Resilience of river flow regimes

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Contributed by Andrea Rinaldo, June 25, 2013 (sent for review March 3, 2013)

Landscape and climate alterations foreshadow global-scale shifts of river flow regimes. However, a theory that identifies the range of unforeseen impacts on streamflows resulting from inhomogeneous forcings and sensitivity gradients across diverse regimes is lacking. Here, we derive a measurable index embedding climate and landscape attributes (the ratio of the mean interarrival of streamflow-producing rainfall events and the mean catchment response time) that discriminates erratic regimes with enhanced intraseasonal streamflow variability from persistent regimes endowed with regular flow patterns. Theoretical and empirical data show that erratic hydrological regimes typical of rivers with low mean discharges are resilient in that they hold a reduced sensitivity to climate fluctuations. The distinction between erratic and persistent regimes provides a robust framework for characterizing the hydrology of freshwater ecosystems and improving water management strategies in times of global change.

climate change | flow variability | hydroclimatic shift | water uses

The river flow regime identifies the streamflow temporal variability at a station (1), which is the natural byproduct of the sequence of flow pulses conveyed to the stream network from the contributing catchment after rainfall. The flow regime is embodied by the probability distribution function (pdf) of daily flows (2–4), which provides information on the mean water availability, the extent of discharge fluctuations (5), and the frequency of high/low flows. Flow regimes not only constrain anthropogenic uses, such as energy production and irrigation, but shape form and functions of riverine ecosystems owing to the dynamic control of flow magnitude on stream habitats (1, 4, 6–8). In the past decades, natural and anthropogenic modifications of climate drivers (9), jointly with landscape changes, have led to increasingly nonstationary flow regimes (10–14). These ubiquitous and accelerating alterations of river flows challenge the sustainability of water uses (5, 15) and the ecosystem services provided by river biomes (6, 16, 17). However, streamflow alterations are not expected to be uniform (18, 19), owing to heterogeneous climate/landscape drifts and sensitivity gradients across diverse climate zones and regime types.

Here, the flow regimes of pristine rivers are analyzed using a mechanistic analytical model in which streamflow dynamics are driven by a catchment-scale soil–water balance forced by stochastic daily rainfall (2, 3). The analytical model indicates that the nature of flow regimes and their sensitivity to climate change can be discriminated based on the frequency of effective (i.e., flow-producing) rainfall events and the time scale of the hydrological response through which these rainfall inputs are propagated across catchments. This hypothesis is tested through extended climate and flow records taken from 44 US and Italian catchments belonging to the US Geological Survey/National Oceanic and Atmospheric Administration and the Regional Agency for Environmental Protection of the Veneto Region monitoring networks (Table S1). To comply with the basic assumptions of the mechanistic model (pertaining to the features of climate forcing and the dominant mechanisms of streamflow production), the choice of the catchments is restricted to unregulated, small/medium watersheds weakly influenced by snow dynamics (SI Materials and Methods). In this setting, flow-producing rainfall events result from the censoring operated by catchment soils on daily rainfall, and they are modeled as a spatially uniform marked Poisson process with mean depth α [L] and mean frequency λ [T–1]. Although α quantifies the average daily intensity of rainfall events, λ is smaller than the underlying precipitation frequency because the soil–water deficit created by plant transpiration in the root zone may hinder the routing of some inputs to streams (Eq. S3). Therefore, λ crucially embeds rainfall attributes; soil/vegetation properties; and other climate variables, such as temperature, humidity, and wind speed.

The time scale of the hydrological response, defined as the mean water retention time in the upstream catchment, is operationally identified by the inverse of the flow decay rate (k [T–1]) observed during recessions, conveniently assumed to be exponential (2, 3, 20). The term k quantifies catchment-scale morphological and hydrological attributes [e.g., the mean length of hydrological pathways and upscaled soil conductivity (3)]. High k values imply low duration of the flow pulses released from the catchment after rainfall, typical of fast-responding catchments.

When flow-producing rainfall events are relatively frequent, such that their mean interarrival is smaller than the duration of the flow pulses delivered from the contributing catchment (λ > k), the range of streamflows observed at a station between two subsequent events is reduced, and a persistent supply is guaranteed to the stream from catchment soils. Therefore, river flows are weakly variable around the mean (Fig. 1A, Lower) and quite predictable. This type of regime (hereafter termed persistent) is typically expected during humid, cold seasons in slow-responding catchments (high λ, low k).

When the mean interarrival between flow-producing rainfall events is larger than the typical duration of the resulting flow pulses (λ < k), a wider range of streamflows is observed between events because the reach is allowed to dry significantly before the arrival of a new pulse. The temporal patterns of streamflows are thus more unpredictable (Fig. 1A, Upper), leading to erratic regimes with significant streamflow fluctuations. Under these circumstances, the preferential state of the system is typically lower than the mean. Erratic regimes are likely expected in fast-responding catchments during seasons with sporadic rainfall events (low λ, high k). However, this type of regime also can frequently be observed during hot, humid seasons (where relatively high rainfall rates are compensated by enhanced evapotranspiration).

The analytical mechanistic model on which the proposed classification of hydrological regimes is grounded allows the river flow pdf to be expressed as a gamma-distribution with shape parameter α/k and rate parameter αk (2, 3) (Materials and Methods). The parameters α, λ, and k (which we hereafter term hydroclimatic parameters) summarize the underlying morphological and environmental conditions of the gauged catchment and hence define the regimes represented in the study area. This framework allows an explicit consideration of the combined effects of hydroclimatic shifts and anthropogenic disturbances on the flow regime variability, becoming crucial in times of global change. The approach is applied to a new set of 600 US and Italian catchments, encompassing the full range of available climate variability and large, medium, and small catchments, all with different levels of water demand.

The results show that: (i) flow variability is strongly dependent on climate, local landscape, and anthropogenic influences (Fig. 2); (ii) the dominance of the different flow variability patterns depends both on climate and anthropogenic activities (Fig. 3); and (iii) the shift in flow variability is a robust, macroscopic signal of the changing climate regime that might be used for monitoring purposes (Fig. 4).

The findings have important implications for water management and planning, particularly in times of global change, and they suggest a new way to interpret and predict the impacts of future climate changes on river flow regimes.
Remarkably, the estimated ratios analyzed (64 of 110 cases) are characterized by erratic regimes: Persistent regimes are characterized by enhanced frequencies of events that decrease the average of the ratio $\lambda/k$. Due to the spatial and temporal heterogeneity of climate and landscape attributes, the estimated ratios $\lambda/k$ span one order of magnitude. The majority of the cases analyzed (64 of 110 cases) are characterized by erratic regimes ($\lambda < k$). Remarkably, the estimated ratios $\lambda/k$ explain most of the seasonal variability of daily flows observed in different catchments across regimes, quantified here through the coefficient of variation of daily flows ($CV_Q$). Fig. 1B shows that in the majority of the cases analyzed, the observed mean of the $CV_Q$ (evaluated on a seasonal basis) matches the corresponding estimate of the mean of $\sqrt{\lambda/k}$, representing the theoretical prediction of the analytical model for the $CV_Q$. The limited number of observed data lying outside the screened area reveals that most cases classified as erratic (persistent) actually display, on average, a pronounced (reduced) flow variability. The reduced deviations from the theoretical prediction suggest the reliability of the proposed classification, which [although far from being perfect and applicable to all the settings (see below)] is able to frame the wide range of cases analyzed properly.

A strong seasonality of the flow regimes is observed owing to the underlying climatic controls, with regime shifts across seasons being the rule rather than the exception. Persistent regimes were found in most alpine catchments during the summer but were also detected in the United States, especially in the western and the northeastern United States, during the winter. Erratic regimes are widespread throughout the United States during the summer (Fig. 1C) and the fall, owing to larger rainfall interarrivals and to the enhanced transpiration rates. In some cases (especially winter and spring), the frequency of flow pulses was found to be close to the recession time constant, leading to $0.9 < CV_Q < 1.1$. A significant number of these cases, classified as intermediate in Fig. 1C and D, were found to be located in the southeastern United States. The $CV_Q$ (and thus the type of flow regime) is poorly correlated with the average seasonal rainfall but quite strongly anticorrelated ($\rho = -0.9$) with the mean specific discharge, $(Q)$, in agreement with the results of Destouni et al. (5). In particular, a large majority of the cases where $(Q) < 0.1$ cm/d were found to be erratic, thereby suggesting that a low $(Q)$ may represent a sufficient but not necessary condition for the erraticity of the regime (Fig. S5). The smallest ratios $\lambda/k$ (corresponding to extremely erratic hydroclimatic conditions, and can thus be evaluated based solely on rainfall, climate, and soil/vegetation information. However, to reduce the burden of the data requirement for their estimation, in this paper, $\lambda$, $\alpha$, and $k$ have been evaluated by combining rainfall and discharge data (Materials and Methods and Figs. S1 and S2). The reliability of the estimates of $\lambda$, $\alpha$, and $k$ has been checked posteriori through comparison of the observed and theoretical distributions of daily flows (Figs. S3 and S4). The flow regime of the available combinations of catchments/seasons has then been classified as erratic or persistent depending on the long-term average of the ratio $\lambda/k$. Due to the spatial and temporal heterogeneity of climate and landscape attributes, the estimated ratios $\lambda/k$ span one order of magnitude. The majority of the cases analyzed (64 of 110 cases) are characterized by erratic regimes ($\lambda < k$). Remarkably, the estimated ratios $\lambda/k$ explain most of the observed intraseasonal flow variability ($r^2 = 0.52$), as documented by the scatterplot of the observed $CV_Q$ vs. the corresponding estimate performed on the basis of the empirical values of $\lambda/k$, representing the theoretical prediction of the analytical model. Each circle identifies a given catchment during a season (spring, summer, fall, or winter). (Insets) Maps show the locations of the 44 study catchments. (C and D) Spatial distribution of the flow regimes among the US study catchments during summer (06/01–08/31) and winter (12/01–02/28), supported by the corresponding box plot of the frequency distribution of $\lambda$ and $k$ (outliers are not represented). In the two maps, based on the average value of $CV_Q = (\lambda/k)^{1/2}$, catchment regimes are classified as persistent ($CV_Q < 0.9$), intermediate ($0.9 \leq CV_Q \leq 1.1$), or erratic ($CV_Q > 1.1$).
regimes) were observed in the south/southwestern areas of the United States. Some of these cases (especially in the summer and the fall) are typically characterized by extremely low average discharges and were excluded from the analysis owing to the practical difficulties in estimating $k$ from the few recessions available. Similarly, no catchments belonging to the mountainous northwestern area of the United States were included in the analysis, because their regime is typically affected by human regulation and/or snow dynamics (thereby violating the assumptions required by the analytical model).

To assess the regime sensitivity to interannual modifications of climate/landscape properties, we analyze how the flow regimes respond to long-term changes in the driving hydroclimatic parameters $\lambda$, $a$, and $k$. Interannual fluctuations of $a$ quantify the interannual variability of the mean intensity of the events, whereas interannual modifications of $\lambda$ describe the combined action of changes in precipitation (frequency and depths) and other climate variables affecting the soil–water balance (temperature, wind, humidity, and radiation). Dry and warm years, for instance, should likely result in drastically reduced frequencies of effective rainfall events. Similarly, the interannual variability of $k$ quantifies interannual changes in soil responsiveness and the partitioning between fast/slow flows, jointly with possible changes in short-term rainfall dynamics. The interannual variability of $\lambda$ and $k$ may also mirror natural or human-triggered change in the landscape, such as shifts in soil cover and soil use. However, because the majority of the selected rivers belong to pristine landscapes, the climate fluctuations in this study are most likely the primary driver of change.

Climate time series typically feature complex, multiscaling behaviors (13, 21), which often make it difficult to separate natural fluctuations objectively from sustained trends. To circumvent this issue, we use the theory of superstatistics (22–24) and we assume that long-term climate/streamflow dynamics result from the juxtaposition of several stationary subperiods (each spanning a suitable number of years), within which the flow regimes are evaluated and classified based on the corresponding values of $\lambda$, $k$, and $a$. The combined effect of hierarchical fluctuations operating at different time scales is thus handled by assuming that the parameters defining the randomness of rainfall and transport processes during each subperiod (namely, $\alpha$, $\lambda$, and $k$) may, in turn, vary across the different subperiods identified (Fig. 2A). Because the primary focus of this study is the regime responsiveness to hydroclimatic forcings (independent of their nature), the analyses have been carried out using two different aggregation time scales, namely, 2 y (representative of natural interannual fluctuations around stable states) and 8 y (representative of longer term fluctuations and sustained shifts). The corresponding variations of $\lambda$, $a$, and $k$ between these periods will be referred to as hydroclimatic fluctuations, regardless of the underlying time scale. Fig. 2A shows the 2-y variability of $\lambda$, $a$, and $k$ for a sample catchment considered in the study. Nonstationary features are particularly evident for the pulse frequency $\lambda$ (which mainly mirrors interannual changes in rainfall and temperature; Fig. S2), a character shared by the majority of the catchments considered in this study. An example of the effects produced by hydroclimatic fluctuations on hydrological regimes is represented in Fig. 2B, where the observed shift in the streamflow distribution is primarily related to the observed decrease in the rainfall frequency. Quantitatively, the change produced by hydroclimatic fluctuations in the seasonal flow distributions (which we term flow regime instability) is evaluated here through the regime instability index ($RI$), defined as the relative fraction of probability shifting from one flow range to another in response to hydroclimatic fluctuations (cross-hatched areas in Fig. 2B). The $RI$ is a synthetic measure of the fluctuations of the seasonal flow distribution (including mean, variance, and frequency of high/low flows) over different periods/years (Materials and Methods). Provided that both the ecological functions of riverine environments and the anthropogenic exploitability of running waters are strongly constrained by the entire distribution of observed flows (4, 15), the $RI$ is a meaningful measure of the potential impact of time-variant flow regimes on stream habitats and anthropogenic water uses.

The magnitude of the hydroclimatic fluctuations driving regime instability can be quantified using different metrics. Here, we first analyze the relative interannual fluctuations of $\lambda$, $a$, and $k$ to identify the interannual variability in the number, magnitude, and response time of flow-producing rainfall events. On this

![Fig. 2. Hydroclimatic fluctuations produce flow regime instability. (A) Hydroclimatic fluctuations in the Piave River at Cancia, Italy, during the summer, identified by the underlying fluctuations of $\lambda$, $a$, and $k$ across consecutive, disjointed groups of 2 y (representing the variability of the number, magnitude, and response time of flow-producing rainfall events). (B) Experimental evidence of the effect of hydroclimatic fluctuations on the streamflow distribution. The frequency changes are particularly evident for the range of flows, $0.1 \pm 0.15$ cm/d, that had not been observed during 1998–1999 but became relatively frequent during 2000–2001. (C) Relative magnitude of the long-term variability of hydroclimatic parameters $\lambda$, $a$, and $k$ (including the shape and rate parameters of the flow pdf: $s = \lambda/k$ and $r = ak$) increases with the seasonal CV$_0$.](image-url)
basis, the relative interannual fluctuations of the shape and rate parameters of the streamflow distribution (which are explicitly related to $\lambda$, $\alpha$, and $k$ through the analytical model) can be estimated. This allows evaluation of the actual extent of hydroclimatic fluctuations, properly discounting self-compensating external changes like the simultaneous increases of $\lambda$ and $k$ (i.e., more frequent but faster events) that maintain unaltered the flow variability. Finally, to summarize the overall exposure to climate change into a single indicator, we defined the exposure index ($E$) representing the sum of relative variations of the shape and rate parameters of the flow distribution (disregarding their sign). The $E$ synthetically represents the extent of the observed hydroclimatic parameters...

Fig. 3. Resilience of erratic flow regimes to climate change. Average exposure ($A$), regime instability ($B$), and sensitivity ($C$) for any available combination of catchments/seasons, plotted as a function of the seasonal $CV_Q$. Dashed lines identify the least-squared regressions, whose slopes are indicated in the figure. The average $r^2$ values for $E$, $RI$, and $S$ are 0.37, 0.1, and 0.41, respectively. Erratic flow regimes, notwithstanding their enhanced exposure to climate change, are characterized by lower sensitivity and lower regime instability. (Inset) Agreement between the observed sensitivities and the pattern predicted by the analytical model (SI Discussion). (D) Reduced sensitivity of erratic regimes identifies their ability to buffer climate change (hydrological resilience), as evidenced by the comparison of the streamflow pdfs observed in two streams with contrasting regimes: the Rivanna River (persistent) and the Big Eau Pleine River (erratic). (E) Comparison of the temporal evolution of the seasonal flow pdfs in these catchments during the past 50 y indicates that the flow pdfs observed in the Big Eau Pleine River during different periods are much more similar to one another with respect to the regime successions recorded in the Rivanna River. (F) Resilience of erratic flow regimes is also shown by the different responsiveness of the 8-y flow pdfs to a reference change ($E = 0.2$) of the underlying hydroclimatic parameters.
unpredictable discharges during each season may be more stable (and thus not equally unpredictable) across different years.

The ratio between regime instability and exposure provides a measure of the changes observed in the flow regime in response to a given (unit) perturbation of hydroclimatic parameters, and thus represents the regime sensitivity to climate change. High sensitivities imply that the underlying hydroclimatic fluctuations are amplified by flow regimes, with relevant modifications in the frequencies associated with discharges of any size. Reduced sensitivities, instead, indicate the ability of flow regimes to buffer changes in the external forcing, a feature that is referred to as hydrological resilience. The hydrological resilience of river regimes provides a robust basis for characterization of the expected response of riverine ecosystems to external disturbances (ecological resilience), and the related socioeconomic impact. Fig. 3C shows a clear pattern of sensitivity across regimes with the mean regime sensitivity of erratic regimes, $\bar{S}$, which is smaller than the mean sensitivity of persistent regimes (with a significance of 0.05). The structural resilience of erratic regimes identifies the reduced responsiveness of the whole streamflow pdf to interannual hydroclimatic fluctuations (Fig. 3D–F), a feature that cannot be automatically transposed to other flow metrics (e.g., the mean flow). Interestingly, when the time scale used to analyze the regime instability increases (from 2 to 8 y), the average exposures and instabilities decrease consistently, although maintaining their characteristic dependence on the CV$_{O}$. Remarkably, the sensitivity pattern does not appear to be altered (Fig. 3C), suggesting that the regime responsiveness to changes in the underlying climatic conditions depends only on the internal dynamics through which rainfall inputs are spatially and temporally integrated by watersheds. Because the regime sensitivity is strongly affected by the type of flow regime but is essentially independent of the time scale of the driving change, the observed sensitivity patterns should also apply to forthcoming climate shifts. The observed reduced sensitivity of the erratic flow regimes also complies with the reduced sensitivity of the corresponding analytical streamflow distributions to changes in the shape and rate parameters (Materials and Methods), as shown in Fig. 3C (Inset) (SI Discussion).

The analysis pinpoints that seasonality of flow regimes can be a critical issue for the description of river flow availability and the supply of water needs. Most catchments experience regime shifts and seasonal variation that the hydrologic variability and the sensitivity to climate change may be radically different in diverse periods of the year. Even though the analytical approach underlying this study relies on significant simplifications, which pose concerns for applications to ephemeral streams or large basins (> 10$^3$ km$^2$) and require a cautious approach to snow-dominated catchments, the proposed classification of flow regimes is deemed especially valuable. The diverse degree of flow variability of persistent and erratic flow regimes may have an impact on some key features of river ecosystems, particularly the temporal heterogeneity of habitat conditions and the river–floodplain connectivity, with significant implications for water quality and river food-web dynamics (25–31). The actual ability of stream biota to exploit riparian and riverbed resources may indeed be strongly influenced by the frequency and duration of low/high flows subsumed by the flow regime, notwithstanding the key role of geochemical, morphological, and biotic factors. In engineered rivers, the ability to characterize the underlying natural flow regimes can contribute to the assessment of the hydrological alteration produced by water infrastructures and the potential benefits of their decommissioning (32), thereby providing an objective support tool with which to embed environmental externalities in the definition of management strategies, services, prices, and incentives. The different sensitivity of erratic and persistent regimes may also bring important socioeconomic consequences, because the resilience of erratic regimes may contribute to buffer forthcoming changes of low flows in rivers with reduced water availability, thereby constraining the security of municipal, agricultural, and industrial water uses (5, 15). A proper classification of the flow regimes can also help to set targeted and flexible policy actions. For instance, minimum flow discharge prescriptions may not be suited to erratic regimes where, owing to the enhanced streamflow variability, any fixed minimum flow is typically disproportionate to the incoming flows during several weeks per season (being too small during high flows but too large under low-flow conditions). An objective characterization of flow regimes and their responsiveness to external forcing may thus offer important clues to the hydrology of freshwater ecosystems and the management of water resources.

Materials and Methods

Analytical Characterization of the Flow Regime. Daily stream flow dynamics are assumed to result from the superposition of a sequence of flow pulses triggered by precipitation, suitably censored by (catchment-scale) soil moisture dynamics. In particular, the sequence of streamflow-producing rainfall events during a given season is approximated by a Poisson process similar to the overall rainfall $(\lambda)$, characterized by frequency $\lambda$ and exponentially distributed depths (with mean $\alpha$). The reduced frequency of effective rainfall events $\lambda$ with respect to the precipitation frequency $\lambda_p$ (Eq. S3) expresses the ability of the soil to filter the rainfall forcing by exploiting some inputs to fill the soil–water deficit created by plant transpiration (thereby hindering the routing of these inputs). If subsurface environments are assumed to behave like a linear storage with rate constant $k$, each pulse determines a sudden increase of the stream flow followed by an exponential-like recession with rate $k$. Under these circumstances, the specific (per unit catchment area) discharge at time $t$, $Q(t)$, is expressed by:

$$Q(t) = \sum_{i=1}^{n} h_i \exp(-k(t-t_i)),$$

where the couples $(t_i, h_i)$ identify the arrival time and the depth of the $i$th pulse, and define a 2D Poisson process whose mean measure is $\mu(t)$ (Eq. S3). The steady-state pdf of the $k$th pulse, and rate parameter $r = ak$ (2, 3):

$$p_i(q) = \frac{\Gamma(n/k)}{\Gamma(2)} \frac{1}{2} \left( \frac{q}{\alpha} \right)^{n/k} \exp \left( -\frac{q}{\alpha} \right),$$

where $\Gamma(x)$ is the complete Gamma-function of argument $x$. Because the exponent of the power-law term in Eq. 2 is positive only for $x > k$, the shape of the river flow pdf is radically different in the two regimes (Fig. 1A): monotonic for erratic regimes ($\lambda < k$) and hump-shaped in the case of persistent regimes ($\lambda > k$). Eq. 2 is also able to explain the different degree of variability associated with erratic/persistent regimes. According to Eq. 2, the CV$_{O}$ can be analytically expressed as $\sqrt{\lambda/k}$ (SI Materials and Methods), implying that persistent regimes characterized by low erratic regimes are featured by a CV$_{O}$ > 1. Significant assumptions are required to derive Eqs. 1 and 2, which express analytically the pdf in terms of three physically based measurable parameters embedding rainfall, soil, vegetation, and morphological attributes of the contributing catchment. Most of these assumptions, however, can be suitably relaxed, allowing power-law recesions (34), spatial/temporal variables $k$ (3, 20), and heterogeneous rainfall/landscape attributes (3) to be tackled properly in the same framework. The above approach proved robust in predicting the observed streamflow pdfs in many temporary catchments under a variety of climate and morphological conditions (SI Materials and Methods). Model performances were satisfactory also in the catchments investigated in this study (Fig. S2).
Exposure to Climate Change and Regime Instability. The analyses allowed an objective estimate of the observed interannual variability of $\lambda$, $\alpha$, and $k$, and of the corresponding fluctuations of the shape and rate parameters that define the seasonal flow regime ($s = \lambda/k$ and $r = nk$). On this basis, we calculated the exposure to climate change in the catchment regimes. The exposure index $E$ is defined as the sum of the modulus of the relative variations of $s$ and $r$: $E = |\Delta s|/s + |\Delta r|/r$ (SI Materials and Methods). Note that according to the definition, the highest exposures are associated with the largest variations of the relevant hydroclimatic parameters, particularly the long-term changes of the ratio $\lambda/k$ (Fig. 2). Similarly, the interannual fluctuations of the river flow pdf were computed on the basis of the available discharge records through the $R_I$. The $R_I$ defines the fraction of probability shifting from one flow range to another in response to climatic fluctuations. Specifically, the $R_I$ between two subsequent periods (say, periods 1 and 2) characterized by the flow pdfs $\rho_1(Q)$ and $\rho_2(Q)$ is proportional to the area comprised between the two flow pdfs: $R_I = \int (\rho_1(Q) - \rho_2(Q))dQ/2$ (SI Materials and Methods and Fig. S5). The extreme cases $R_I = 0$ and $R_I = 1$, respectively, identify cases in which the flow regimes of the considered periods are perfectly overlapping and completely disjoint. The exposure and the regime instability were calculated for each combination of catchment/season (Fig. S6) at different time scales (namely, 2 and 8 y) and were then averaged to get the points shown in Fig. 3 A–C. Note that to reduce the scattering of the points, all the cases where $E < 0.1$ (5% of the cases analyzed) were excluded from the analysis (SI Materials and Methods).

Sensitivity. The sensitivity of the flow regime to climate change is computed as the ratio between the regime instability and the exposure: $S = R_I/E$. Reduced sensitivities identify the hydrological resilience of flow regimes. The sensitivity to climate change can be also characterized analytically through the stochastic analytical model embedded in Eq. 1, starting from the definition of regime instability and expressing the difference between the flow regimes in the two reference periods $[\rho_1(Q) - \rho_2(Q)]$ as a function of the underlying variations of $\lambda$, $\alpha$, and $k$ via a first-order Taylor expansion. If the observed changes of the shape and rate parameters of the flow pdfs ($\Delta s$ and $\Delta r$) have the same sign, the sensitivity can be expressed as ($SI$ Materials and Methods):

$$S = \frac{R_I}{E} = E_s = \int \left( \frac{\rho_1(Q)}{\rho_2(Q)} \right) \frac{|\Delta \rho(Q)|}{\rho_2(Q)} dQ + \left[ 1 - E_s \right] \int \left( \frac{\rho_1(Q)}{\rho_2(Q)} \right) \frac{|\Delta \rho(Q)|}{\rho_2(Q)} dQ,$$

where $E_s = |\Delta s|/s$ and $E_r = |\Delta r|/r$ represent the contribution provided by the variability of $\lambda/k$ and $r$, respectively, identified cases in which the flow regimes of the considered periods are perfectly overlapping and completely disjoint. The exposure index $E$ is defined as the sum of the modulus of the relative variations of $s$ and $r$: $E = |\Delta s|/s + |\Delta r|/r$ (SI Materials and Methods). Note that according to the definition, the highest exposures are associated with the largest variations of the relevant hydroclimatic parameters, particularly the long-term changes of the ratio $\lambda/k$ (Fig. 2). Similarly, the interannual fluctuations of the river flow pdf were computed on the basis of the available discharge records through the $R_I$. The $R_I$ defines the fraction of probability shifting from one flow range to another in response to climatic fluctuations. Specifically, the $R_I$ between two subsequent periods (say, periods 1 and 2) characterized by the flow pdfs $\rho_1(Q)$ and $\rho_2(Q)$ is proportional to the area comprised between the two flow pdfs: $R_I = \int (\rho_1(Q) - \rho_2(Q))dQ/2$ (SI Materials and Methods and Fig. S5). The extreme cases $R_I = 0$ and $R_I = 1$, respectively, identify cases in which the flow regimes of the considered periods are perfectly overlapping and completely disjoint. The exposure and the regime instability were calculated for each combination of catchment/season (Fig. S6) at different time scales (namely, 2 and 8 y) and were then averaged to get the points shown in Fig. 3 A–C. Note that to reduce the scattering of the points, all the cases where $E < 0.1$ (5% of the cases analyzed) were excluded from the analysis (SI Materials and Methods).

Supporting Information

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SI Materials and Methods
In this section, additional information is provided on the methods used in the paper to characterize the river flow regimes and their exposure/sensitivity to climate change.

Analytical Characterization of the Flow Regime. The basis of the analytical model on which the classification of flow regimes proposed in the paper is built is a stochastic description of daily stream flow dynamics, which are assumed to result from the superposition of a sequence of flow pulses triggered by precipitation. In particular, the sequence of streamflow-producing rainfall events during a given season is assumed to be a suitable subset of the overall rainfall. This subset, often termed excess precipitation, is created by the events bringing enough water to fill the soil–water deficit resulting from plant transpiration, driving the soil moisture in the unsaturated region above the field capacity. The overall rainfall forcing can typically be assimilated to a marked Poisson process with frequency $\lambda_p$ and to exponentially distributed depths with average $\alpha$ (1). As a consequence, the sequence of events producing streamflows can also be approximated by a zero-sum process similar to the main rainfall, although characterized by a reduced frequency, $\lambda < \lambda_p$ (2). The ratio $\lambda/\lambda_p$ expresses the ability of the near-surface soil moisture to filter the incoming rainfall forcing, and it can be analytically expressed as a function of climate, soil, and vegetation attributes (Eq. S3). When precipitation determines an excess of water in the root zone, such excess water is eliminated through the catchment hydrological response. If the subsurface catchment storage is assumed to behave like a linear reservoir with time constant $k$, each pulse determines a sudden increase of the stream flow followed by an exponential-like recession.

In mathematical terms, a pulse with an excess depth $h_i[L]$ released at time $t_i$ from the root zone provides a contribution to the overall specific (per unit catchment area) streamflow, $Q$, which is equal to $h_i k \exp\left[-k(t-t_i)\right]$. Hence, the instantaneous streamflow increment determined by the above water flow impulse at the time when the pulse is produced from the root zone (i.e., for $t = t_i$) is $kh_i$ (i.e., $k \times$ pulse depth). Provided that the system is linear, the overall streamflow is just the sum of the contribution of the different effective pulses taking place, and the presence of overlapping pulses does not change the recession time constant. Hence, the stochastic dynamical equation for $Q(t)$ at a daily time scale is (2):

$$\frac{dQ(t)}{dt} = -k Q(t) + \xi,$$

[S1]

where the first term on the right-hand side expresses the exponential decay of the flow between the events and the second term ($\xi[L/T^2]$) formally embeds the series of stochastic jumps induced on $Q$ by the sequence of flow pulses. Given the assumptions made on the pulse occurrences, the flow-producing events have instantaneous durations (i.e., $\xi$ is different from zero only during a set of finite times) and produce a sequence of positive jumps in the dynamics of $Q$. The “Poissonianity” of the events also implies that the interarrival times between these jumps are exponentially distributed with mean $1/\lambda$. Given the exponential distribution of the rainfall depths, the extents of the jumps experienced by $Q$ are random and exponentially distributed with mean $ka$ ($k \times$ pulse depth). Under these assumptions, the master equation associated with the probability density function (pdf) of the flow $Q$ at time $t$, $p(Q,t)$, reads (2, 3):

$$\frac{dp(Q,t)}{dt} = \frac{\partial}{\partial Q} \left[ Q p(Q,t) \right] - \lambda p(Q,t) + \frac{\lambda}{ak} \int_0^Q p(Q-z,t) \exp\left[-z/(\lambda k)\right] dz.$$ 

[S2]

The steady-state pdf of the specific river discharge is thus given by the solution of the master equation for $t \to \infty$, which leads to Eq. 2. The steady-state mean and variance of the process are $\lambda \alpha$ and $\lambda k \alpha$ (respectively), implying that the coefficient of variation of daily flows ($\text{CV}_Q$) is $\sqrt{k/\lambda}$. Despite the fact that some of the related hydrological processes are somewhat simplified (e.g., rainfall dynamics, hydrological response of the catchment) and other processes are completely disregarded (e.g., geomorphological and hydrodynamic dispersion in the river network), the above approach provides a robust linkage between the river flow regime and a few (directly measurable) rainfall and landscape attributes of the contributing catchment. The model was able to predict the observed frequency distribution of river discharges in many temperate catchments of the Alps and the United States successfully under a range of climate and morphological conditions (4, 5).

Catchment Selection. In this study, 44 different catchments with synchronous discharge and rainfall records were selected to analyze their flow regime and investigate the flow regime variability on different temporal scales. The study catchments are scattered throughout the United States and the Alps so as to cover a wide range of hydrological and climatic conditions. Thirty-two catchments are located in the United States, whereas the remaining watersheds are located in the Italian Alps. Hydrological and climatic records have been collected by the Regional Agency for Environmental Protection of the Veneto Region and by the US Geological Survey (http://waterdata.usgs.gov) and the National Climatic Data Center (http://cds.ncdc.noaa.gov/). The size of the catchments spanned one order of magnitude (from 10 to 10^5 km^2), a range within which the characterization of the flow regime through spatially averaged parameters proved meaningful (4, 5).

The seasons of the year were identified on the basis of calendar dates (spring: 03/01–05/31, summer: 06/01–08/31, fall: 09/01–11/30, and winter: 12/01–02/28). In the selection, highly engineered rivers characterized by anthropogenic regulation were excluded from the analysis, as well as snow-impacted regimes observed in cases of intense snow melting or accumulation. In particular, all the combinations of catchments/seasons for which the snow input was greater than 70% of the overall input (rain and snow) were assumed to be affected by snow accumulation processes and discarded. Similarly, cases in which the mean rainfall was found to be equal to (or smaller than) the mean streamflow were considered to be affected by melting processes and discarded. The overall number of catchments/seasons combinations considered in this study was 110. Additional information on the selected catchments and the datasets used is provided in Table S1.

Parameter Identification. The analytical model identifies three major parameters as the primary controls on the flow regime: (i) the recession time constant, $k$; (ii) the mean depth of rainfall events, $\alpha$; and (iii) the frequency of streamflow-producing events, $\lambda$. These three parameters could be estimated from hydrological and climatic data, as detailed below.

The mean depth of rainfall events, $\alpha$, can be computed from rainfall records as the observed mean daily depth during wet
days. The average frequency of streamflow-producing events, $\lambda$, can be estimated exploiting the crossing properties of soil moisture from the frequency of daily rainfall, $\lambda_P$, and other climate/soil/vegetation parameters (1, 6) as:

$$
\lambda = \frac{\eta \exp(-\beta^{-1})}{\Gamma(\lambda_P/\eta, \beta^{-1})},
$$

[33]

where $\eta(a, b)$ is the lower incomplete Gamma-function of parameters $a$ and $b$, whereas $\eta$ and $\beta$ are the mean transpiration rate and the mean rainfall depth (both normalized to the depth of water available to plants in the root zone), respectively. The parameter $k$, which represents the inverse of the time scale of the hydrograph, could be obtained through morphological and pedological features (e.g., by dividing the mean length of unchanneled paths by a scale velocity representing the mean hydraulic conductivity of subsurface environments).

However, to make the estimation of $\lambda$ and $k$ easier, and to allow for their calculation in case of missing landscape information, $\lambda$ and $k$ have been estimated in this paper by combining rainfall and streamflow data. In particular, $\lambda$ is estimated by equalling the observed mean specific discharge, $Q$, and the analytical mean of $Q$ according to the stochastic model (i.e., $\lambda = Q/\alpha$). The consistency of the estimate of $\lambda$ has been verified through the comparison of theoretical and observed pdfs and by comparing the estimated value of $\lambda$ with the rainfall frequency $\lambda_P$ (which is derived by comparing the probability distribution of the number of wet days in a reference time period and the corresponding Poisson pdf assumed by the rainfall model; Fig. S1A). Note that in Alpine catchments, to account for the marked heterogeneity of rainfall fields, rainfall analyses were performed using spatially averaged daily precipitation rates obtained by averaging the records available in all the precipitation stations located within or nearby the considered catchments. In the remaining study catchments, instead, due to the enhanced uniformity of rainfall and to exploit as much as possible the long-term flow records available, we considered only the station with the longest rainfall record among the available meteorological stations. The robustness of the estimate performed has then been verified a posteriori by comparing the estimates made using only one station and those obtained with multiple stations during selected periods in which synchronous precipitation measurements in different stations are available. The recession rate, $k$, is derived instead from observed streamflows through a regression analysis [i.e., a linear regression between the estimated temporal derivatives of $Q$ ($dQ/dt$) and the corresponding observed discharges (7)]. To exclude the effect of fast flows, which have a limited impact on the flow distribution (especially on daily time scales) but may significantly constrain the recession, only the discharges falling within the 0.9 quantile of the distribution are considered.

An example of the estimation procedure based on rainfall and discharge data for the Drowning Creek catchment is illustrated in Fig. S1. In particular, Fig. S1A compares the probability distribution of the number of wet days observed in a reference time period in a gauging station chosen among those used in the study and the corresponding Poisson pdf assumed by the rainfall model. The procedure is used to estimate the rainfall frequency, $\lambda_P$, which is used as a term of comparison for the estimated values of $\lambda$. Similarly, Fig. S1B shows the comparison between the observed distribution of the daily depths and the exponential distribution assumed by the analytical model. A relevant example of regression analysis is presented in Fig. S1C. Despite the observed scattering, which has an impact on only the higher order moments of the flow pdf (8), the procedure allowed an objective description of the heterogeneity in the hydrological response of the study catchments (Fig. 1).

To assess the robustness of the estimation procedure based on rainfall and streamflow data for a selected catchment chosen among the available sites (the Boite River at Cancia), we have performed an independent estimate of the parameters $\lambda$ and $k$ based only on climate and landscape data. In particular, $\lambda$ has been estimated by means of Eq. S3 using only climatic, soil, and soil-use data, which are necessary to calculate the parameters $\eta$ and $\beta$ (4). The soil parameters have been determined based on the literature (5), whereas the potential evapotranspiration rate, on which $\eta$ depends, has been obtained by multiplying a crop coefficient, $K_c$ (estimated on the basis of the soil cover), and the reference potential evapotranspiration estimated based on temperature data using the Blaney–Criddle equation. Furthermore, the interannual average of $k$ has been estimated as the ratio between the mean length of unchanneled paths (calculated from a digital terrain map) and the mean hydraulic conductivity (estimated based on the soil type distribution in the catchment). Then, the interannual variability of $k$ has been linked to the interannual variability of the mean rainfall intensity, assuming that $k$ is proportional to the corresponding mean rainfall depth during each period. Fig. S2 shows a comparison between the estimated values of the hydroclimatic parameters $\lambda$, $k$, and $\alpha$ obtained using climate and landscape attributes and those obtained from both rainfall and streamflow data. The two methods provide significantly similar results, also in terms of sensitivity, exposure, regime instability, and $\lambda/k$ ratio, reinforcing the robustness of the estimation method used in the paper.

**Model Performances.** The streamflow pdf predicted by the analytical model has then been compared with the observed frequency distribution of daily flows for all the selected combinations of catchments/seasons. The comparison has been undertaken for the whole period of record and for consecutive nonoverlapping periods of 2 and 8 y contained within each dataset. The parameters of the flow pdf have been estimated coherently from the available observations for each time span. Relevant examples of the fitting between the stochastic analytical model and the observed river flow pdfs are reported in Fig. S3. A summary of the model performances is shown in Fig. S3A through the pdf of the (percentage) integral error between the analytical and observed flow pdfs, calculated as the cumulative error in the probability, which is attributed by the analytical model to the $N$ intervals of amplitude, $\Delta Q$, used to characterize the frequency distribution of the observed flows:

$$
e = \frac{1}{2} \sum_{i=1}^{N} \left[ \frac{\Delta Q}{C12} \frac{\Gamma(\lambda/k, Q_i/(\Delta Q))}{\Gamma(\lambda/k)} - e(\Delta Q/(\Delta ak)) \right].$$

[41]

where $Q_i = 0$, $Q = Q_i + \Delta Q$ ($i > 1$), and $n_i$ represent the number of observed streamflows falling in the interval $[Q_i, Q_i + \Delta Q]$ (among the $m$ data available during the considered period). On the 8-y time scale, 90% of the cases analyzed are characterized by a percentage areal error, $e$, less than 30%. The performance of the model obviously decreases when shorter time spans are considered (60% of the cases with an error smaller than 30% for the 2-y regimes), possibly due to the limited ergodicity of the time series at those time scales. Overall, the performances of the model are judged satisfactory, especially in view of the simplicity of the model and the limited number of parameters (which were not calibrated but only calculated from available hydrological data). In selected case studies, in which both daily and subdaily flow data were available, we have also checked the robustness of the results obtained in the paper in comparison to the underlying temporal scale of the data used by comparing the pdf of the daily streamflow and the pdf of the streamflows evaluated at subdaily time scales. In none of the cases analyzed has the temporal resolution been found to have a significant impact on the result. As an example, Fig. S4 shows
the comparison between the daily and 15-min streamflow pdfs in the Flat Creek (NC), which is one of the smallest catchments considered in the study (and where the effect of subdaily streamflow dynamics is thus enhanced). Regardless of the season considered, and regardless of the type of regime, the observed impact of the temporal resolution of data on the flow pdf is negligible, reinforcing the robustness of the approach used in the study.

**Flow Regimes and Mean Specific Discharge.** Although the type of flow regime has been found to be almost independent of the underlying precipitation pattern, the nature of the regime is quite strongly correlated with the mean specific (per unit catchment area) discharge, \( \langle Q \rangle \). In particular, Fig. S5 shows that the mean specific discharge sensibly decreases with the CVQ, clearly suggesting that erratic regimes are infrequent in rivers with specific discharges larger than 0.1 \( \text{cm/d} \). On the other hand, a large majority of the cases where \( \langle Q \rangle < 0.1 \text{ cm/d} \) are found to be erratic (but not vice versa), thereby suggesting that low \( \langle Q \rangle \) may represent a sufficient but not necessary condition for the erraticity of the regime.

**Exposure Index.** According to the analytical model, the streamflow pdf is a Gamma-distribution with shape parameter \( s = \lambda/k \) and rate parameter \( r = \alpha k \). Hence, in this framework, the variability of the flow regime across different periods is related to the variability of the shape and rate parameters of the Gamma-pdf, which is, in turn, induced by the interannual fluctuations of \( \lambda, \alpha, \) and \( k \). Such fluctuations were found to be weakly correlated (\( \rho_{\lambda,\alpha} = 0.21 \), \( \rho_{\lambda,k} = 0.04 \), and \( \rho_{\alpha,k} = 0.31 \)) and quite significant at all the time scales, especially for the frequency of the events (with an average coefficient of variation of \( \lambda \) close to 0.96). On this basis, the exposure to climate change of the flow regime was estimated for each catchment and season through the exposure index (\( E \)), defined as the sum of the modulus of the relative variations of the shape and rate parameters of the Gamma-pdf in Eq. 2:

\[
E = \left| \frac{\Delta \lambda}{\lambda} \right| + \left| \frac{\Delta \alpha}{\alpha} \right| + \left| \frac{\Delta k}{k} \right|. \tag{S5}
\]

Eq. S5 incorporates the overall variability induced by hydroclimatic fluctuations in the ratio \( \lambda/k \) and in the product \( \alpha k \), properly discounting the self-compensating changes in the number, persistency, and intensity that maintain unaltered the flow pdf (e.g., simultaneous increases of \( \lambda \) and \( k \) maintaining unaltered the ratio \( \lambda/k \), and thus the type of regime). Note that the right-hand side of Eq. S5 is the sum of two moduli; hence, possible tradeoffs related to contrasting changes of the shape and rate parameters (e.g., \( r \) increasing and \( s \) decreasing) are not considered. The \( E \) has been computed for each catchment/season by calculating the relative variations of \( r \) and \( s \) across all the nonoverlapping groups of 2 and 8 y contained in the datasets. Note that for the analysis of the 8-y regimes, only catchments with at least 50 y of data were considered.

**Regime Instability Index.** The regime instability is quantified through the regime instability index (RI), which is defined by the integral of the modulus of the difference between the river flow pdfs pertaining to two distinct periods \([p_2(Q) \) and \( p_1(Q)]:

\[
RI = 0.5 \int_0^\infty |p_2(Q) - p_1(Q)| \, dQ. \tag{S6}
\]

The \( RI \) is thus bounded between 0 and 1, where \( RI = 0 \) implies that the flow regimes in the considered periods are perfectly overlapping (long-term stability of the flow regime) and \( RI = 1 \) implies disjoint river flow pdfs (a radical change of the flow regime, where all the flows recorded during the first period are not observed in the second period, and vice versa). The \( RI \) properly summarizes the volatility of the flow regime across different years, including high/low-flow frequencies, modal flows, and intraseasonal flow variability. Fluctuations in the temporal correlation of the flows are instead disregarded. The numerical computation of the \( RI \) from observed discharges poses serious challenges due to the strong dependence of the result on the integration interval, \( \Delta Q \). When \( \Delta Q \) is large, the \( RI \) is artificially small because of the enhanced smoothing of the resulting estimates of \( p_1 \) and \( p_2 \) (Fig. S6).

On the contrary, when the sampling interval \( \Delta Q \) is too small, the \( RI \) tends to be artificially large because of the huge fluctuations of the pdfs. To overcome this difficulty, we have computed the integral of Eq. S5 using a number of flow intervals, \( N \), ranging from 1 to 500. The behavior of the \( RI \) as a function of \( N \) has then been analyzed. For the reasons discussed above, the \( RI \) was generally found to be a growing function of \( N \); however, in most cases, it presents a stable plateau (i.e., similar values of \( RI \) within a range of \( N \)). The regime instability index \( RI \) is calculated as the average of the function \( RI(N) \) calculated within the observed plateau, thereby assuming that the independence of \( RI \) on \( N \) indicates that the corresponding \( \Delta Q \) values used for the numerical integration are large enough to limit the effect of fluctuations in the sampling of the flow pdfs but small enough to capture the behavior of the flow regimes in the two periods (Fig. S6). The cases where the function \( RI(N) \), after the application of a suitable moving average aimed at removing the high-frequency fluctuations, does not display a range of 50 consecutive values of \( N \) with nearly constant values of \( RI \) (at most \( \pm 5\% \) of the initial value) were disregarded. The procedure has been repeated for all the combinations of catchments/seasons and for all the periods of 2 and 8 y available in each dataset. Different ways of computing the integral in Eq. S6 (e.g., by using a fixed number of classes or classes with an amplitude proportional to the mean discharge) provide results that are qualitatively analogous to those shown in Fig. 3.

**Sensitivity to Climate Change.** The sensitivity, \( S \), of the flow regime to climate changes is computed as the ratio between the regime instability and the exposure. High sensitivities imply that the underlying hydroclimatic fluctuations produce amplified effects in the flow regime, with relevant changes in the frequencies associated with discharges of any size. It should be emphasized, however, that the regime instability cannot be entirely related to interannual fluctuations of the number, persistency, and mean intensity of the flow pulses. In fact, regime instability may also arise due to, for example, changes in the temporal distribution of the events, lack of ergodicity within the considered periods, and interannual variability of processes that are not explicitly included in the analytical model. As a result, in a few cases, the calculated value of the \( RI \) was found to be much larger than the corresponding exposure (mainly because of the constancy of \( \lambda, \alpha, \) and \( k \)). This leads to overestimated values of the sensitivity, which, however, mirror only the circumstantial stability of \( \lambda, \alpha, \) and \( k \) and emphasize the role of second-order processes (e.g., episodic snowfalls, untracked changes in the stage-discharge relation) whose effect on the flow regime is typically beclouded. To focus on the role played by the interannual fluctuations of the number, persistency, and mean intensity of the flow pulses, we have thus disregarded all the cases in which the estimated exposure was lower than 0.1, assuming that the related estimates of the sensitivity could not be reliable below this threshold. Were these points included, the main conclusions of the paper would remain unaltered, with the major consequence being an increased scattering of the points in Fig. 3C. The sensitivity of the flow regime to climate changes can also be characterized analytically using the stochastic analytical model embedded in Eq. 2.

The change of probability density associated with any discharge of size \( Q \) (between the periods 1 and 2) can be approximated using a first-order Taylor series expansion as:

\[
\Delta p(Q) \approx \frac{\partial p}{\partial Q} \Delta Q + \frac{\partial p}{\partial R} \Delta R. \tag{S7}
\]
where $\Delta r$ and $\Delta s$ are the variations of shape and rate parameters of the flow pdf in the considered periods. Hence, the $RI$ can be expressed using Eqs. S6 and S7 as:

$$RI = 0.5 \int_0^\infty |\Delta p(Q)|dQ \simeq$$

$$0.5 \int_0^\infty |\Delta s \left( \frac{\partial p(Q)}{\partial s} \right) + \Delta r \left( \frac{\partial p(Q)}{\partial r} \right)|dQ. \quad [S8]$$

If we further assume that the functions $\frac{\partial p}{\partial s}$ and $\frac{\partial p}{\partial r}$ have the same sign for all the values of $Q$ (which proves nearly true in most cases), and if we focus only on the cases where the changes of $s$ and $r$ are in concordance (so that $\Delta s$ and $\Delta r$ have the same sign), Eq. S8 can be rewritten as follows:

$$RI \simeq \frac{\Delta s}{s} \int_0^\infty \left[ \frac{s}{2} \left| \frac{\partial p(Q)}{\partial s} \right| - \frac{\Delta r}{r} \left| \frac{\partial p(Q)}{\partial r} \right| \right]dQ +$$

$$\int_0^\infty \left[ \frac{s}{2} \left| \frac{\partial p(Q)}{\partial s} \right| - \frac{\Delta r}{r} \left| \frac{\partial p(Q)}{\partial r} \right| \right]dQ +$$

$$\left[ \frac{\Delta s}{s} f_s(s) + \frac{\Delta r}{r} f_r(s), \right]. \quad [S9]$$

where $f_s(s)$ and $f_r(s)$ are suitable dimensionless functions of the ratio $\lambda/k$, whose analytical expressions are given by:

$$f_s(s) = \frac{\exp(-s)s^3}{\Gamma(s)}, \quad [S10]$$

$$f_r(s) = \frac{s}{2} \left( \frac{\psi_0(s)}{\Gamma(s)} \right) C_{2,3}^{\lambda,0} \left( \psi_0(s) \frac{1, 1}{0, s} \right). \quad [S11]$$

where $\psi_0(s)$ is the Digamma-function and $G$ is the Meijer G-function. From Eq. S9, the following expression of the sensitivity is finally obtained:

$$S = \frac{RI}{E} = E_f(s) + \left[ 1 - E_f(s) \right] f_s(s), \quad [S12]$$

where $E_f = |\Delta s|/(sE)$ represents the contribution of the variability of $\lambda/k$ to the overall exposure. Eq. S12 shows that the sensitivity is a weighted average of $f_s$ and $f_r$, which are both monotonic increasing functions of $s$.

**Hypothesis Testing.** The diverse degree of exposure and sensitivity of the two regime types has been quantitatively assessed using some hypothesis testing based on the distribution of the values of $E$ and $S$ of the cases classified as persistent and erratic (intermediate regimes have been excluded from the analysis). We first tested the hypothesis of normality of the two samples using a Lilliefor test, which was indeed accepted at the 5% significance level for both of the variables ($E$) and ($S$) at both of the considered time scales (2 and 8 y). Then, a standard $t$ test was used to assess the different mean sensitivity and exposure of the two groups. The test was performed formulating the null hypothesis that $E$ and $S$ in erratic and persistent regimes have the same mean with unknown variances. For all the cases analyzed, the null hypothesis was rejected at $P < 0.05$, thereby implying that the exposure ($E$) and the sensitivity ($S$) of erratic and persistent rivers are statistically different (Fig. 3).

**SI Discussion**

Eqs. S10–S12 show that sensitivity is mainly a function of the ratio $s=\lambda/k$, implying that the sensitivity is directly related to the in-traseasonal flow variability, $CV_Q = s^{-1/2}$, as also suggested by observational data. Fig. 3C (Inset) shows a comparison between the observed sensitivity between all the pairs of 2-y periods characterized by concordant changes of $s$ and $r$, and the theoretical lines given by Eqs. S10 and S11, where $s$ is expressed as a function of $CV_Q$ via $s = CV_Q^{-2}$. Despite the scattering of the data, the agreement with the theoretical pattern is remarkable. The observed reduced sensitivity to climate change of erratic flow regimes is thus also explained theoretically by the nature of the frequency distribution of river flows. The reduced sensitivity of erratic regimes can also be explained on physical grounds as follows. The reduced flow variability associated with persistent regimes is guaranteed by the occurrence of a sufficient number of events bringing a suitably continuous water supply to the river. As such, persistent regimes are more sensitive to changes in precipitation features $\lambda, \alpha$ with respect to erratic regimes, where the presence of stream water is primarily related to the ability of catchments to modulate the release of water stored in the subsurface. Hence, erratic regimes are more sensitive to changes in the features of the hydrological response, $k$. Any variation of $k$, however, entails a simultaneous and concordant change in the shape and rate parameters of the flow pdf, leading to a tradeoff that decreases the variability of the flow pdf and reduces the $RI$. 

Fig. S1. Parameter identification. (A) Comparison between the pdf of the number of rainy days $p(W)$ in a reference time span, $T = 10$ d, observed at the gauging station of Jackson Springs during the spring from 1985 to 1992 (histogram) and the corresponding Poisson distribution assumed by the analytical model (red dots). The vertical dashed line indicates the mean number of wet days within the reference time period, $\lambda_\text{p} T$. (B) Comparison between the distribution of the daily rainfall depths $p(h)$ observed at the gauging station of Jackson Springs during the spring from 1985 to 1992 (histogram) and the exponential distribution assumed by the analytical model (red solid line). The mean rainfall depth, $\alpha$, is also indicated (vertical dashed line). (C) Regression analysis of the streamflows observed in Drowning Creek during the spring season of the years 2001–2008. The flow decay rate, $k$, is derived from observed streamflows by a linear regression of the estimated temporal derivatives of $Q$ ($dQ/dt$) plotted vs. the corresponding observed discharges $Q$ (6).

Fig. S2. Comparison of model parameter estimates using different methods. (A) Temporal evolution of the parameters $\lambda$, $k$, and $\alpha$ estimated based on climate and landscape information (solid lines) compared with the corresponding estimate made using rainfall and streamflow data (dashed lines) for the Boite catchment at Cancia. (B) Comparison between the estimates of $\lambda/k$, $E$, the $R_I$, and sensitivity ($S$), which result from the use of rainfall and streamflow data (red histograms), and the corresponding values estimated based on climatic and landscape data (blue histograms).
Fig. S3. Model performances. (A) Frequency distribution of the error estimated for all the combinations of catchments/seasons and for all the available nonoverlapping periods of 2 and 8 y contained within each dataset. (B–G) Comparison between the observed streamflow distributions (histograms) and the corresponding estimates of $p(Q)$ provided by the analytical model (red lines) for selected combinations of catchments/seasons and different time scales (2-y and 8-y regimes). (B) Fall streamflow regime of the Big Eau Pleine River at Stratford from 1989 to 1996. (C) Summer streamflow regime of the Boite River at Cancia from 1986 to 1993. (D) Summer streamflow regime of the Bear Butte Creek at Deadwood from 1989 to 1996. (E) Summer streamflow regime of the Piave River at Ponte della Lasta from 1998 to 2005. (F) Fall streamflow regime of the Youghiogheny River at Oakland from 1961 to 1962. (G) Spring streamflow regime of the Deer Creek at Fountain Springs from 1979 to 1980.
Fig. S4. Daily and 15-min streamflow distributions in the Flat Creek (NC) during the fall (A and B) and the spring (C and D), evaluated during two different time periods (2008–2009 and 2010–2011).

Fig. S5. Anticorrelation between mean specific discharge and intraseasonal flow variability. Mean specific (per unit area) discharge, plotted as a function of the $CV_{Q}$ for each available combination of catchments/seasons. The dashed line indicates the least-squared regression (slope = 0.9, $r^2 = 0.3$). The plot suggests that erratic regimes are infrequent in rivers with high specific discharges.
Fig. S6. Computation of the regime instability. Springtime $RI$ observed between the periods 1979–1986 and 1987–1994 in the Rivanna River as a function of the number of flow intervals, $N$, used to compute the streamflow probability distributions (Eq. S6). (Left Inset) When $N$ is small, the $RI$ is artificially small because of the enhanced smoothing of the estimated pdf. (Right Inset) On the contrary, when too many intervals are used, the $RI$ is artificially large because of the increased number of intersections between the two pdf estimates produced by their enhanced fluctuations. (Middle Inset) Presence of a plateau in the function $RI(N)$ allows one to single out the proper value for the regime instability between the considered periods.
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<td>Hibbing (MN)</td>
<td>Spring, summer, autumn</td>
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<td>Castor River</td>
<td>Missouri (United States)</td>
<td>1,096</td>
<td>1936–1991</td>
<td>Zalma (MO)</td>
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<td>Spring, summer, autumn, winter</td>
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<td>Salt Creek</td>
<td>Nebraska (United States)</td>
<td>433</td>
<td>1953–2002</td>
<td>Roca (NE)</td>
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<td>Spring, summer, autumn</td>
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<td>Gallinas Creek</td>
<td>New Mexico (United States)</td>
<td>218</td>
<td>1990–1999</td>
<td>Montezuma (NM)</td>
<td>Wesner Springs (NM)</td>
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<td>Rio Nutria</td>
<td>New Mexico (United States)</td>
<td>185</td>
<td>1972–1995</td>
<td>Ramah (NM)</td>
<td>McGaffey (NM)</td>
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<td>Drowning Creek</td>
<td>North Carolina (United States)</td>
<td>474</td>
<td>1952–2012</td>
<td>Hoffmann (NC)</td>
<td>Jackson Springs (NC)</td>
<td>Spring, spring, autumn, winter</td>
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<td>Fiat Creek</td>
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<td>20</td>
<td>1989–2012</td>
<td>Inverness (NC)</td>
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<td>Indian Creek</td>
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<td>179</td>
<td>1953–2012</td>
<td>Laboratory (NC)</td>
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<td>Jacob Fork</td>
<td>North Carolina (United States)</td>
<td>67</td>
<td>1961–2012</td>
<td>Ramsey (NC)</td>
<td>Casar (NC)</td>
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<td>Lookingglass Creek</td>
<td>Oregon (United States)</td>
<td>409</td>
<td>1955–1998</td>
<td>Brockway (OR)</td>
<td>Reston (OR)</td>
<td>Spring, summer, autumn</td>
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<tr>
<td>Bear Butte Creek</td>
<td>South Dakota (United States)</td>
<td>43</td>
<td>1988–2011</td>
<td>Deadwood (SD)</td>
<td>Deadwood (SD)</td>
<td>Spring, summer, autumn</td>
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<td>Spring Creek</td>
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<td>159</td>
<td>1983–1993</td>
<td>Flandreau (SD)</td>
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<tr>
<td>Cowhouse Creek</td>
<td>Texas (United States)</td>
<td>1,178</td>
<td>1992–2007</td>
<td>Pidcock (TX)</td>
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<td>Redgate Creek</td>
<td>Texas (United States)</td>
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<td>1962–2012</td>
<td>Columbus (TX)</td>
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<td>Santa Clara River</td>
<td>Utah (United States)</td>
<td>48</td>
<td>2005–2012</td>
<td>Pine Valley (UT)</td>
<td>Gardner Peak (UT)</td>
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<td>Virginia (United States)</td>
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<td>Palmyra (VA)</td>
<td>Charlottsville (VA)</td>
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<td>Rock Creek</td>
<td>Washington (United States)</td>
<td>64</td>
<td>1944–1971</td>
<td>Cedarville (WA)</td>
<td>Elma (WA)</td>
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<td>Sand Run</td>
<td>West Virginia (United States)</td>
<td>37</td>
<td>1946–2012</td>
<td>Buckhannon (WV)</td>
<td>Buckhannon (WV)</td>
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<td>Wisconsin (United States)</td>
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<td>1949–2012</td>
<td>Stratford (WI)</td>
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<td>Wyoming (United States)</td>
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<td>1980–2011</td>
<td>Shell (WY)</td>
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<td>Italy</td>
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<td>1995–2010</td>
<td>Borgo Valsugana</td>
<td>Vetrilo, Canenza, Levico, Telve di Sopra, Rifugio Cruscolo, Longana</td>
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<td>1995–2010</td>
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<td>Italy</td>
<td>82</td>
<td>1992–2008</td>
<td>Podestagno</td>
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<td>Catchment</td>
<td>State (country)</td>
<td>Area, km²</td>
<td>Period</td>
<td>Streamflow gauging station (state)</td>
<td>Rainfall gauging stations (state)</td>
<td>Seasons</td>
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<td>313</td>
<td>1986–2008</td>
<td>Cancia</td>
<td>Podestagno, Faloria, Borca, Cortina</td>
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<td>Trento</td>
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<td>130</td>
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<td>355</td>
<td>1990–2006</td>
<td>Ponte della Lasta</td>
<td>Passo Monte Croce Comelico, Malga Campobon, Santo Stefano di Cadore, Casamazzagno, Costalta, Cimacanale, Sappada</td>
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<td>1986–2007</td>
<td>Feltre</td>
<td>Monte Avena, Feltre</td>
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