



Strength and persistence of streamflow memory across Europe

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5 **Abstract.** Streamflow is typically autocorrelated, although the strength of this memory varies through time and between catchments. The degree to which prior conditions influence streamflow informs how we predict future streamflow and can drive temporal clustering of hydrological extremes. We introduce memory decay curves, which are exponential decay functions that summarize streamflow autocorrelation over time lags from one month to three years. These curves can be summarized using two parameters: initial memory and memory half-life. We fit these memory decay curves to weekly
10 streamflow data from 9352 stations across Europe for the years 1980–2021 and identify four archetypes based on the combination of strong (or weak) initial memory and long (or short) memory half-life. These archetypes show distinct geographic patterns across Europe, with strong and long memory most common in regions with large aquifers or deep bedrock, including the Paris Basin and parts of Poland and eastern Germany. Weak, short-lived memory is widespread, especially in humid catchments. Streamflow memory, empirically and conceptually, relates to existing streamflow signatures – including
15 the baseflow index and coefficient of variation – but explicitly represents memory across multiple timescales. This memory primarily originates through catchment processes rather than memory of meteorological forcing because the latter is generally weaker than and geographically unaligned with streamflow memory. Streamflow memory at monthly to yearly time steps consistently empirically links to climate characteristics, whereas memory more strongly connects to surface features at shorter timescales and to subsurface features at longer timescales. We compare memory of streamflow predictions from two
20 hydrological models (mHM and EFAS) and find that modelled streamflow, on average, has weaker monthly memory but stronger yearly memory compared to observed streamflow. There also exist large regional variations in memory between models and between models and observations leading to both over- and under-estimations of memory. The streamflow memory decay curves presented here bridge commonly studied event and annual timescales in streamflow autocorrelation. Moreover, they identify regionally distinct memory behaviours across multiple timescales, which can help advance process understanding
25 and hydrological modelling.



1 Introduction

Understanding and predicting the dynamics of river flow is essential for water resource management and for adaptation and mitigation of floods and droughts (Brunner et al., 2021). Antecedent conditions play an important role in present and future streamflow rates. Particularly at short timescales, near-future streamflow rates are highly dependent on current conditions. The strength and timescale of this dependence – or “memory” – varies between rivers: in very flashy headwater streams memory may dissipate in minutes, whereas in some rivers this memory may persist for months or even years (Alvarez-Garretón et al., 2021; Golden et al., 2025). The degree to which rivers “remember” these antecedent conditions can be understood as the ability of a river to buffer hydrological variability and as the degree to which anomalous conditions persist. The processes causing this memory can therefore influence the frequency of floods or droughts, drive temporal clustering of hydrological extremes (Merz et al., 2016), affect the resilience of rivers to climatic fluctuations (Botter et al., 2013) and drought (Alvarez-Garretón et al., 2021; Marcinkowski, 2026), and help to sustain human and ecological systems (Scanlon et al., 2023).

Antecedent catchment conditions including groundwater levels, soil moisture, and river discharge, play key roles in determining how a catchment responds to precipitation at timescales of hours (Knapp et al., 2025), days (Berghuijs and Slater, 2023; Sharma and Mujumdar, 2024), and weeks or months (Rateb et al., 2024; Shukla et al., 2013; Bertola et al., 2021). These conditions can impact individual events at short timescales and often lead to temporal clustering and memory at longer timescales. Seasonal persistence of streamflow exists in European rivers for both high- and low-flow seasons, with the latter more strongly correlated to streamflow in prior months (Iliopoulou et al., 2019). Merz et al. (2016) showed that most German rivers display yearly and multi-annual clustering of floods, with stronger temporal clustering for lower flood severity thresholds. Berghuijs et al. (2025) demonstrated the strength of annual memory in terrestrial water storage, evaporation, and streamflow globally, and suggested that hysteretic drainage dynamics are needed to model this multi-annual memory. Multi-annual hydrological memory has been identified in lake levels (Leader et al., 2024), and decadal streamflow trends have been shown across the world (Grigg and Hughes, 2018; Hurst, 1951; Blöschl et al., 2020; Chagas et al., 2024).

Streamflow memory can be influenced by surface characteristics such as the structure of the river network or topography (Gnann et al., 2025; Mudelsee, 2007; Basso et al., 2023), as well as by subsurface characteristics such as soil moisture memory (Ghannam et al., 2016; Orth and Seneviratne, 2013), the relationship between soil moisture and vegetation (Fan et al., 2017), and groundwater levels (Lo and Famiglietti, 2010). Thompson and Katul (2012) conducted spectral analysis of streamflow time series for eight rivers in the eastern US and found that daily frequencies were most related to landscape and hydrologic functioning, whereas climate appeared to drive seasonal and longer frequencies. When studying urban rivers near Berlin (Germany), López Moreira Mazacotte et al. (2025) found that climate and river discharge were correlated at 6–12 month frequencies, but that groundwater trends were important at scales of 1–6 years, particularly during dry years. Shukla et al. (2013) found that the runoff and soil moisture prediction accuracies in Europe were more often influenced by initial



60 hydrological conditions at a one-month lead time, but dominated by climate forecast skill after six months. Candogan Yossef
et al. (2013) also identified initial hydrological conditions as generally influencing streamflow forecast skill in parts of Europe
at timescales of 1-2 months. Studies at European and Swiss scales have identified initial hydrological conditions as dominant
sources of skill for seasonal streamflow forecasts (Bierkens and Van Beek, 2009; Staudinger and Seibert, 2014; Greuell et al.,
2019). Across these studies, the presence of snowmelt and large groundwater stores increased hydrologic predictability and
65 persistence.

Despite the demonstrated presence of memory in hydrological systems, models tend to poorly represent these memory
dynamics, especially at longer timescales. Comparison of both hydrological and land surface models to trends from Gravity
Recovery and Climate Experiment (GRACE) data in total terrestrial water storage shows that models underestimate changes
70 at decadal timescales and have difficulty reproducing seasonal fluctuations. This particularly occurs where those models have
insufficient ground- or soil-water storage, or where delayed processes like river flooding and storage are excluded entirely
(Scanlon et al., 2018; Scanlon et al., 2019). When studying the Millennium drought in Australia, Fowler et al. (2020) found
that long and slow dynamics were not represented in commonly used rainfall-runoff models, leading to poor hydrological
predictions during anomalous multiyear conditions. This is of particular concern when considering how to model future
75 conditions under climate change, especially when these future conditions are outside the climatic and hydrological range of
calibration periods. Models of groundwater depth show great uncertainty (Reinecke et al., 2024), and hydrological models
tend to underestimate the role of groundwater recharge and discharge in the hydrological cycle (Berghuijs et al., 2022; Gnan
et al., 2023), despite the importance of groundwater in sustaining river flow (Xie et al., 2024). Moreover, typical metrics used
to evaluate models can show high levels of accuracy despite missing interannual dynamics, particularly in highly seasonal
80 systems (Ruzzante et al., 2026). De Lavenne et al. (2022) demonstrated that including multi-annual memory improves
understanding of catchment elasticity in France and Sweden, showing that consideration of hydrological memory can improve
our understanding of hydrological functioning.

We introduce *memory decay curves* as an approach to quantify streamflow memory dynamics at multiple timescales across
85 thousands of catchments using an exponential decay function. We apply these *memory decay curves* to streamflow
measurements from 9352 gauging stations across Europe to characterize how strongly streamflow is autocorrelated at lag times
of months to years, thereby bridging the more commonly studied short-term (e.g. event-based) and long-term (e.g. annual)
timescales in streamflow autocorrelation (Euser et al., 2013; Zhang et al., 2022; Berghuijs et al., 2025; Merz et al., 2016;
Andrés-Doménech et al., 2015; Brooks et al., 2021). These decay functions can be summarized by their initial strength and
90 their persistence of memory, which we use to identify distinct geographic patterns of streamflow memory across Europe. We
examine potential drivers of streamflow memory at multiple timescales and identify relationships to catchment attributes
including climate characteristics, surface features, and subsurface catchment structure. We also compare this observation-
based streamflow memory to the memory of modelled streamflow for Europe to understand how well these dynamics are



represented in modelled data. The memory decay curves presented in this study demonstrate the presence of hydrologic
 95 memory in European catchments at timescales from months to years and can improve the understanding and prediction of
 streamflow dynamics.

2 Methods

2.1 Data

Streamflow time series are from the EStreams pan-European dataset v1.4 (Do Nascimento et al., 2024). EStreams provides
 100 weekly mean streamflow values in mm/day for 17,130 gauging stations across Europe, along with catchment polygons and
 catchment attribute information. We filtered these catchments based on the following requirements: a minimum of 15 years of
 data during the period 1980–2024; removal of catchments with a long-term runoff ratio greater than 1.5; and visual inspection
 of hydrographs to remove those with probable data errors or shifts in anthropogenic influence (e.g. dam construction or mine
 filling upstream during the period of study). The remaining 9352 catchments range in size from 0.56 km² to 1.37 million km²
 105 and are located across different European geographic and climatic regions, with the highest concentrations of stations in France,
 Germany, Denmark, and Great Britain. The EStreams dataset also provides corresponding time series of climate data from E-
 OBS for each station (Cornes et al., 2018).

We combined the catchment characteristics in EStreams with data from the Global Lakes and Wetlands Database (GLWD v2)
 110 (Lehner et al., 2025), which provides gridded distributions of 33 distinct waterbody and wetland classes as sub-pixel
 percentages at 15 arc-second resolution. Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation (FPAR)
 were obtained from MODIS data for the years 2002–2021 (Myneni et al., 2021), and nighttime light intensity from VIIRS data
 for the years 2012–2019 (Elvidge et al., 2021)

Modelled discharge time series are from the mesoscale Hydrologic Model (mHM) and from the European Flood Awareness
 System (EFAS). Although it is not explicitly designed for drought prediction, mHM is most frequently used to model droughts
 and low flows (Addor and Melsen, 2019), whereas EFAS is explicitly designed for flood prediction. MHM is a process-based,
 spatially distributed hydrologic model (Samaniego et al., 2010). We used the results from the 4DHydro data catalogue
 (Droppers et al., 2024), which provides a reference dataset of land surface and hydrologic model simulations. The mHM model
 120 simulation for Europe uses forcing data from E-OBS and provides daily discharge estimates from 1990–2021 at 0.125-degree
 resolution. We use the EFAS historical simulation discharge data (Mazzetti et al., 2023), which is produced using the spatially
 distributed rainfall-runoff model LISFLOOD, and forced with climate observations to produce historical discharge time series.
 Version 5.0 of this data is produced at a 1 arc-minute resolution and 6-hourly timestep, from 1992 to present; we used data for
 the period 1992–2022. We aggregated both discharge datasets to a weekly temporal resolution in alignment with EStreams.



2.2 Memory decay curves

We define *memory decay curves* using the two parameters of the exponential decay curve to describe streamflow memory at timescales of one month to three years (i.e. 4–160 weeks) using the initial monthly memory (M_m [-]) and memory decay rate (β [weeks⁻¹]) (Eq. (1)). Rather than directly referring to β , we instead use the memory half-life ($t_{1/2}$ [weeks]) obtained from β (Eq. (2)). The combination of initial strength and memory half-life provides four archetypes representing the different combinations of strong or weak initial memory combined with long or short memory half-life.

$$M(t) = M_m e^{-\beta(t')} \quad (1)$$

$$t_{1/2} = \frac{\ln(2)}{\beta} \quad (2)$$

These memory decay curves describe the autocorrelation present in a streamflow time series. However, unlike typical autocorrelation functions these memory decay curves do not begin at a time lag of 0 with a uniform autocorrelation of 1. Instead, the decay curves begin at a target initial timestep and consequently with station-specific initial autocorrelation values less than 1. In our calculations using weekly data, M_m describes the degree of autocorrelation at the initial monthly (i.e. 4-week) timescale and t' (Eq. (1)) is the difference between lag t in weeks and the initial 4-week lag. This approach can be applied to different timescales or to data at other timesteps (i.e. daily or monthly) provided that the definitions of M_m and t' are modified to reflect the underlying data.

2.2.1 Calculation of memory decay curves

We calculated streamflow memory for each EStreams gauging station based on time series autocorrelation of that station's weekly mean streamflow anomaly. All memory calculations were performed for individual stations; that is, we compare the streamflow values at a single station to these same values in the past weeks and months. We also used these memory decay curves to calculate how much memory exists at selected timescales (4 weeks, 12 weeks, 26 weeks, 52 weeks, and 104 weeks) at each station. The process of calculating memory decay curves is the same for all variables, including measured streamflow, modelled streamflow, and climate variables. Here, we describe the process of calculating a memory decay curve for streamflow measurements from a single EStreams station, although the process is identical for all other variables.

We used the weekly streamflow time series (Fig. 1a) to calculate the station's long-term average annual cycle (i.e. mean streamflow values for each day of the year). We resampled this time series to create a time series of daily mean streamflow using all non-null weekly mean values. We calculated long-term average intra-annual cycle using a geometric mean to dampen outlier values. For the geometric mean calculations, we replaced all non-null zero values with values of 0.0001mm/day. We then smoothed this intra-annual cycle with a 3-day rolling mean to minimize fluctuations and produce an average streamflow value for each day of the year (Fig. 1b). We then used the average intra-annual cycle to remove the influence of seasonality by subtracting the values of the average intra-annual cycle from the weekly streamflow values (Fig. 1c). This produced a time series of weekly streamflow anomalies Fig. 1d), which were used for all proceeding memory calculations.



We calculated autocorrelations of the weekly streamflow anomaly time series beginning with *lag 4* (i.e., autocorrelation after roughly one month; Fig. 1e) and continuing to *lag 160* (i.e. roughly three years after the initial 4-week lag). Beginning the calculations at lag 4 removed the strong immediate autocorrelation inherent in most hydrologic systems, thus allowing the memory decay curves to more closely fit the autocorrelation values at the target timescales. Using the autocorrelations beginning at lag 0 or lag 1 would emphasize shorter-term streamflow memory dynamics whereas our aim is to understand streamflow memory at longer (monthly to multi-annual) timescales.

We fitted an exponential decay function to these three years of autocorrelation values (Fig. 1f) using least squares (Branch et al., 1999; Virtanen et al., 2020). This exponential decay curve (*memory decay curve*) determines two key parameters to understand streamflow memory: the initial memory M_m [-] and persistence β [t^{-1}], from which we obtain the memory half-life.

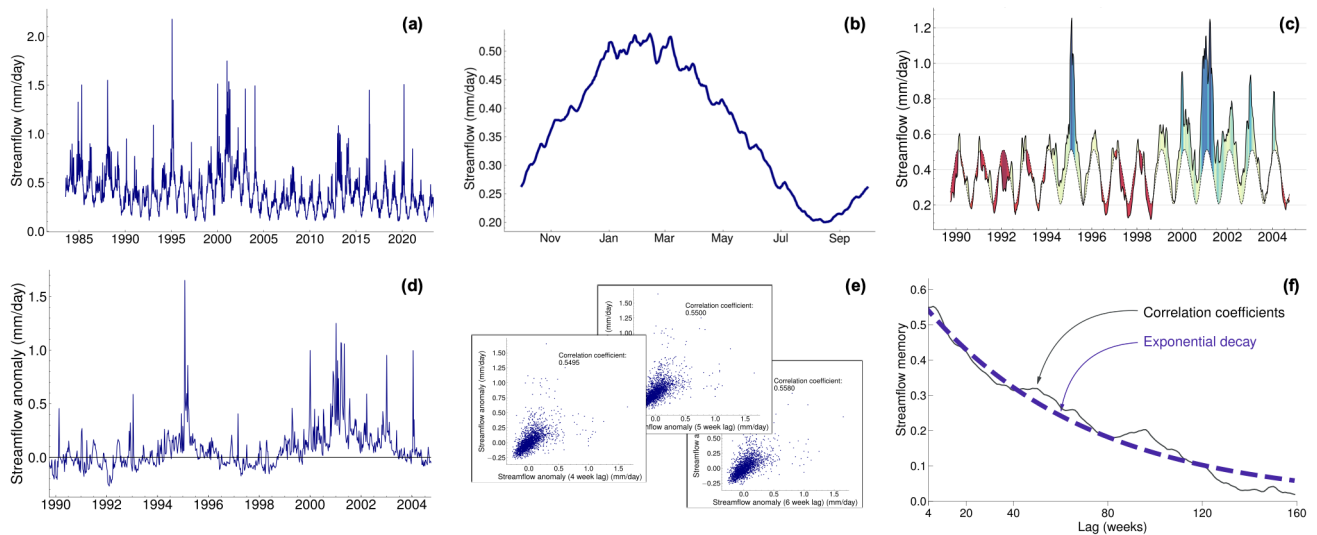


Figure 1. Calculation of streamflow memory for a selected catchment in France. From the station's time series of weekly mean streamflow (a) we derive the average annual streamflow cycle (b) and then use this to produce a time series of streamflow anomalies (c, d). In panel (c), red shades indicate streamflow values below average for that time of year, and blue shades indicate streamflow values above average. Beginning at a 4-week lag, we calculate the autocorrelation of this anomaly time series (e) and repeat this at weekly timesteps up to and including 160 weeks (i.e. total three years of autocorrelations). We then fit an exponential decay curve to this series of autocorrelation values (f).

2.3 Memory decay curves for additional variables

We used the same methods as above to calculate the memory decay curves of additional time series data for the same EStreams stations. Climate data are provided in EStreams v1.4 for each station at a daily timestep derived from E-OBS 0.1-degree resolution data. We used the temperature and E_p (Penman-Monteith method) time series as provided by EStreams, and we estimated combined rainfall and snowmelt for each station from the daily mean temperature and daily precipitation values

from EStreams using a simple day-degree model with a temperature threshold of 1°C. For only the precipitation time series, we then created a smoothed time series using a backwards 4-week rolling mean to reduce the larger variability of precipitation compared to other variables.

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We used the EStreams catchment polygons to extract the mean LAI and FPAR values derived from MODIS data (Myneni et al., 2021) for each EStreams catchment polygon in Google Earth Engine. These catchment averages were calculated at the original 4-day time step of the MODIS data to produce a time series for each vegetation index.

190 For comparison with modelled discharge, we matched EStreams gauging stations to gridded discharge data from both EFAS and mHM. For each model, we first extracted the upstream area of the grid cell containing each EStreams point. Following the approach of EStreams, we allowed a $\pm 10\%$ difference between either the measured or reported EStreams catchment area and the model's upstream catchment area value. If there were multiple EStreams points within a single grid cell, we allowed that grid cell to match multiple stations, provided that the area criteria were met. This method produced matches for 1,346 EStreams
 195 catchments with their underlying mHM grid cells, with sizes from 80 km² to 786,297 km². For the higher resolution EFAS data, 6,763 EStreams catchments matched their underlying grid cells, with sizes from 4 km² to 786,297 km². We then extracted the discharge time series for each selected EStreams point from the gridded simulation results and converted the discharge values from both models to specific discharge using that model's upstream catchment area.

200 We resampled all climate, vegetation, and modelled discharge time series from their original temporal resolutions to match the weekly time step of the EStreams streamflow data. We then used the same approach described in Sec. 2.2.1 to calculate memory decay curves for each variable. In all cases, we used the same target timescales of 4–160 weeks.

2.4 Analysis of catchment characteristics

Most catchment attribute data come from the EStreams database, which provides both static and dynamic attributes for each
 205 catchment. We used the EStreams catchment boundaries to calculate the percent catchment area covered by each of the GLWD v2 wetland and waterbody classes. These classes were then grouped to produce relevant types (Table S1). We calculated the average nighttime light intensity across each catchment using annual data for the years 2013–2022 (Elvidge et al., 2021). We also averaged the LAI time series produced in Sec. 2.3 to determine the mean LAI value of each catchment for the years 2002–2021. A description of selected attributes, as well as any aggregation thereof, is shown in Table S1.

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We compared these catchment attributes to the distribution of streamflow memory at different timescales. We selected potential characteristics by calculating rank correlation coefficients to determine the correlation between each characteristic and streamflow memory at four timescales (Fig. S3), by visual comparison of the geographic distribution of each characteristic compared to that of streamflow memory (Fig. S4), and based on plausibility of each characteristic as a driver of streamflow



215 memory. This combined approach allowed us to identify features with small correlation coefficients but a strong association
 with memory in a relatively small number of catchments (e.g. lake extent).

We used random forest models (Breiman, 2001) to investigate potential drivers of streamflow memory. Random forest models
 have frequently been used to assess and predict hydrologic processes and signatures due to their interpretability and low
 220 computational demands (Addor et al., 2018; Holt and Mcmillan, 2025; Messenger et al., 2021; Araki et al., 2026). We used the
scikit-learn Python library (Pedregosa et al., 2011) to develop random forest models using 10-fold cross-validation to predict
 memory from catchment characteristics at four timescales: monthly (4 weeks), seasonal (12 weeks), half-yearly (26 weeks)
 and yearly (52 weeks). Through iterative testing, we reduced the total number of catchment characteristics to 18 features while
 maintaining model performance (Table S1) by removing or combining using principal component analysis (PCA) highly
 225 correlated (Spearman $\rho > 0.75$) features. The aim of this modelling approach was to predict potential drivers of streamflow
 memory, and we therefore retained select features (e.g. reservoir capacity, forest cover) which were plausible drivers of
 streamflow memory despite consistently low feature importance. We also used a consistent set of variables for predicting
 memory at all timescales, although not all selected features were useful predictors at all timescales. Catchments without data
 for any of the selected variables were removed from this analysis, resulting in 9236 catchments used in random forest analysis.

230 Each model used 800 trees, and we applied a cross-validation grid search once at each timescale to determine other parameters
 for that timescale (Table S2). These parameters were then used across the ten cross-validation folds. The model results were
 averaged across the ten folds at each timescale to produce mean values of model performance (R^2) for each timescale. Feature
 permutation importance was calculated as the mean contribution of each feature to R^2 model performance across all folds. To
 235 provide a site-specific interpretation of the relationship between catchment characteristics and streamflow memory, we also
 calculated the Shapley values (Shapley, 1952), which indicate the marginal contribution of each feature to the predicted
 streamflow memory at each individual station (Lundberg et al., 2020).

3 Results

3.1 Streamflow memory archetypes

240 Streamflow memory, in terms of both initial memory strength and memory half-life, shows distinct geographic patterns across
 Europe. There are 486 stations (5%) with strong initial memory ($M_m \geq 0.6$) These are primarily located in France ($n = 92$),
 Finland ($n = 74$), Poland ($n = 63$), Great Britain ($n = 60$), Spain ($n = 57$), and Germany ($n = 51$). These regions of strong
 memory are often concentrated around specific geographic features in these countries, including the chalk aquifers in England
 and northern France, as well as in the region of northern Poland and into eastern Germany (Fig. 2a). More moderate initial
 245 memory ($M_m \geq 0.3$) is geographically widespread, with a total of 2908 stations (31%) reaching this threshold; 673 of these



stations are in France. Additionally, most stations in Spain ($n = 410$, 67%), Portugal ($n = 66$, 73%) Hungary ($n = 45$, 59%), and Denmark ($n = 160$, 56%) have $M_m \geq 0.3$.

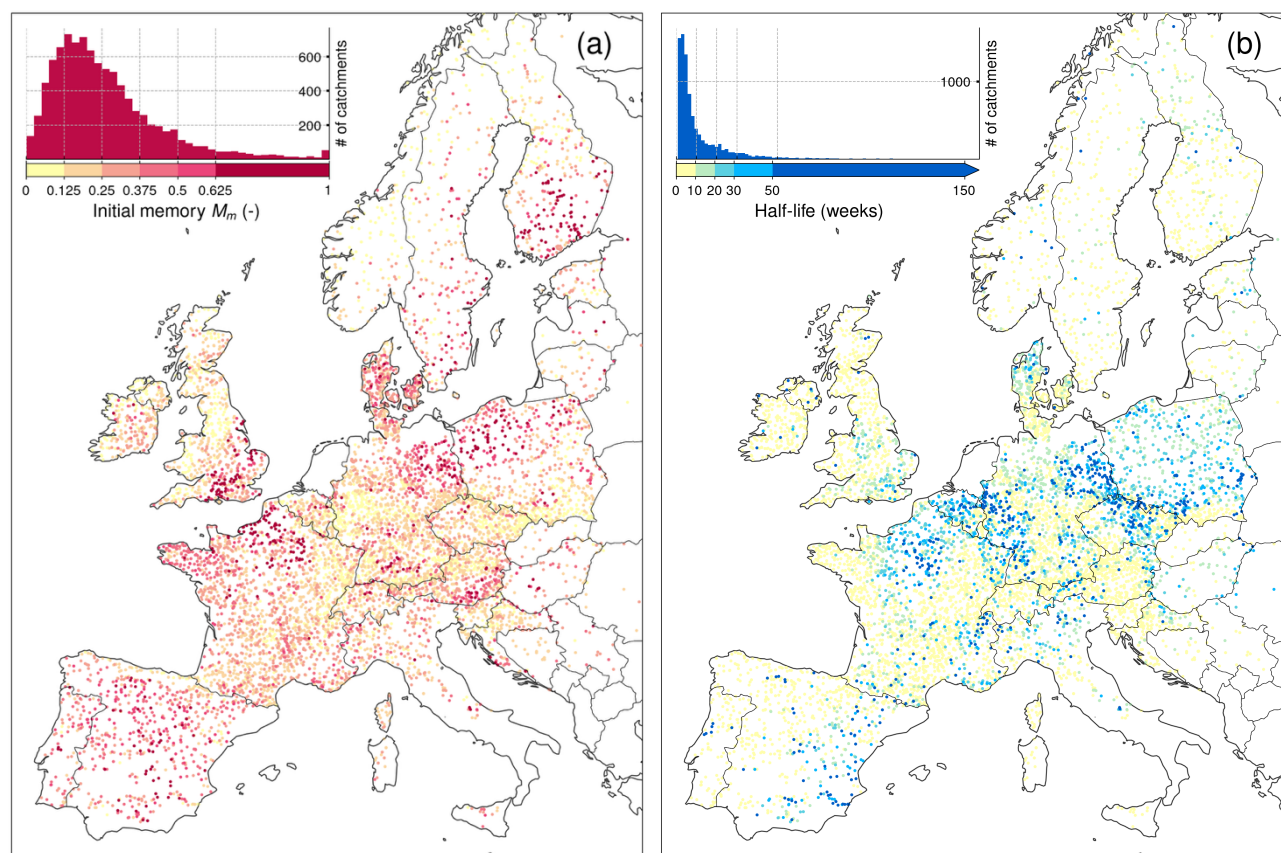


Figure 2. Initial memory (a) and memory half-life (b) of streamflow memory for EStreams stations, with inset histograms showing the distributions of each parameter. Strong initial memory, as indicated by darker red shades, is present in southern Finland, northern Poland and eastern Germany, chalk aquifers in southern England and northern France. Most of Spain displays medium to strong initial memory. Long memory half-lives, indicated by darker blue shades, has large clusters around the Paris Basin and in eastern Germany, Poland, and the Czech Republic. Although maximum half-lives exceed 150 weeks, the number of stations ($n = 118$, 1.3%) with longer half-lives is too low to visualize on the histogram.

Memory half-life shows a different geographic distribution than initial memory, and most stations have short memory half-lives (Fig. 2b). There are 6136 stations (66%) with a half-life of ten weeks or less, and 729 stations (8%) have a half-life longer than 40 weeks, demonstrating the wide range of memory half-life values across Europe. Of these stations with very long memory half-lives, the largest number are in Germany ($n = 216$), France ($n = 116$), Poland ($n = 104$), the Czech Republic ($n = 75$), and Spain ($n = 69$). Belgium, Poland, and the Czech Republic are also notable as these countries have widespread moderately persistent memory (half-life > 20 weeks) displayed in 51% ($n = 99$), 44% ($n = 300$), and 34% ($n = 170$) of stations, respectively. Within these regions, there are distinct clusters of long memory visible in eastern parts of Germany and southern Poland and central Czech Republic, as well as the regions around the Lower Rhine and Belgium.



265 Combining the initial strength and half-life of streamflow memory allows us to identify catchments based on the combinations
of these two gradients and provides four basic archetypes representing the different combinations of strong or weak initial
memory, combined with long or short half-lives (Fig. 3). We also present an example of the memory decay curves for four
highlighted catchments (Fig. 3c–f), each of which was selected to represent a distinctive example of the extremes found at the
ends these gradients, i.e. examples having very high or very low initial memory, combined with very long or very short half-
270 lives. However, most catchments fall between these examples.

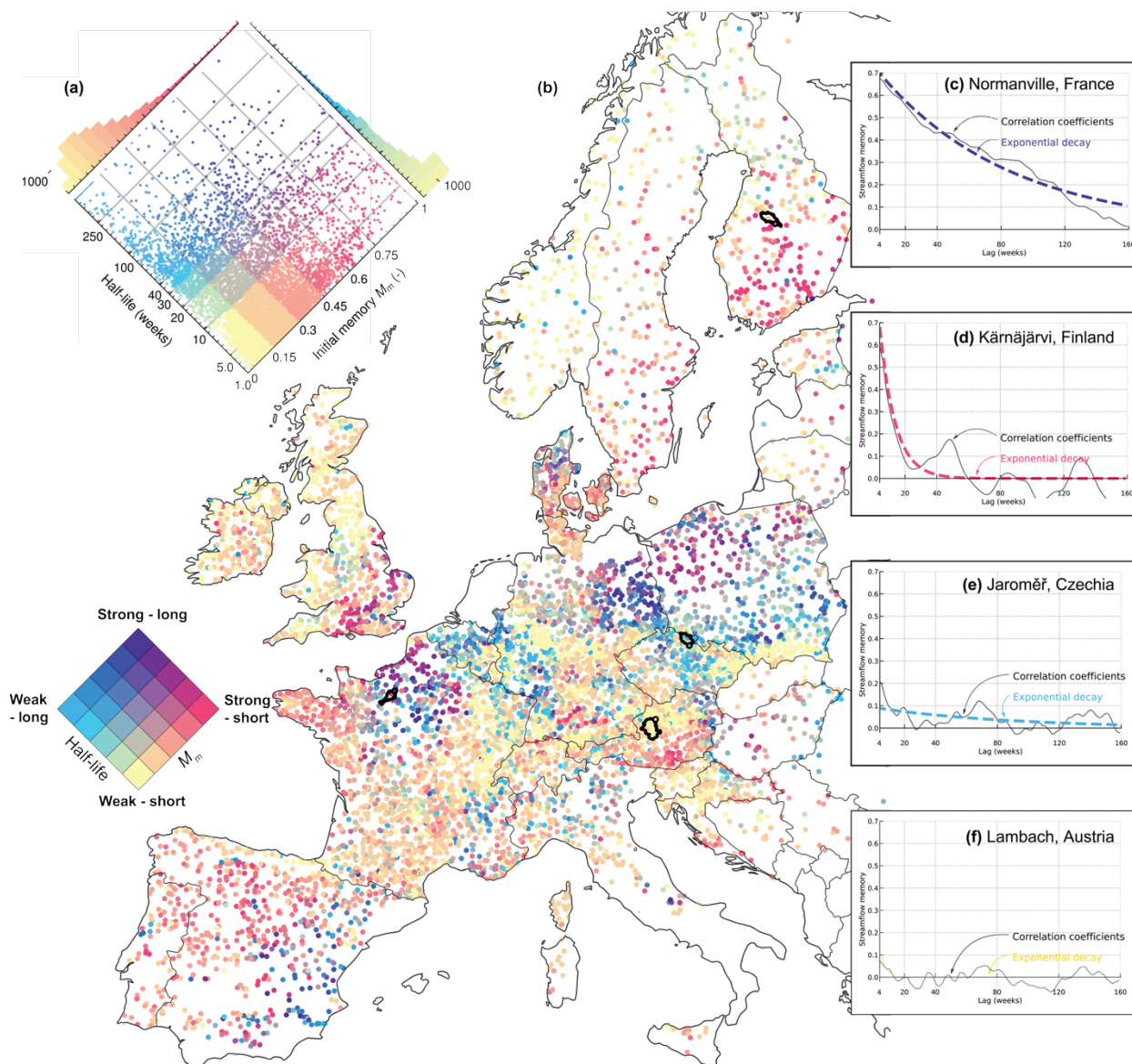


Figure 3. Scatterplot (a) and map (b) showing the memory persistence (half-life) vs. initial strength (M_m) of streamflow memory across Europe. Persistence is shown in a yellow-to-blue gradient and initial strength is shown in a yellow-to-pink gradient, with dark purple indicating a combination of high initial strength and long half-lives. Inset graphs (c–f) display memory decay curves for four example catchments, each representing one streamflow memory archetype. Catchment locations are presented on the map with black polygon outlines.

Most catchments ($n = 5203$) have weak memory with a short half-life ($M_m \leq 0.3$ and half-life ≤ 20 weeks), and fall in the bottom quadrant of Fig. 3a. Although the density of catchments decreases when considering stronger initial memory and longer persistence (Fig. 3a), there remains a wide distribution of values, with 2314 catchments displaying strong memory with short persistence ($M_m > 0.3$, half-life ≤ 20 weeks) and 1241 catchments displaying weak memory with long persistence ($M_m \leq 0.3$,



half-life > 20 weeks). Finally, 594 catchments display strong memory combined with long persistence ($M_m > 0.3$, half-life > 20 weeks); of these, 50 catchments combine very high strength and persistence of streamflow memory ($M_m > 0.6$, half-life > 40 weeks).

285 These archetypes have distinct geographic patterns across Europe (Fig. 3b). Out of the 50 catchments with very strong memory with very long half-lives (purple), most are in the Paris Basin and eastern Germany. There are 206 catchments with very strong memory and very short half-lives (pink; $M_m > 0.6$, half-life ≤ 10 weeks), primarily located in the southern parts of Finland and Sweden, as well as in southern Austria and across Spain. The 311 catchments with very weak memory and very long half-lives (blue; $M_m \leq 0.15$, half-life > 40 weeks) have clusters in the Czech Republic and in the lower reaches of the Rhine and Meuse
 290 Basins. The 1795 catchments with very weak memory and very short half-lives (yellow; $M_m \leq 0.15$, half-life < 10 weeks) are the most widespread, particularly in Norway and the UK, and in parts of the Alps and the Carpathians. There are also clusters of moderately high initial strength and long half-lives of memory in northern Poland, Denmark, and southern England.

3.2 Streamflow memory at different lag times

295 When evaluating streamflow memory, we further investigate specific time lags to determine how strong streamflow memory is at timescales of 4 weeks (*monthly*, or M_m), 12 weeks (*seasonal*), 26 weeks (*half-year*), 52 weeks (*yearly*), 104 weeks (*two-year*), and 156 weeks (Fig. 4). At a time lag of four weeks (monthly memory), 30.8% ($n = 2889$) of stations display memory > 0.3. This decreases to 8.6% ($n = 805$) for seasonal memory, 3.8% ($n = 351$) for half-year memory, and 1.3% ($n = 125$) for yearly memory. When considering lags of two and three years, only 0.5% ($n = 45$) and 0.3% ($n = 30$) of stations still display
 300 memory > 0.3.

Snow-dominated catchments (e.g. Alps, Nordic countries) and wet Atlantic regions (e.g. Ireland and the northwestern parts of France and Spain) have a notable decrease in memory between monthly and seasonal timescales. Memory in lake-dominated Finland and Sweden is weakened after 26 weeks, and mostly absent at a yearly timescale. At yearly and longer timescales, the
 305 proportion of catchments with notable memory is concentrated primarily in regions with large aquifers or deep bedrock. More spatially fragmented patterns of long memory also exist in Spain.

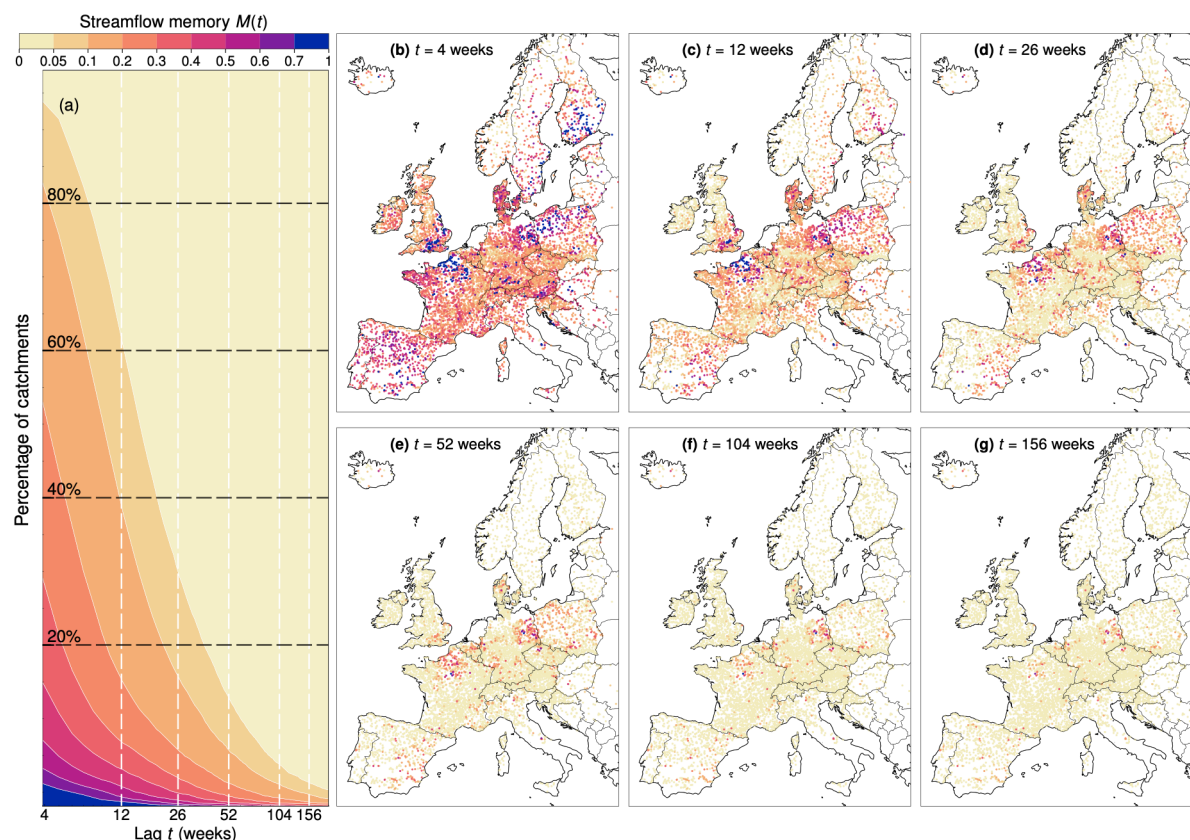


Figure 4. Patterns of streamflow memory strength at different timesteps. Panel (a) displays the how the proportion of catchments with strong streamflow memory declines between one month and two years at weekly intervals; the colour intervals represent the memory strength and the height at each timestep indicates the percentage of all catchments in each interval (left axis). Darker colours indicate stronger memory, with the strongest memory class (0.7–1.0) shown in blue at the bottom of the chart. The maps (b–g) show the strength of memory at timescales from 4 to 156 weeks.

3.3 Relationship to other hydrologic signatures

Streamflow memory overall relates to existing streamflow signatures while also capturing additional information. Streamflow memory correlates with both the catchment baseflow index and the mean annual coefficient of variation of daily streamflow (CV_Q). Both characteristics are conceptually and mathematically related to streamflow memory and have been used together for hydrological classification (Kuentz et al., 2017; Ariano and Ali, 2025).

The coefficient of variation of daily streamflow (CV_Q) measures the variability of streamflow and indicates how erratic or persistent river flow regimes are (Botter et al., 2013; Basso et al., 2023). This hydrologic signature reflects both climate properties of the river as well as the role of the catchment in translating precipitation into streamflow (Müller et al., 2021; Quin and Destouni, 2018). The catchment CV_Q indicates the amount of variability in a streamflow timeseries. This metric does not consider whether this variability is sequential; however, catchments with more overall variability are likely to have weaker

streamflow memory. Streamflow memory decreases with the coefficient of variation of daily streamflow (Spearman $\rho = -0.52$, $\rho = -0.76$, $\rho = -0.72$, $\rho = -0.67$), indicating that catchments with greater daily streamflow variability tend to have less memory.

The baseflow index is the proportional contribution of baseflow to streamflow, indicating the contribution delayed sources to streamflow and providing an estimate of which catchments are groundwater-dominated (Smakhtin, 2001). The baseflow index, calculated from hydrograph filtering, indicates the response speed and attenuation of precipitation events thus presenting an event-based memory, and is correlated with multi-annual memory in France and Sweden (De Lavenne et al., 2022). Streamflow memory across all selected timesteps (monthly, seasonal, half-year, yearly) increases with baseflow index values (Spearman $\rho = 0.53$, $\rho = 0.68$, $\rho = 0.62$, $\rho = 0.57$), with a steeper increase for baseflow index values of approximately 0.6 or higher (Fig. 5b).

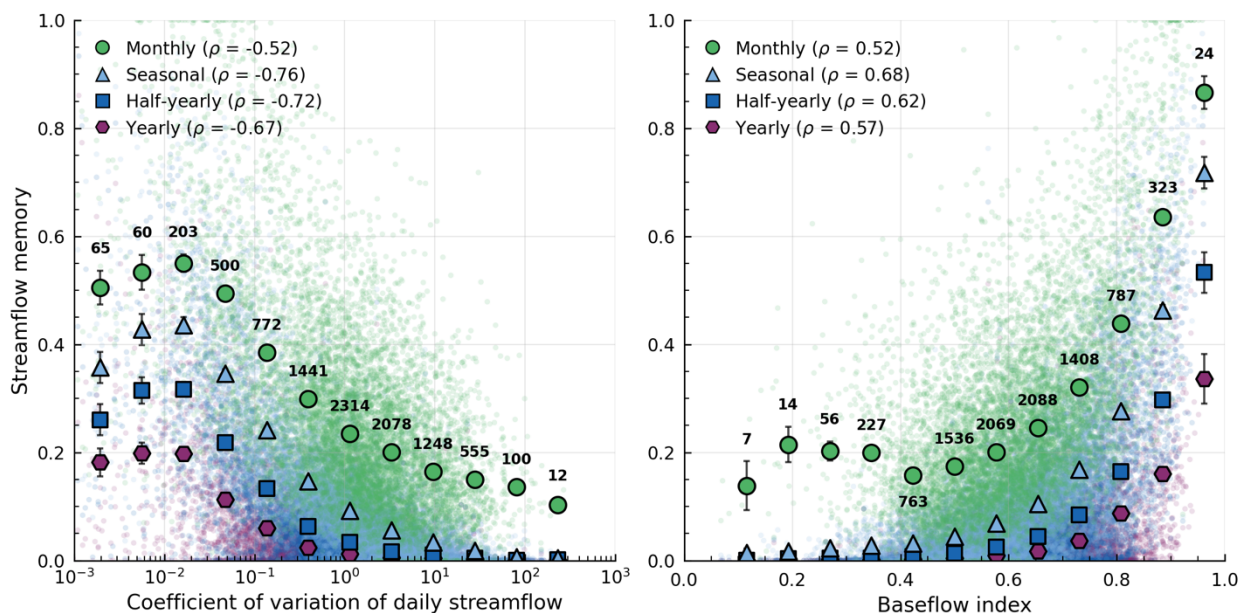


Figure 5. Comparison of streamflow memory values with the coefficient of variation of daily streamflow (left) and the baseflow index (right). Comparisons are presented for monthly ($t = 4$ weeks; green), seasonal ($t = 12$ weeks; light blue), half-yearly ($t = 26$ weeks; dark blue) and yearly ($t = 52$ weeks; purple) memory, with memory at all timescales negatively correlated with the coefficient of variation of daily streamflow and positively correlated with the baseflow index. Spearman's rank correlation coefficients are calculated for non-binned data (shown in the background). Markers show the mean streamflow memory values for each bin, whiskers show the standard error of the mean, and counts indicate the number of stations in each bin. Mean value markers are not displayed for bins with fewer than five stations.

3.4 Memory in climate forcing

To evaluate whether streamflow memory is primarily driven by precipitation and climate patterns, we evaluate whether the streamflow memory mirrors memory in climate time series. A catchment-level comparison of streamflow memory to memory in precipitation (i.e. combined rainfall and snowmelt), temperature, and evaporative demand (PET) (Fig. 6) shows that climate



memory, while overall much weaker than streamflow memory, weakly correlates with streamflow memory. M_m of precipitation is generally weak, except for arid parts of Spain and Portugal and near the Mediterranean (Fig. S1). Precipitation M_m is otherwise negligible except for in Northern Ireland, which does not display strong streamflow memory. The memory present in the time series of temperature and evaporative demand are also generally weak in comparison to the memory of streamflow, with M_m most concentrated at values less than 0.1 (Fig. 6). However, these small values of M_m of precipitation, temperature, and potential evapotranspiration are weakly correlated (Spearman $\rho = 0.21$, $\rho = 0.05$, $\rho = 0.19$) with streamflow M_m . For precipitation, these correlations decrease at longer timescales, whereas they increase for temperature and PET (see Fig. S2 for comparison at all timescales). The strongest correlation between temperature memory and streamflow memory occurs at a 26-week lag ($\rho = 0.23$) and between PET memory and streamflow memory at a 52-week lag ($\rho = 0.25$).

Memory in vegetation – whether caused by land-use changes or climate effects – could affect streamflow memory via resulting changes in evapotranspiration. We thus include memory of LAI and fPAR as vegetation indices for comparison, despite these not being climate variables; for visualization purposes we only include LAI in Fig. 6. Streamflow memory is weakly correlated or uncorrelated with LAI memory at all timescales (maximum Spearman $\rho = 0.10$ for seasonal memory). Streamflow M_m is also not correlated to fPAR M_m ; however, streamflow and fPAR memory are weakly correlated at longer timescales with the strongest correlation (Spearman $\rho = 0.30$) for seasonal memory (Fig. S2).

These correlations indicate that while streamflow memory is related to climate memory, patterns in climate are not sufficient to explain the presence of streamflow memory. Moreover, very high levels of streamflow memory are found in many catchments with near-zero memory in these climate variables (Fig. 6, Fig. S1), indicating that although climate memory overall increases streamflow memory, streamflow memory can exist in the absence of climate memory.

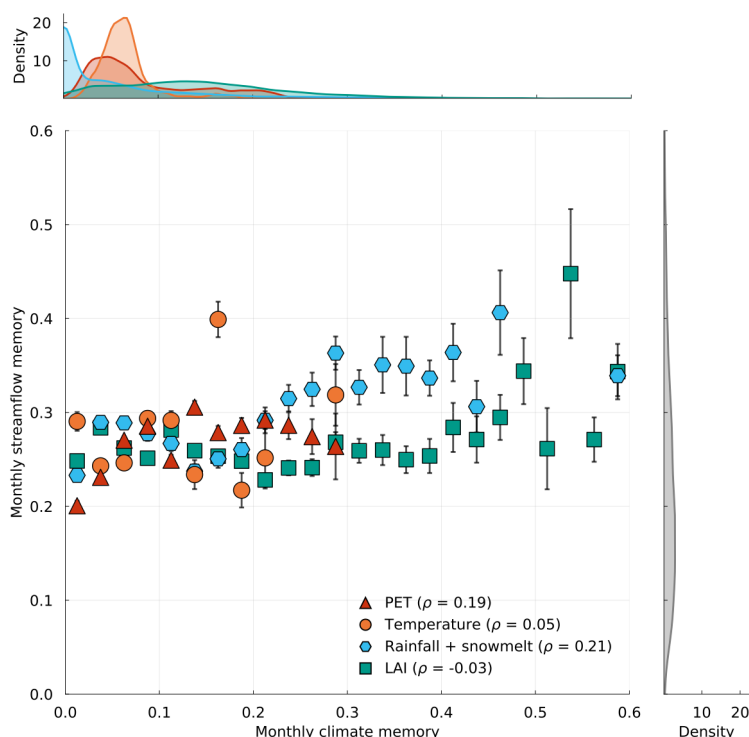


Figure 6. Initial memory (M_m) of streamflow versus M_m of temperature (orange), rainfall and snowmelt (blue), potential evapotranspiration (red), and LAI (green). Markers indicate the mean binned streamflow M_m for all bins with a minimum of five catchments, based on climate memory intervals of 0.025. Error bars mark the standard error of the mean. Density plots on the upper axis indicate the distribution of memory values, with climate M_m values highly concentrated at values below 0.1; LAI M_m (green, upper axis) and streamflow M_m (grey, right axis) are more evenly distributed. The presented correlation coefficients are calculated for un-binned data and show that streamflow M_m is weakly correlated with M_m of rainfall and snowmelt and of evaporative demand, and uncorrelated with M_m of temperature and LAI.

3.5 Catchment characteristics associated with streamflow memory

Streamflow memory does not closely mirror memory in meteorological forcing (Fig. 6), which suggests that the functioning of the catchment largely shapes streamflow memory. We find that available catchment characteristics are most strongly related to shorter timescales of streamflow memory, as indicated by both the rank correlation coefficients between individual characteristics and memory (Fig. S3) and by the predictive ability of the random forest models. The predictive ability of these models is higher for monthly, seasonal, and half-year memory ($R^2 = 0.64, 0.66$ and 0.58 respectively) than for yearly ($R^2 = 0.45$) and two-yearly ($R^2 = 0.3$) memory (Fig. 7). While we focus on feature importances from permutation analysis to understand overall drivers, Shapley values are used to understand the influence of catchment characteristics on individual streamflow memory predictions.

Permutation feature importance analysis indicates that the relationships between different catchment properties and streamflow memory vary at different timescales. Surface characteristics (e.g. lakes, land cover) have higher feature importances for shorter memory timescales, whereas subsurface characteristic feature importances increase for yearly memory (Fig. 7). Climate and



topographic characteristics are consistently strong predictors of streamflow memory at all timescales, although the predictive
 390 ability of topography decreases for longer timescales. Human impact features have little predictive power at all timescales.

Climate characteristics (aridity, potential evapotranspiration, precipitation seasonality, and snow fraction of precipitation) are
 the strongest predictors of streamflow memory, and aridity is ranked as the third predictor for monthly memory and first for
 all other timescales. Catchments with low aridity and evaporative demand display less memory at all timescales, particularly
 395 in energy-limited catchments. The relationship of memory with snow fraction and precipitation seasonality appears non-
 monotonic, although at seasonal to annual timescales, catchments with precipitation concentrated in the warm season have
 more memory than those with cold-season precipitation dominance (Fig. S6).

Topographic features have their highest feature importance at monthly and seasonal timescales. The elevation feature (i.e.
 400 principal component combining catchment slope and minimum, maximum, and mean elevation) is the most important feature
 for monthly memory and ranks second or third at longer timescales (Fig. 7). Catchment size has a low overall feature
 importance at all timescales but is weakly associated with stronger memory in large catchments for monthly and seasonal
 memory (Fig. S6).

405 Vegetation and land cover feature importance is also at its highest for monthly and seasonal memory. At a monthly timestep
 LAI is ranked fourth overall and high LAI values are associated with less memory. Cropland extent is moderately associated
 with more streamflow memory at all timescales. Both pasture and forest cover consistently display little predictive power, with
 the presence of pastures associated with less streamflow memory (Fig. S6).

410 The importance of hydrological features in predicting streamflow memory varies greatly for different timesteps, although both
 lakes and wetlands are consistently positively correlated with streamflow memory (Fig. S3). Upstream lake area is the second
 ranked overall predictor of monthly streamflow memory but decreases in importance for longer timescales, showing negligible
 importance for yearly memory. By contrast, the presence of wetlands has a small but persistent predictive ability across all
 timescales. Both these hydrological features have a strong influence on memory predictions in a subset of catchments (Fig.
 415 S5). Lakes predominantly influence (monthly and seasonal) memory in Finland, Sweden, and Poland, while wetlands influence
 memory in Belgium and Germany near the Dutch border (Fig. S4).

Subsurface characteristics have increased predictive ability at timescales longer than monthly, despite the decrease in overall
 model predictive ability at longer timescales (Fig. 7e). Limestone, which is prominent in the Paris Basin and English chalk
 420 regions, is consistently one of the most important features at all timesteps. The presence of unconsolidated sediments –
 covering much of Poland and eastern Germany – has low feature importance for monthly memory but increasing importance
 at longer timescales, with the strongest predictive ability for yearly memory. The extent of limestone and of unconsolidated



sediments, as well as the bedrock depth, are associated with more streamflow memory. Out of the subsurface characteristics, soil properties display a small but consistent predictive ability, likely indicating that while soil influences streamflow memory deeper groundwater interactions are overall more dominant.

Although human modifications to hydrology in Europe are omnipresent, human impacts on streamflow memory appear weak or unsystematic. We considered direct anthropogenic influence via the reservoir volume in a catchment relative to annual discharge, as well as nightlight intensity as an overall indicator of upstream anthropogenic pressure. Reservoir capacity ranks last for overall predictive power at all timescales, although reservoir capacity is positively associated with memory predictions in some catchments at half-yearly and yearly timescales (Fig. S4).

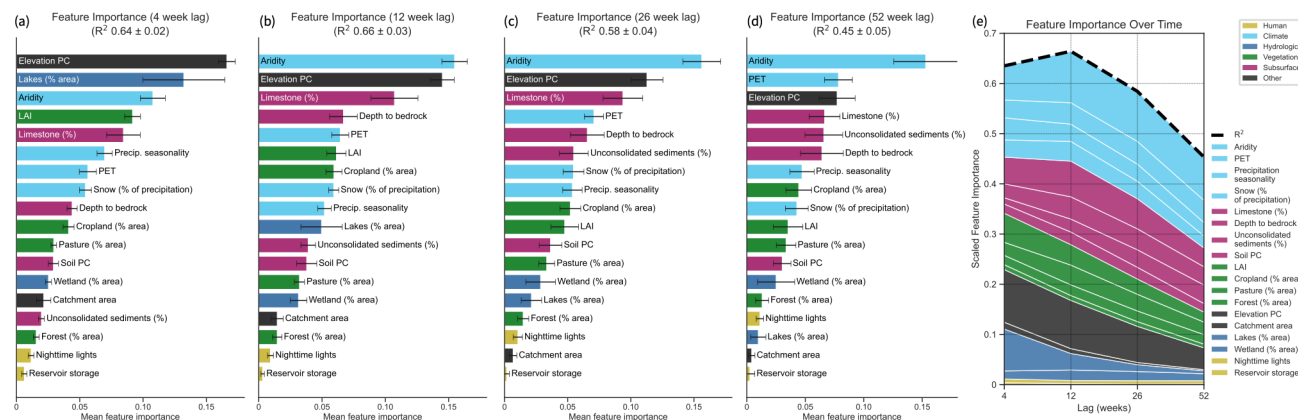


Figure 7. Feature importance values of catchment characteristics used to predict streamflow memory at four timescales (a-d). Bars show the average permutation feature importance across all folds and whiskers indicate the standard deviation of importance. Panel (e) displays the importances of all features at each timestep grouped by class and scaled so that the sum of all values at each timestep is equivalent to the model R^2 score, providing a visual approximation of the predictive ability of each feature at that timestep. Features are grouped into the categories of climate (light blue), subsurface (purple), land cover (green), topography (black), hydrological features (dark blue), and human impact (yellow).

3.6 Memory in modelled streamflow

We calculated memory decay curves for modelled catchment discharge from two commonly used models (mHM and EFAS) to test whether similar streamflow memory behaviour exists in modelled streamflow. We refer to this memory as “modelled memory” and to streamflow memory calculated from EStreams data as “observed memory” to differentiate between observed and modelled dynamics, although we calculate their decay curves using the same methodology.

Modelled mHM M_m is, on average, slightly weaker than observed M_m (mean difference -0.07, or -23% compared to mean observed M_m), and its distribution is more spatially homogeneous (Fig. 8c). Modelled mHM M_m is present in Poland and Spain; both regions also display observed memory, although the observed memory is less spatially constant (Fig. 8a). By contrast,



observed initial memory hotspots in Finland and English chalk aquifers show very little modelled memory, and the strong
 450 observed memory of the Paris Basin is not visible from the results of modelled memory. Differences between mHM and
 observed memory decrease for seasonal (-16%) and half-yearly (-5%) memory; modelled yearly memory is on average slightly
 stronger (+13%) than observed memory (Fig. 8d). When comparing absolute difference regardless of directionality, mHM M_m
 versus observed M_m has a mean absolute error of 0.14 (48% of mean observed M_m) which decreases to a mean absolute error
 of 0.03 for yearly memory, although this is proportionally high (121%) compared to mean observed yearly streamflow
 455 memory. This difference corresponds to the average half-life of mHM memory being longer (mean difference +6.9 weeks)
 than that of observed memory. Despite this, notable regions display significantly less yearly mHM memory compared to
 observed memory, including the Paris Basin and southern Spain. These two examples have differing causes – where the Paris
 basin has both lower mHM M_m and slightly shorter mHM half-life compared to observed memory, the region in southern Spain
 has a higher mHM M_m but much shorter mHM half-life.

460
 Modelled EFAS M_m is likewise slightly weaker (mean difference -0.05; 19%) than observed M_m . Although EFAS M_m is broadly
 more spatially aligned with observed M_m , significant differences remain (Fig. 8). There is noticeable EFAS M_m in the Paris
 Basin but these values are nonetheless weaker than observed M_m . By contrast, EFAS M_m is strong in northern and western
 Austria whereas observed M_m is generally weak in these regions. EFAS yearly memory is on average weaker than observed
 465 yearly memory (+0.02; +63%). Many regions such as central Germany, southeastern France, and Ireland show stronger EFAS
 yearly memory linked to the widespread long memory half-lives present in EFAS memory (Fig. 8f). These memory half-lives
 are on average 35 weeks longer than those of observed memory, and the spatial similarity between the differences in annual
 memory and differences in half-lives indicates that this stronger annual memory is likely driven by speed of decay rather than
 initial memory strength. Despite this overall trend, EFAS underestimates yearly memory in the Paris Basin and eastern
 470 Germany (Fig. 8h). The mean absolute error of EFAS M_m is 0.14 (52%) and of yearly EFAS memory is 0.05 (174%),
 demonstrating the increasing difficulty of accurately modelling dynamics at this longer timescale.

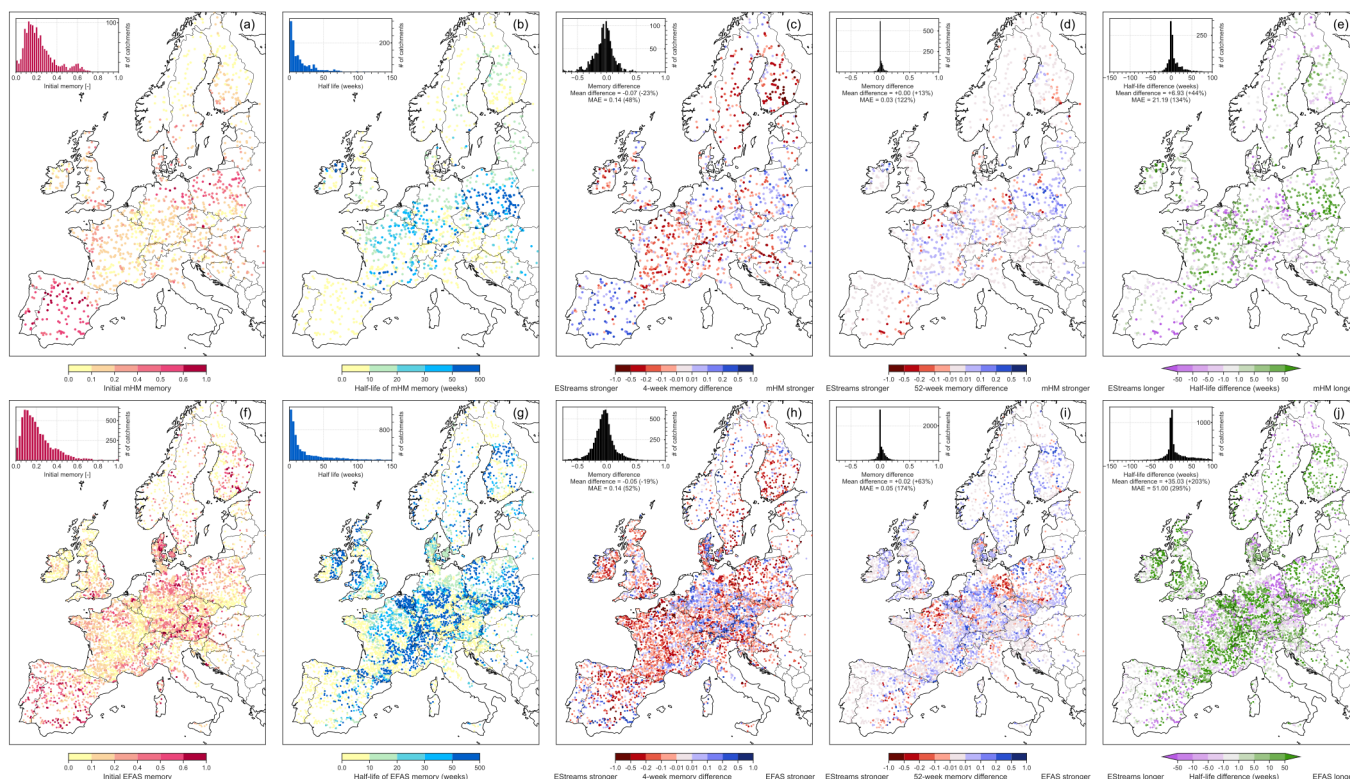


Figure 8. Initial memory (M_m) (a, f) and memory half-life (b, g) for streamflow memory curves derived from mHM (top row; a-e) and EFAS (bottom row; f-j) streamflow simulations. Differences between observed and modelled memory are shown at monthly (c, h) and yearly (d, i) timescales, with red indicating more observed memory and blue indicating more modelled memory. Comparison of half-lives (e, j) shows that most stations have longer half-lives for modelled than for observed streamflow.

4 Discussion

4.1 Memory decay curves

Memory decay curves provide a concise way to summarize streamflow memory at timescales from months to years. These memory decay curves allow us to distinguish four main memory archetypes based on strength and persistence, as well as to assess memory at different timescales. In applying these memory curves at the European scale, we can distinguish elements that influence the occurrence of memory at different timescales. This multi-temporal approach allows for the understanding of memory at multiple timescales, building on previous studies which focused on memory at monthly (Iliopoulou et al., 2019) or annual (Berghuijs et al., 2025) timescales.

The memory decay curves used to represent streamflow memory capture both strength and persistence, thereby summarizing memory in two key parameters and allowing for comparison across many catchments. The selected exponential decay function more effectively captures memory in catchments with strong initial memory compared to catchments with weak memory. For



490 catchments with weak initial memory, the difference in behaviour between long and short half-lives is more uncertain and reflects only very small memory differences at any selected timescale despite the different speed of decay. Despite this, catchments with weak initial memory still have regionalized spatial patterns of half-lives (Fig. 2), suggesting small but systematic differences in memory behaviour between regions.

495 Our application of memory decay curves identifies memory across the entire range of observed streamflow values, and does not isolate whether catchments have memory under specific conditions – for example, catchments may experience rapid wetting but slow drying dynamics or vice versa (Leader et al., 2024). Future applications of the memory decay curves could identify whether catchments experience memory under specific conditions, including during periods where streamflow is increasing or decreasing. Such applications also could isolate whether memory exists specifically for high or low flows, as
 500 research shows more hydrologic memory for low than for high flows (Berghuijs et al., 2025), and the spatial patterns and drivers of high flow and low flow memory differ (Iliopoulou et al., 2019).

4.2 Drivers of streamflow memory

We identified catchment characteristics that are both empirically and physically linked to streamflow memory, and the role of
 505 these drivers in memory and delayed streamflow dynamics are supported by the results of both regional and large-sample studies. Our application of memory decay curves allows us to compare the presence and plausible drivers of memory across much of Europe, identifying patterns which may not be visible when analysis is limited to fewer countries (Iliopoulou et al., 2019; De Lavenne et al., 2022).

510 Streamflow memory is weakly correlated with climate memory (Fig. 6), which suggests that streamflow memory is not primarily driven by temporal climate dynamics (e.g. memory in precipitation), but rather by the functioning of the catchments. This catchment functioning likely substantially but not fully overlaps with processes that determine baseflow index and overall streamflow variability, both of which are correlated with streamflow memory (Fig. 5). This suggests that rivers with strong memory are likely supported by groundwater and tend to display more persistent flow regimes (Botter et al., 2013).

515 The set of catchment characteristics we examined explains nearly 50% of between-catchment differences of annual memory and has more explanatory power for shorter memory timescales (Fig. 7). At timescales exceeding one year, predictive ability decreases, indicating that available catchment characteristics explain less of the memory at longer timescales. Although memory in meteorological forcing is only weakly correlated with streamflow memory (Fig. 6), the climatic setting affects
 520 streamflow memory. Drier catchments have generally stronger streamflow memory, with aridity emerging as both the most important overall feature for the random forest predictions of streamflow memory and as the most individually correlated to streamflow memory (Spearman $\rho = 0.35$ – 0.5 for different memory timescales, see Fig. S3). Globally, aridity heavily influences



hydrology, including groundwater recharge and resilience, streamflow elasticity, and streamflow variability (Berghuijs et al., 2024; Lun et al., 2021; Cuthbert et al., 2019; Andréassian et al., 2026; Rau et al., 2026), all of which could impact streamflow memory. This importance of aridity has also been highlighted in Europe by a previous hydrologic classification (Kuentz et al., 2017) and in studies of long-term hydrologic persistence (Markonis et al., 2018). Similarly, temperature is positively correlated and mean annual precipitation is negatively correlated with Hurst coefficients of daily runoff in Europe (Szolgayova et al., 2014).

We find that streamflow memory increases with aridity for energy-limited catchments – i.e. the majority of catchments in this study – but the relationship between aridity and streamflow memory is less distinct for more water-limited ($E_P/P > 1.1$) catchments (Fig. S4). At seasonal, half-year, and yearly timescales, streamflow memory in water-limited catchments is either uncorrelated or negatively correlated with aridity, indicating that streamflow memory at these timescales may be strongest in catchments with an aridity index close to 1. However, the water-limited catchments make up a relatively small proportion of this study ($n = 2231$, 24%) and the most arid catchments are spatially concentrated in the Iberian Peninsula (of the 456 catchments with $E_P/P > 1.5$, 403 are in Spain and Portugal). This unclear memory relationship to aridity in these catchments may therefore be driven by more local factors, such as high levels of river regulation and consumptive water use (Grill et al., 2019), limiting a broad interpretation of the relationship between aridity and streamflow memory in water-limited catchments. Previous studies at European and global scales have found the strongest long-term hydrological and soil moisture memory in catchments where $E_P/P \approx 1$ (Markonis et al., 2018; Seneviratne et al., 2006), and Iliopoulou et al. (2019) identified the clearest decrease in seasonal streamflow autocorrelation for high flow in very humid catchments.

Groundwater emerges as a likely driver of streamflow memory. Streamflow memory at all timescales is correlated to the baseflow index (Fig. 5), which reflects delayed contributions – often from groundwater – to streamflow. The spatial distribution of memory also reflects such groundwater connections, particularly at longer timescales (Fig. 4), and subsurface characteristics contribute significantly to the predictive ability of the random forest models (Fig. 7). For example, we find that strong and long memory exists in the Paris Basin where streamflow dynamics are highly correlated to aquifer groundwater levels as evidenced by piezometer measurements (Pelletier and Andréassian, 2023) and isotope analysis (Négrel and Petelet-Giraud, 2005). We also find strong and long memory in eastern parts of Germany, where López Moreira Mazacotte et al. (2025) found that groundwater shapes how discharge responds to precipitation at annual to multi-annual timescales. There is strong memory with varying persistence in southern England, where aquifers supply a large fraction of discharge and often control floods and droughts (Tallaksen et al., 2009; Peters and Van Lanen, 2005; Morris et al., 2018), with the Jurassic limestone, chalk, and greensand aquifers leading to rivers with different seasonal or lagged hydrologic dynamics depending on the underlying geology (Oldham et al., 2023). In Brittany – where we find strong and short memory – groundwater contributes to streamflow in seasonal cycles (Molenat et al., 2008; Aubert et al., 2013; Fovet et al., 2015). In Spain, despite the overall importance of aridity in driving streamflow memory, there is significant variability in long and short memory which may be due to



groundwater; for example, the Segura basin, where inter-basin aquifers support dry season streamflow (Pellicer-Martínez and Martínez-Paz, 2014), displays long memory.

560 Lake area influences streamflow memory at monthly and seasonal timescales (Fig. 7), and short, strong memory co-occurs with high lake density in Sweden and Finland (Fig. 3, Fig. S4). In Sweden, upstream lake area has been found to correlate with reduced runoff variability downstream (Quin and Destouni, 2018) and to correlate with streamflow memory at lags of one to two months (Iliopoulou et al., 2019). In Finland, lake-dominated catchments have similarly been shown to have smooth and strong seasonality with fewer hydrologic extremes when compared to other regions (Korhonen and Kuusisto, 2010). Our results
 565 also show that the importance of lakes is short-lived and no longer present for yearly memory – this corresponds to previous work using annual data which did not find a strong relationship between lake cover and memory (De Lavenne et al., 2022), and highlights the multi-temporal analysis enabled by memory decay curves. In a pan-European catchment classification, Kuentz et al. (2017) identified regions in Poland and southern Sweden as having dampened hydrological dynamics characterized by high baseflow index and low CV_Q , with dynamics controlled by large water bodies and floodplains; we
 570 similarly identify these regions as having strong streamflow memory related to lakes.

Wetlands also show a weakly positive relationship to streamflow memory, with the strongest correlation to seasonal memory ($\rho = 0.22$; Fig. S3). Wetlands play a role in buffering surface and groundwater dynamics and sustaining baseflows (McLaughlin et al., 2014), although their influence is dependent on surrounding subsurface characteristics (Holt and Mcmillan, 2025). These
 575 wetlands comprise a small percentage ($< 5\%$) of catchment area in most European catchments (Fig. S3) and thus have relatively low permutation feature importance values at all timescales. Shapley analysis reveals that larger wetland extents predict stronger streamflow memory at seasonal and longer timescales (Fig. S6) and suggest that wetlands are locally important drivers of streamflow memory despite their weak influence at the European scale.

580 Topography also appears as a likely driver of streamflow memory, although it is difficult to disentangle the influence of topography from that of climate. In Austria, Iliopoulou et al. (2019) found that higher elevation is correlated with higher monthly streamflow memory during the low-flow season; however, these high elevation areas are also snowy regions with winter-dominated precipitation regimes. We likewise identify strong monthly memory in the high-elevation regions of Austria but do not find an overall positive correlation between memory and elevation at the European scale. Memory is only weakly
 585 negatively correlated with elevation and slope (Fig. S3), but these elements have very high predictive ability in our random forest model (Fig. 7), suggesting that there is a non-monotonic relationship to memory. Monthly memory strength increases in very steep, high-elevation catchments as well as in lower elevation catchments with shallow slopes (Fig. S4). Seasonal and longer timescales show stronger memory at lower elevations, consistent with our finding that when streamflow memory exists at higher elevations it is generally short-lived (Fig. 3). We suggest that interactions of climate and topography lead to the
 590 existence of short and strong memory in these high-elevation regions.



Land cover is also correlated with streamflow memory, with increased cropland associated with stronger streamflow memory, and increased LAI values, pasture extent, and forest cover associated with weaker streamflow memory (Fig. S4). Although these features correlate with streamflow memory, it is unclear whether these land uses drive the presence (or absence) of streamflow memory. In some areas, wetland drainage for agricultural use has resulted in decreased catchment storage, which may reduce streamflow memory (Meriö et al., 2019); However, although Europe has experienced significant wetland drainage for cropland (Fluet-Chouinard et al., 2023), the impacts of this drainage on water storage and downstream hydrology are dependent on local context (Bacon et al., 2017). Moreover, the distribution of cropland and grassland in Germany is strongly *influenced by* the hydrological setting – cropland is more likely to exist in drier areas which also exhibit more streamflow memory while the opposite is true for grassland (Emde et al., 2026). These land-use patterns shifted over time subsequent to changing hydrology, meaning that the high occurrence of cropland (pasture) in catchments with high (low) streamflow memory is unlikely to indicate that land use causes streamflow memory in this region. We therefore caution that although cropland can function as a predictor of streamflow memory, this predictive capacity may be due to catchments with higher memory being more conducive to farming rather than cropland driving streamflow memory.

Reservoir storage capacity is weakly correlated to streamflow memory ($\rho = 0.1$ for monthly memory). Reservoir storage capacity has the lowest feature importance of all considered catchment characteristics (Fig. 7), although it appears to increase memory predictions for catchments with very large reservoir capacity (Fig. S5). Although reservoir storage may impact memory at individual stations, the impact of reservoirs on memory will depend on their purpose (e.g. reservoirs used for hydropower may be managed differently than reservoirs primarily used for flood protection), and reservoir storage has an overall minimal influence on streamflow memory distribution in Europe.

4.3 Presence of memory in modelled streamflow

Model evaluation typically focusses on short-term streamflow dynamics, with common performance metrics not clearly representing how well long-term behaviour is captured, often leading to poor representation of inter- or multi-annual dynamics (Fowler et al., 2020; Ruzzante et al., 2026; Zhang et al., 2026). Our comparison of measured and modelled memory provides an example of how models can be evaluated for their longer-term dynamics. The large-sample approach further allows us to distinguish regionally systemic discrepancies from localized differences.

At monthly timescales measured memory is overall stronger than modelled memory from both mHM and EFAS streamflow simulations (Fig. 8), whereas at longer timescales modelled memory is on average slightly stronger than measured memory. This temporal change is driven by the longer half-lives of modelled memory. Despite the overall stronger annual memory of both models, a visual comparison reveals that EFAS annual memory is greatly underestimated in some of the most significant



areas of strong and long observed memory, namely the Paris Basin and eastern Germany and Poland (Fig. 8). Correspondingly, the EFAS memory half-lives in these regions are much shorter than those derived from observations despite the higher overall half-life values. Both models show overall higher absolute errors for modelled annual memory than for modelled monthly memory, reflecting previous findings that models which display memory tend to be limited to monthly or seasonal memory and poorly capture interannual memory (Fowler et al., 2020).

Modelled memory – particularly that of mHM – is overall more spatially homogeneous at regional scales than measured memory. These differences in memory produced by mHM may be partially explained by the choice of geological map used in the model run, which does not clearly distinguish the Paris Basin from other geological features and has less detail than regional or continental geological maps (Do Nascimento et al., 2025). Although both modelled and observed memory exist in Poland and eastern Germany, the mHM results overestimate both the spatial homogeneity and the temporal persistence in this region. Some of this spatial homogeneity may be explained by the stronger relationship between climate (especially aridity) and mHM memory when compared to observed memory (Fig. 8, Fig. S3). While aridity also drives observed memory, other catchment characteristics appear to modulate the influence of climate locally, leading to more spatial variability in measured memory. The evaluation of EFAS memory is less distinctly related to specific climate or geological inputs, and available catchment characteristics are overall less correlated with EFAS memory than with mHM or observed memory (Fig. S3).

To improve hydrological models and their performance under our changing climate and in poorly gauged regions, there are calls for models to be evaluated by their functional behaviour to guide systematic model improvements (Gnann et al., 2023; Sharif and Ameli, 2025; Gnann and Wagener, 2026). Hydrologic signatures have been used to represent hydrologic processes (Mcmillan et al., 2022) to evaluate, calibrate, and constrain models (Mcmillan, 2020; Kavetski et al., 2018; Hrachowitz et al., 2014), and evaluate model robustness to climate change (Santos et al., 2025). Our application of memory decay curves demonstrates their ability to compare temporal dynamics of simulated streamflow. Further applications of streamflow memory could investigate how memory dynamics are affected by changes in model parametrization or model structure, potentially elucidating where different components of the hydrological system contribute to streamflow memory and improving representation of interannual dynamics (Fowler et al., 2020; Ruzzante et al., 2026; Zhang et al., 2026). Here, we analyzed streamflow at timescales of three years or less, targeting timescales that have shown the strongest memory effects in parts of Europe (De Lavenne et al., 2022). However, future applications of streamflow memory decay curves, particularly in other regions, may benefit from extending analysis to longer timescales (Grigg and Hughes, 2018; Fowler et al., 2021).

5 Conclusions

Streamflow memory at timescales of months to years exists in many regions across Europe, and can be effectively represented by *memory decay curves* calculated for 9352 stations across Europe. These memory decay curves provide information about



streamflow dynamics at multiple timescales, bridging event-based and longer-term timescales of memory or autocorrelation. This approach provides an efficient way to summarize and compare memory across multiple timescales and at many locations, making use of large-sample catchment data.

660 The memory decay curve approach exposes clear spatial patterns of streamflow memory dynamics across Europe, with clusters corresponding to distinct geographic regions (Fig. 3). From these curves, we calculate strength of memory at different timesteps. This allows us to distinguish regions with stronger memory only at shorter (e.g., monthly) timescales from those with strong memory persisting over multiple years (Fig. 4). In Europe, snow-dominated, high-elevation regions and regions with lakes tend to display short and strong memory, whereas long and strong memory is generally concentrated in areas with
 665 large aquifers and deep bedrock (e.g., Paris Basin and parts of Poland) (Fig. 6). This memory primarily originates through catchment processes rather than memory of precipitation, potential evaporation, or temperature, all of which are generally weaker than and geographically unaligned with streamflow memory. While memory of these meteorological conditions only weakly affects streamflow memory, the climatic setting consistently influences streamflow memory, with more arid locations tending to have more memory at monthly to yearly timescales. Our comparison of memory decay curves derived from
 670 observations to those derived from streamflow predictions of two commonly used hydrological models (mHM and EFAS) indicates that modelled streamflow, on average, has weaker monthly memory but stronger yearly memory compared to observed streamflow (Fig. 8). These overall biases and the distinct regional differences between modeled and observed memory (Fig. 8) helps to better understand how well longer-term streamflow dynamics are captured by existing models.

675 The presented memory behaviour of catchments bridges commonly studied event and annual timescales in streamflow autocorrelation. Moreover, it identifies regionally distinct memory behaviours across multiple timescales, which can help advance process understanding and hydrological modelling. Catchments with strong streamflow memory may be more resilient to short-term climate perturbations but are also catchments where anomalies are likely to persist for long times. Understanding of streamflow memory may also help the prediction of hydrological extremes, as strong streamflow memory could lead to
 680 temporally clustered extremes (Merz et al., 2016; Brunner and Stahl, 2023), and can increase understanding of when climatological conditions will lead to floods or droughts (Pelletier and Andréassian, 2020; Han et al., 2025; Sharma et al., 2018; Tarasova et al., 2023; Reager et al., 2014; Berghuijs and Slater, 2023).

Data availability

685 The core data used in this analysis are from EStreams v1.4 (Do Nascimento et al., 2024), which is available at <https://doi.org/10.5281/zenodo.10733141>. The mHM model results used for this analysis are available from the 4DHydro open science catalog (<https://4dhydro.eu/catalog>) as described by Droppers et al. (2024). EFAS v5.0 (Mazzetti et al., 2023) is



available from the Copernicus Emergency management service at <https://doi.org/10.24381/cds.e3458969>. Lake and wetland data is from GLWD v2, which is available at <https://doi.org/10.6084/m9.figshare.28519994>. Vegetation indices (Myneni et al., 2021) and nighttime lights (Elvidge et al., 2021) data were accessed via Google Earth Engine.

Author contributions

The methods were designed by MA and WRB. MA conducted all analyses and led the writing of the paper. All authors contributed to the interpretation of results and writing of the paper.

Competing interests

At least one of the (co-)authors is a member of the editorial board of Hydrology and Earth System Sciences.

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