \text{ m}^3 \text{ s}^{-1}</math>

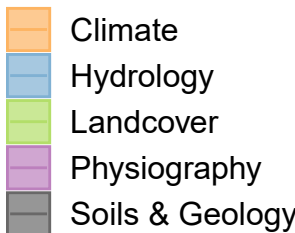


Variable importance (actual impurity reduction)

More important

Less important

Category



b. Gauges with mean annual discharge $\geq 1 \text{ m}^3 \text{ s}^{-1}$

